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THE ROLE OF EDUCATION-INDUSTRY MATCH IN COLLEGE EARNINGS PREMIA

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There is substantial variation in the returns to a college degree. One determinant is whether a worker's employment is "matched" with their education. With a novel education-industry crosswalk and panel data on 295,000 graduates, we provide the first estimates of an education-industry match premium leveraging within-person variation in earnings. We document which majors have the most and least matching, how earnings premia vary across fields and gender, and how premia evolve over time. With robust estimators, we show that workers in industries "matched" with their degree experience an average earnings premium of 7-11%, with variation by degree level and major. (*JEL*: I20, I26, J24, J31)

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I. Introduction

While the individual and societal benefits of earning a college degree have been well documented over time (Carneiro et al., 2011; Heckman et al., 2018; Oreopoulos & Petronijevic, 2013), rising tuition and fee rates have produced a renewed focus on the “return on investment” of degrees. Individuals and policymakers alike increasingly worry whether the economic benefits of receiving a degree exceed its net present costs (Carnevale et al., 2019; Nietzel, 2023; Vandenbroucke, 2023). While college degrees do, on average, yield meaningful wage premia, there is substantial variation in the magnitude of these economic returns by individual ability, race, gender, institution, credential, and more (Grosz, 2020; Jepsen, 2014; Lovenheim & Smith, 2022; Oreopoulos et al., 2012; Ost et al., 2018). Understanding these sources of variation is of particular interest to individuals given their decision making around investments in a degree and subsequent occupational choice; to policymakers given their subsidization of higher education and concerns for larger workforce trends; and to researchers seeking to understand why returns to even the same credential vary across the population. One growing area of focus on the variation in these earnings premia pays particular attention to the role of alignment (or “match”) between an individual’s education and their work.

It has been well documented that earnings vary by major selection and occupational choice (Andrews et al., 2022; Sloane et al., 2021; Webber, 2016; Witteveen & Attewell, 2023). The intersection of these investigations focuses on quantifying an earnings premium for individuals who have matched their education and occupation (Cassidy & Gaulke, 2023; Light & Wertz, 2022; Robst, 2007; Yakusheva, 2010); when they hold a degree related to the role they perform. These include considerations of “vertical” match, or how earnings vary when one is over or under-educated for their job, and “horizontal” match, how earnings vary when one does or does not hold a degree topically or technically related to their occupation. This consideration draws upon the notions of human capital acquisition and signaling to suggest that employers pay workers more if they possess specialized knowledge, skills, and abilities—or signals of those traits—directly related to their job (Leighton & Speer, 2020; Lemieux, 2014; Sellami et al., 2018; Silos & Smith, 2015).

The relationship between majors, occupations, and earnings is complex, however, and prior works attempting to disentangle it have been challenged by a variety of factors, including endogeneity given individual selection into majors and occupations alongside data limitations inherent in existing cross-sectional or survey-based sources (Cassidy & Gaulke, 2023; Light & Wertz, 2022; Robst, 2007; Yakusheva, 2010). Beyond these concerns, research into the returns to college degrees has also failed to consider another important factor in wages: the specific industry within which an individual works.

Equipped with detailed student and worker-level panel data over a 10-year period, we leverage heterogeneity robust estimators and “within-person” variation in employment and earnings to estimate a distinct but likely overlapping measure of “horizontal” match—the match between one’s education and industry of employment. We empirically improve the precision of prior estimates on education-work “match” earnings premia by (1) controlling for the industry within which an individual works and (2) minimizing selection bias by exploiting within-person variation through individual worker fixed effects models—following the same workers over time and across “matched” and “unmatched” industries. We construct a novel education-industry crosswalk and present the first estimates to date of an *education-industry match* premium at the college level.[1] With more robust data, we also document heterogeneity in this match premia by level (e.g., bachelor's and associate degree), major, gender, and industry—and observe how these premia evolve over time.

Specifically, our study leverages panel records from the P20 Connect Tennessee Longitudinal Data System, which covers over 1.1 million students ever enrolled in a Tennessee public technical college, community college, or university between 2010 and 2020. These data capture students' actual education records, including credentials received by field, level, and institution. Over 295,000 ultimately earned at least one bachelor's or associate degree. We match these graduates to their earnings data using quarterly unemployment insurance (UI) records and follow them over time. Then, using the distribution of workers by occupation across industries nationally, we construct a novel crosswalk between Classification of Instructional Program (CIP) codes and three-digit North American Industry Classification System (NAICS) codes to identify whether these graduates are working in industries aligned with their degree. When combined, our administrative records and crosswalk allow us to assess whether labor market returns are higher when graduates work in industries closely aligned to their field of study. We follow these credentialed workers—by degree level, major, and gender—to document evidence of an education-industry match by first comparing earnings of workers with an education-industry match to those without, conditional on holding the same degree and, importantly, working in the same industry. Second, using a subset of workers who "switch" between matching and non-matching industries, we provide the first within-person estimates of an education-industry match premium. We also document which fields have the most education-industry match/mismatch and how premia evolve over time.

[1] Brunner et al. (2024) document an education-industry earnings premia for high school graduates who completed career and technical education in Connecticut.

Prior studies that quantify education-work "match" earnings premia focus on education-occupation match. The "education" component of this equation refers to one's formal program of study (i.e., typically their major), while the "work" component refers to their occupation (i.e., the specific role they perform). Our microdata capture individuals' industry of work but not their occupation. This allows us to explore a novel conceptualization of education-work alignment that emphasizes the context of *where* an individual works (i.e., industry) rather than just *what* they do (i.e., occupation). Because we cannot observe workers' occupations in addition to their industry of work, we are (like prior works) unable to fully disentangle an education-occupation match premium from an education-industry match premium. It is possible that if education and industry are aligned for a worker, their education and occupation could also be aligned. Therefore, our education-industry match estimates should be interpreted as a general measure of "horizontal" match which could reflect an education-occupation match or an independent education-industry match. An ideal improvement in this area would identify education-occupation match premia conditional on industry of work—or education-industry match premia conditional on occupation, though we are aware of no existing administrative datasets that have both industry and occupation identifiers to make disentangling these separate components possible.

We find that workers with an education-industry match enjoy a meaningful earnings premium of between 3% and 17%, with the exact premia depending on level of degree and time spent in the matched industry. This equates to roughly $800-$3,800 more in annual earnings for the average worker. Match wage premia are slightly larger for bachelor's degrees (7-17%) than for associate degrees (3-9%). For workers with associate degrees, we detect slightly larger effects for men than women (11-14% vs. 1-7%), but for workers with bachelor's degree, returns to education-industry match are meaningfully larger for women (8-19% compared to 7-14% for men). Within each level of degree, the importance of match in determining returns varies across fields of study with match particularly important for education, legal, and health degrees. We also show that workers with degrees in particularly specialized fields (e.g., health, engineering, education) represent larger shares of education-industry matched workers. Workers with "semi-specialized" degrees (e.g., electronics, management/administration, media and communications) or degrees that match to jobs particularly hard to obtain (e.g., aeronautics and aviation) represent smaller shares of matched workers; workers with general degrees (e.g., liberal arts, consumer economics, general studies) often never work in a matched industry.

Our robust evidence of a within-person difference in earnings between matched and unmatched industries contributes to the ongoing debate on whether different returns to even the same major or credential are due to differences in individual ability or to occupational factors (Andrews et al., 2022; Webber, 2016). We fully remove the role of individual ability and control for a host of other omitted variables present in prior works and show that industry remains a key explanatory factor in the variation in returns to a college degree—as well as an unexplored avenue for workers to increase the returns to their degree by way of an education-industry match premium.

This work also holds practical implications for institutions, credentialed jobseekers, and policymakers. Namely, our work not only identifies which majors most commonly experience industry matching but also what wage premia are associated with those matches. This may not only inform student and parent decisions around specific investments in education (or major or job choices) but may also support colleges and universities at targeting career transition supports overall and to students in majors more or less likely to experience matching after graduation.

This work also represents a new source of information for policymakers seeking to better understand why the returns to specific degrees vary across graduates, as well as which degree programs may be economically worthy of additional emphasis or public investment.

In what follows, we review prior works examining the returns to college degrees with a particular emphasis on education-occupation match and describe our extension of these studies. We then present our data, construction of a novel education-industry crosswalk, and our empirical strategy. We conclude with a discussion of our results, contributions, and key implications for future research and policy.

A. The Role of Industry in Explaining Worker Wages

Occupations correspond to roles of work (e.g., management, sales), whereas industries correspond to fields of work (e.g., healthcare, manufacturing). Most work on returns to education match focus on occupation rather than industry (Cassidy & Gaulke, 2023; Light & Wertz, 2022; Robst, 2007; Yakusheva, 2010). However, if the effect of one's education on wages is moderated by the occupation they perform, then so too should the effect be moderated by the industry within which they perform that work. That is, we hypothesize that the returns to a college degree also, in fact, depend on the industry of work and that the link between education and industry are important predictors of wages. In doing so, we emphasize the labor market salience of human capital acquisition and signaling of specialized training in the specific *field* within which one works. In doing so, we expand the conceptualization of determinants of the returns to college degrees by not only considering the role of occupation but also the role of industry. Conceptually, both of these matches (occupation and industry) relate to wages, as suggested by our proposed framework in Appendix Figure A.1. It is possible that the returns to a college degree vary if a worker's (1) education and occupation are closely linked [e.g., a biomedical engineer with a biomedical engineering degree, regardless of where they work (e.g., in government, medicine, or in the private biotechnology sector)], (2) education and industry are closely linked [e.g., a worker with a biomedical engineering degree working in biomedical or related industries, regardless of their role (e.g., administrator, engineer, or salesperson)], or (3) education, occupation, and industry are jointly linked [e.g., a biomedical engineer with a biomedical engineering degree working in the biomedical or a related industry].

The ability of prior works to consider education-industry matches has been limited by (1) an inability to empirically link majors and fields of study with industries, rather than occupations, and (2) available panel datasets that not only capture workers' education and wages linked to industries of work but that also follow workers over time, including across industries. Equipped with a novel education-industry crosswalk and individual panel data on up to 10 years of employment activity, our work fills these gaps by focusing on how an education-industry match—when one's education (i.e., major) and the field within which they work (i.e., industry) are closely linked—helps explain workers' earnings.

B. Estimating Earnings Premia from Education-Work Matching

It is common for credentialed workers to perform jobs unrelated to their specific education and training. Using the 1993 National Survey of College Graduates (NSCG), Robst (2007) found that only 55% of graduates reported working in a "closely related" field to their degree, while 25% reported performing a "somewhat" related job and 20% reporting work "not related" to their degree. In their recent update to Robst (2007), Cassidy and Gaulke (2023) observed that this incidence of "not related" mismatch has persisted over time, declining only marginally to 17% as of 2019. This nontrivial level of mismatch (i.e., a lack of alignment between individuals' education and their occupation) may help explain variation in the returns to college degrees.

Prior works have found that the economic returns to degrees are higher for graduates who "match" their education and occupation. That is, alignment between one's field of study and occupational role can yield higher wages than peers without such a match; conversely, "mismatch" can yield an earnings penalty. Most prior works have focused on quantifying this mismatch penalty. Robst (2007) found that men and women experienced a 10-11% wage penalty overall when they reported working in a field not related to their degree. However, this penalty varied substantially by degree field, increasing to 33% for men in health professions (i.e., among men who held a health degree, those who did not work in the health field [a mismatch] earned 33% less than those who did work in the health field [a match]) and 41% for women in computer and information science. Likewise, in their update to Robst (2007), Cassidy and Gaulke (2023) added cross-sectional observations from the 2003, 2010, and 2019 NSCG waves to show that the 10-11% mismatch wage penalty grew to 23% by 2019. Along this same line of inquiry, Yakusheva (2010) explored wages among students in the High School and Beyond (1980/92) cohort linked to Occupational Information Network (O*NET) codes and found that workers with an education-occupation match earned 29-30% more than peers without a match; up to 42% for bachelor's degree holders. While these works almost exclusively focus on education-occupation match premia (or mismatch penalty) for bachelor's degree holders and rely upon survey measures or cross-sectional records, they consistently point to the role of alignment between education and occupation in explaining earnings.

Despite these important contributions, no prior works to our knowledge have investigated earnings differences by industry of work. This is not only a limitation given our framing presented above, but this failure has likely also introduced bias given that industries with higher levels of education-occupation matching are also industries where workers enjoy higher earnings, on average. Indeed, both Robst (2007) and Cassidy and Gaulke (2023) showed that students in more specialized or technical majors were more likely to select into an education-occupation match after graduation. Fields with the highest levels of matching included computer and information sciences, health professions, engineering, and STEM broadly, suggesting that estimates from prior studies investigating an education-occupation earnings premia were heavily driven by students in these fields—capturing the effect of a match premia conflated with simple differences in earnings across industries. In fact, though they were also not able to condition on workers' industry, Witteveen and Attewell (2023) showed that, after controlling for one's degree of major specialization (a measure of the specificity or generality of one's education and training), the education-occupation match wage premium fell to as low as 3-5% in their sample.

Second, as noted, most prior works in this area have not only relied on survey data or cross-sectional cohorts but have also almost exclusively focused on estimating an earnings premium for bachelor's degree holders. We leverage individual student and worker-level panel records and consider how returns vary across bachelor's and associate degree holders, as well as by gender and field of study. We also further document which fields have the most education-industry match/mismatch and observe and how earnings premia evolve as worker spends more quarters "matched."

II. Data

Our data come from the P20 Connect Tennessee Longitudinal Data System. P20 captures the universe of public and private postsecondary enrollments and awards in the state, as well as UI records covering any in-state workforce participation. Our primary unit of analysis is an individual-quarter earnings record, allowing us to compare (1) earnings for workers in an industry closely linked to their field of study (i.e., an education-industry "match") to the earnings of workers with equivalent degrees who work in an "unmatched" industry, as well as (2) within-worker differences in earnings across quarters when they worked in a matched industry to quarters when they did not. We accomplish these comparisons by linking P20's workforce and academic records and following credentialed workers—by level of degree and major of degree—over time and across industry changes. We focus exclusively on post-graduate employment and earnings so as not to conflate our estimates with the effect of earning a degree or to conflate working while enrolled with work in other periods. All workers in our sample have already attained a postsecondary credential, and none are concurrently enrolled in higher education.

Our employment records capture individual-quarter workforce participation, including employment status, earnings, and employer characteristics. These cover all workers in the state from Q3 2010 through Q4 2020, allowing us to follow a potential 1,672,355 million unique individuals over 42 possible quarters. P20's employer characteristics classify each record by its respective NAICS code, allowing us to observe an individual's industry of work in every given quarter. NAICS codes are federal designations identifying separate industries of work in the U.S. economy and are maintained by the Census Bureau under the Office of Management and Budget. NAICS codes divide the economy into 20 large sectors (e.g., Health Care and Social Assistance, Manufacturing) which are comprised of multiple related sub-industries.[2] For our definition of education-industry match, we use NAICS codes at the three-digit level (e.g., the larger 62 [Health Care and Social Assistance] industry code, as well as more specific sub-categories, such as 621 [Ambulatory Health Care Services], 622 [Hospitals], 623 [Nursing and Residential Care

[2] For more information on NAICS, see https://www.census.gov/naics/reference_files_tools/2022_NAICS_Manual.pdf.

Facilities], and more).[3] These fields tell us the industry (subsector) within which an individual works, regardless of the role they perform. We do not observe workers' occupations.

P20 academic records capture whether and when a student earns any postsecondary credential in the state by degree level, as well as the field of the credential by 6-digit major CIP code. CIP codes organize academic degree programs by disciplinary or topical focus and are maintained by the U.S. Department of Education's National Center for Education Statistics (NCES). For example, CIP 26 identifies Biological and Biomedical Sciences, 26.08 identifies the sub-field of Genetics, and 26.0804 identifies the Animal Genetics sub-specialty. We observe this most comprehensive level of specificity. Between fall 2010 and fall 2020 (Q3 2010 through Q4 2020), our records cover over 1.11 million unique students ever enrolled in a public technical college, community college, or university in Tennessee. Over 308,000 of these students ever earned a bachelor's degree, and over 121,000 ever earned an associate degree; some earned both, representing a unique sample of over 295,000 graduates. In addition to this degree receipt by field, we can also observe a host of student factors, including gender, race, year of birth, residency status, college admissions test scores (i.e., ACT and SAT), GPA upon graduation, and total college credits earned. We drop any records where the CIP code for a credential is missing or undefined.[4] With P20 academic records, we are thus able to identify if, when, at what level, and in what field a worker earned a credential. We link these to P20 workforce records to observe these same individuals' earnings in each quarter and industry of work.

Because we can only observe credentials awarded during our panel window, we are unable to detect whether some workers in our UI data *already* held a certificate, associate degree, or bachelor's degree. We therefore restrict our analytic sample to only those who were ever

[3] 0.03% of our quarter-year observations have a "non-specified" NAICS code. We remove these cases.
[4] This results in the loss of records from 37 associate degree recipients and 2,014 bachelor's degree recipients.

enrolled and awarded a degree within our sample period. We drop any individuals who had more than one major for their awarded degree.[5] Furthermore, we do not consider (1) earnings for individuals who are concurrently enrolled in postsecondary education and working (i.e., those who have constrained time in the labor market and/or may be accumulating a "match") or (2) workers who earn a second degree during our panel (i.e., our sample of associate degree holders do not also hold a bachelor's degree and our sample of bachelor's degree holders to not also hold a graduate degree).[6] That is, we only use post-degree data on workers who earned a degree between fall 2010 and fall 2020 and never re-enrolled in higher education. This allows us to control for the potential effects of general human capital acquisition and/or signaling on earnings for our sample so that we are only differencing across matched and unmatched quarters, rather than earnings in quarters with and without a degree (or with fewer or more college credits). These restrictions give us a panel that starts in Q1 2011 and goes through Q4 2020.

We CPI adjust earnings to 2020 dollars and compute ln(quarterly earnings) based on an individual's total reported earnings in a given quarter. This variable is missing for any workers with no UI record in a given quarter, so regressions are based only on quarters where an individual was working and receiving some positive earnings.[7] We drop any employment records where an individual was younger than 17 or older than 65 at the time earnings were reported. We conduct our analyses separately on the returns to a bachelor's degree-industry match (115,348 graduates) and the returns to an associate degree-industry match (38,457 graduates).

[5] Hanks et al. (2024) show that double majors are more likely to work in occupations that require a diverse set of skills and less likely to work in occupations directly related to either of their majors. Since it is difficult to conceptualize match when a graduate has multiple majors, we drop these graduates.
[6] We only focus on workers' highest degrees. For example, some workers in our sample hold an associate degree and a bachelor's degree. We consider them bachelor's recipients only and analyze them in our BA sample.
[7] We focus on earnings conditional on employment because if someone is unemployed, they have no industry of employment and are thus not "matched" or "unmatched." Therefore, we do not explore employment as an outcome itself.

A. Linking Majors to Industries

Our primary goal is to estimate the difference in earnings premia by degree level, field, and gender for graduates who work in an industry closely aligned to their major field of study (a "match") compared to those who hold the same level of degree but do not work in a related field. To qualify a match between a worker's degree and their industry of work, we construct a novel crosswalk between major CIP codes and workforce NAICS codes. We do this by first linking education fields and occupations of work and then linking occupations with industries.

Construction of our crosswalk utilizes (1) the 2020 CIP to Standard Occupational Classification System (SOC) crosswalk created by the Bureau of Labor Statistics (BLS) and NCES and (2) the BLS Industry-Occupation Matrix Data, by occupation.[8,9] The CIP to SOC crosswalk matches postsecondary programs of study (identified by 2020 CIP codes) with occupations (identified by 2018 SOC codes) that use the skills and knowledge gained in a particular postsecondary program. This pre-existing crosswalk is not based on empirical data but was created by comparing the content of CIP and SOC descriptions by BLS and NCES.

It is important to note that this existing CIP-SOC crosswalk links degrees with occupations, not industries. Occupations correspond to roles of work (e.g., 11-0000 Management or 41-0000 Sales), whereas industries correspond to fields of work (e.g., 62 Health Care or 31-33 Manufacturing). Our paper focuses on the match between a program of study (major) and the field within which an individual works (industry), not the specific tasks they perform (occupation). For this study, we must further link CIP codes to NAICS codes. However, SOC codes serve as an important key in this link.

[8] National Center for Education Statistics. (2023). *CIP SOC Crosswalk*. https://nces.ed.gov/ipeds/cipcode/post3.aspx?y=56
[9] Bureau of Labor Statistics. (2023). *Industry-occupation matrix data, by occupation* (Table 1.8 2022-32 Industry-occupation matrix data, by occupation). https://www.bls.gov/emp/tables/industry-occupation-matrix-occupation.htm

The Bureau of Labor Statistics' Industry-Occupation Matrix Data, by occupation, report the distribution of employment by industry for each 6-digit SOC occupation code. That is, among workers who perform a given occupation (SOC), what share work in a given NAICS-coded industry? We use the distributions corresponding to 3-digit NAICS codes for our crosswalk. We start with the full set of CIP-SOC matches from the BLS-NCES crosswalk. We then add a SOC-NAICS link if at least 10% of people in that occupation are employed in that NAICS 3-digit industry.[10,11] This is visually depicted in Figure 1.

As an illustrative example, consider CIP code 51.0803 [Occupational Therapist Assistant]. This is linked with SOC occupation code 31-2011 [Occupational Therapy Assistants] in the existing BLS-NCES CIP-SOC crosswalk. This means students with majors in occupational therapy assistant typically perform roles as occupational therapy assistants, regardless of industry, as determined by BLS and NCES. When identifying "matched" industries for this occupation, we do not link this SOC with NAICS 611000 [Educational services; state, local, and private] because only 5.5% of occupational therapy assistants work in this industry (an education setting) according to the BLS industry-occupation matrix. We do, however, link this SOC with NAICS 62100 [Ambulatory healthcare services] because 55% of occupational therapy assistants work in this industry (physician clinics, hospitals, home health agencies, and in outpatient centers; above our 10% threshold). Therefore, our final crosswalk matches CIP 51.0803

[10] For government jobs only: Because a 3-digit code corresponding to government employment does not appear in the BLS industry-occupation matrices, we sum the shares of employment in 99100 [Federal government], 999200 [State government], and 99300 [Local government] to create a 999 employment share. Whenever 999 is an industry match for an SOC, we include the full set of government-related 3-digit NAICS codes as matches to enable matches with the NAICS codes in the TN UI data: 921 [Executive, legislative, and other general government support], 922 [Justice, public order, and safety activities], 923 [Administration of human resources programs], 924 [Administration of environmental quality programs], 925 [Administration of housing programs, urban planning and community development], 926 [Administration of economic programs], 927 [Space research and technology], and 928[National security and international affairs].

[11] We also assess robustness of our education-industry earnings premia results to using a 5% or 20% cutoff and find equivalent results.

[Occupational Therapist Assistant] with industry 621 [Ambulatory healthcare services] but not industry 611 [Educational services; state, local, and private]. This match is empirically based on the distribution of workers who are actually employed in these industries nationally.

Our final crosswalk maps all 6-digit CIP codes to 3-digit NAICS codes. For CIP codes appearing in our crosswalk, the median number of matches for a CIP code to NAICS is 4; the minimum is 1, and the maximum is 22. That is, the median number of links for each major is four industries. Some CIP codes do not appear in our crosswalk because the original CIP-SOC crosswalk indicated "NO MATCH" to an occupation for that CIP. These cases are rare and were pre-determined by BLS and NCES.[12] Finally, approximately 8% of our quarter-year observations have more than one NAICS industry, meaning that some workers hold more than one job in a quarter, including jobs across at least two different industries. We code an observation as having an education-industry match in a quarter-year if any industry of work in that period matches to their degree major.

Table 1 reports descriptive statistics on our analytic samples. Among the roughly 38,000 associate degree graduates, 25% only ever work in a matched industry post-degree, 57% never work in a matched industry, and 18% are "switchers" —individuals who work in a matched industry in some quarters and an unmatched industry in other quarters of our panel. Among the roughly 115,000 bachelor's degree recipients in our sample, 25% only ever work in related industries; 51% only ever work in unrelated industries, and 23% switch between working in a related and unrelated industry sometime in our panel. While these are *industry* connections, these

[12] In the associates degree sample, 5% of CIP awarded fall into this group of no SOC match. The share is 14% in the bachelor's degree sample. The two most commonly awarded AA CIPs with no SOC match are 51.9999 "Health Professions and Related Clinical Sciences, Other" and 32.0111 "Workforce Development and Training", and the two most common BA CIPs with no SOC match are 30.9999 "Multi-/Interdisciplinary Studies, Other" and 09.0102 "Mass Communication/Media Studies."

distributions are qualitatively similar to Robst (2007) and Cassidy and Gaulke (2023) who observed that roughly half of workers in their samples reported working in related *occupations*.

We observe an average of 24-28 quarters post-degree, or roughly six years of their labor market trajectory. The average associates graduate in our sample is four years older upon graduation than the average bachelor's graduate (30 versus 26 years old). This difference in age and work experience likely explains the slightly better employment and earnings outcomes for associates graduates relative to bachelor's degree holders. Across our associate sample, the average worker earns over $8,200 quarterly when employed, or roughly $33,000 annually; the average bachelor's degree holder earns over $7,900 quarterly or almost $31,600 annually. The majority of our sample is White (75-82%) and female (56-64%).

Prior works have shown that students in highly specialized majors are more likely to select into an education-occupation match following graduation, including occupations that themselves have higher average earnings (Cassidy & Gaulke, 2023; Robst, 2007). Earnings differences between these workers and others could thus capture differences in education and training or simply differences in worker motivation and individual ability. We find slight evidence of positive selection into an education-industry match among associate and bachelor's degree recipients; however, such differences are relatively small in magnitude. Associate graduates who always work in a matched industry in our sample have ACT scores 0.5 points higher and college GPAs 0.14 higher than those who only ever work in unrelated industries. The difference is 0.6 ACT points and 0.08 GPA points compared to workers who sometimes work in unrelated industries. These differences for bachelor's graduates are 0.5 ACT points and 0.24 GPA points, and 0.6 ACT points and 0.23 GPA points, respectively. Thus, prior descriptive cross-sectional regressions that failed to control for individual characteristics likely overstated the returns to education-occupation matches and would do the same when estimating an education-industry match premium. We not only control for individual differences when comparing earnings across workers but also leverage within-worker variation in our preferred specification to net out any such concerns of selection.

III. Empirical Strategy

Leveraging our novel education-industry crosswalk, we assess whether the labor market returns to a college degree are higher when graduates work in industries closely aligned to their field of study. The simplest approach is to compare earnings between workers with an education-industry match and those without:

$$(1) \qquad y_{ijmct} = \beta \text{Match}_{ijt} + \gamma_j + \delta_m + \rho_c + \phi_t + \theta_{t-t_{i0}} + \mathbf{X}_{i(t)}\Gamma + \varepsilon_{ijmct} \,,$$

where y captures the earnings for individual i, working in industry j, with degree m from college c, in absolute year-quarter t. Match indicates whether individual i was working in an industry matched to their degree field in year-quarter t. Year-quarter fixed effects (ϕ_{t}) control any shocks experienced by all workers in a given period t and ensure earnings between matched and unmatched workers are compared in the same time period. We also condition on industry of work (γ_j) and major of degree (δ_m) fixed effects to absorb variation in earnings and earnings trajectories across industries and ensure that earnings comparisons between matched and unmatched workers are conditional on receiving the same degree by level and field and working in the same industry. We also include institution-of-degree fixed effects (ρ_c) to control variation in earnings and earnings trajectories between graduates from different institutions.

We can estimate equation (1) separately by degree level (associate degree, bachelor's degree) and gender. Additionally, because workers in our setting earned degrees in different year-quarters, we can condition on relative year-quarter fixed effects ($\theta_{t-t_{i0}}$), where t_{i0} is the year-quarter in which an individual received their bachelor's (or associate) degree. This allows us to compare differences in earnings for workers in matched and unmatched periods who are at the same point in their labor market trajectory measured relative to their credential receipt. **X** captures observable time-variant and invariant worker characteristics, including gender, race, college admissions test scores, GPA upon graduation, and total college credits, as well as age polynomials. Here, β is our coefficient of interest and represents the average quarterly earnings premium across individuals who hold a degree linked to their industry of work.

Because our P20 data follow credentialed workers over time and across job changes, we can also leverage within-worker variation to estimate the wage premium of an education-industry match using a conventional two-way fixed effects (TWFE) approach. To isolate this effect, we compare workers' own earnings in quarters when they were in an industry matched to their education to earnings in quarters when they worked in an unmatched industry. This takes advantage of industry "switchers," workers with a degree in a given field who move across matched and unmatched industries across our 10-year panel. Recall, 24% of bachelor's degree holders (n=27,079) and 18% of associate degree holders (n=6,734) in our sample make at least one switch in our study window. Here, we estimate:

(2) $$y_{ijt} = \beta \text{Match}_{ijt} + \alpha_i + \gamma_j + \phi_t + \theta_{t-t_{i0}} + \mathbf{X}_{it}\Gamma + \varepsilon_{ijt} \ ,$$

where the equation is defined similarly to equation (1) but now includes individual worker fixed effects (α_i) which control for time-invariant worker features and allow us to leverage within-person variation in earnings across matched and unmatched quarters of work. This estimation also includes fixed effects for industry and controls for worker age. β is again our coefficient of interest and here represents the average quarterly earnings premium for an individual when they work in an industry closely related to their field of study. We can again estimate equation (2) separately by degree level and gender and consider how this premium varies across majors and industries using models with interaction effects.

However, traditional TWFE may be biased if treatment effects are heterogeneous and evolve in the presence of differential timing across workers (de Chaismartin & d'Haultfoeuille, 2020; Liu et al., 2024). For instance, if the earnings premium from education-industry match varies depending on how many quarters it has been since a worker entered a matched industry, TWFE estimates can suffer from the "negative weights" problem. Therefore, our preferred estimates use the matrix completion (MC) counterfactual estimator from Liu et al. (2024).[13] This estimator allows for treatment reversal (i.e., workers moving in and out of matched industries) and uses data under the control condition to impute counterfactuals for treated observations. Since counterfactuals are constructed using non-treated observations, the negative weights problem is avoided by construction. The MC estimator also has the added advantage of using untreated observations to account for potential time-varying confounders semi-parametrically. In all estimates generated from the matrix completion estimator, we control for age polynomials, industry fixed effects, and quarters relative to degree receipt. Standard errors are obtained through bootstrapping, clustering at the unit (student/worker) level.[14]

IV. Results

A. Matching across Fields and Industries

Before presenting estimates of the education-industry match earnings premium, we explore descriptive patterns in education-industry match rates by CIP code. We classify each graduate in our sample into one of three mutually exclusive categories. A graduate is classified as "only ever matched" if in every quarter with positive earnings they were working in an

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[13] We implement this estimator using the fect package in Stata (Liu et al., 2023).
[14] The procedure iteratively drops one unit's entire time-series from the dataset.

industry matched to their CIP code, “never matched” if they never had a quarter of positive earnings where they were working in an industry matched with their CIP code, or a “switcher” if they have at least one quarter with positive earnings where they are working in a matched industry and at least one quarter with positive earnings where they are working in an unmatched industry. Then, we calculate the share of awardees that fall into each of these categories by CIP code and rank CIP codes by this share.

Table 2 reports the top five CIP codes with the largest shares of awardees who only ever work in a matched industry (Panel A), never work in a matched industry (Panel B), or sometimes match and sometimes do not match (Panel C) for associate and bachelor’s degree recipients separately. Medical degrees dominate among CIP codes with awardees who always work in matched industries. The only non-medical degree that appears on either the associate or bachelor’s degree top five list of “always matchers” is 13.1202 [Elementary Education and Teaching]. Since prior literature has found that medical degrees offer stronger returns than most other types of degrees, particularly among two-year degree options, these descriptive patterns beg the question of whether the high returns to medical degrees are driven specifically by (1) this high degree of alignment between training and employment (i.e., a match premium), (2) positive selection of students into medical degrees, or (3) the development of transferrable skills that could deliver strong earnings returns in a non-medical industry (Liu et al. 2014; Jepsen et al., 2014; Kim and Tamborini, 2019; Stevens et al., 2019; Grosz, 2020).

There is a wider range of fields represented in the group of CIP codes where graduates never work in matched industries or are commonly switching between matched and unmatched industries during our post-degree window. CIP codes where graduates are commonly working in “unmatched” industries include degree programs focused on broad skills and knowledge, such as

24.0102 [General Studies] and 24.0101 [Liberal Arts and Sciences/Liberal Studies], as well as degree programs offering specialized training in a narrow field where employment may be difficult to obtain (e.g., 10.0304 [Animation, Interactive Technology, Video Graphics and Special Effects] and 49.0101 [Aeronautics/Aviation/Aerospace Science and Technology, General]).[15] This lack of education-employment match could explain the relatively weaker returns to liberal arts degrees or specialized fields that offer limited employment opportunities found in prior work (Webber, 2016; Andrews et al. 2022; Odle & Russell, 2023). Finally, CIP codes with high shares of "switchers" include 12.0503 [Culinary Arts/Chef Training], 52.0904 [Hotel/Motel Administration/Management], 51.1001 [Human Resources], and 15.0612 [Industrial Technology/Technician]. These descriptive patterns are important to keep in mind when comparing earnings premia models that use variation across workers versus variation within workers since some fields have greater shares of "switchers" than others.

B. Effects of Education-Industry Match on Earnings

Table 3 presents the estimated earnings premia using convention TWFE models. Across all models, we find a sizeable, statistically significant, and practically meaningful education-industry match premium for both associate and bachelor's degree holders. Across all samples, adding controls for the CIP code of the degree awarded (column 2) substantially decreases estimated earnings premia relative to models with a rich set of student and academic controls, suggesting that selection into major is an important determinant of returns to degree and would otherwise bias estimates of match premia (Andrews et al., 2022; Leighton & Speer, 2020). Adding further fixed effects for the college/university which awarded the degree (column 3), however, does little to alter the estimates. This suggests that there is actually little variation in

[15] The only industry code matched to 24.0101 and 24.0102 is 611 [Educational Services]. This link was generated by the CIP-SOC link between these two CIP codes and the SOC code 25-1199 [Postsecondary Teachers, All Other].

earnings across institutions in the same sector (i.e., associate, bachelor's) in our sample after accounting for an individual's specific major.

As hypothesized, the role of industry does appear important in explaining workers' wages and in estimating an education-industry match premium. Conditioning on industry of work fixed effects reduces the estimated premia by 1-2 percentage points for bachelor's degree recipients, as well as by nearly 5 points for male associate degree holders (column 4). This alone conceptually shows that accounting for one's industry of work is an important factor in explaining wages and the college earnings premium. Overall, match premia are slightly larger for bachelor's degree holders than for associate degree holders. With the TWFE specification which includes both individual and industry fixed effects (column 6), the estimated earnings match premia are 13% for bachelor's degree graduates and 9% for associate degree graduates. Economically, this 9-13% premium is associated with a rough increase in annual earnings of $1,900 for associate degrees and $2,500 for bachelor's degrees. Match also appears to matter more for women than men among workers with a bachelor's (15% for women versus 10% for men), but the reverse is true for associate degrees (8% for women versus 10% for men). Appendix Tables A.2 and A.3 assess robustness of these results to using a 5% or 20% cutoff for the occupational share when constructing our education-industry crosswalk to define match. We find that the estimated premia are very similar if we use a 5% or 20% cutoff rather than 10%.

Next, we turn to the heterogeneity robust matrix completion estimator results. Figure 2 displays dynamic treatment effects plots for the impact of education-industry match on earnings. Visually, we see evidence of parallel pre-trends up to two quarters prior to match. At quarters one and two prior to match, earnings are significantly depressed, consistent with an Ashenfelter-style dip where earnings decline in the quarters immediately prior to an industry transition

(Ashenfelter, 1978). Then, there is an extremely large, statistically significant drop in earnings in the first quarter of education-industry match. Although we cannot observe labor supply intensity (i.e., hours of work), we suspect this drop is due to job transitions. As people quit or leave their unmatched industry job and begin a new matched industry job, they may not be working as intensively during the prior unmatched quarter or first matched quarter. For instance, they may have been unemployed for some months during the quarter, depressing overall earnings. These dynamic plots indicate that it is important to use only longer-run differences and exclude the two periods prior to education-industry match and the first period of match. Appendix Table A.1 repeats the TWFE estimation dropping these three quarters.[16] Results are qualitative similar, though estimated earnings premia are somewhat larger than the original estimates. Although these results account for transient endogeneity, they could still suffer from heterogeneity bias.

In Table 4, we report the heterogeneity-robust matrix completion average treatment effects on the treated (ATT) estimates for 2 quarters after match to 10 quarters after match. (We omit the first quarter of match due to the aforementioned potential for mechanical job transition impacts in that quarter.)[17] As was shown in the dynamic plots, the return to match increases over roughly the first 4 quarters of match. After that point, returns level out to 6-7% for associate degree holders and 12-14% for bachelor's degree holders. There is some variation by gender with men having higher ATTs in the associate degree sample and women having higher ATTs in the bachelor's degree sample. Ultimately, the magnitude and statistical significance of the estimated match premia are fairly similar to the traditional TWFE estimates that include both worker and industry fixed effects.

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[16] Prior work estimating returns to degrees such as Jepsen et al. (2014) has adopted this approach of dropping some quarters prior to treatment.
[17] In results available upon request, we show that any match effects generally level off after this point.

We also explore whether the earnings penalty from exiting education-industry match is comparable to the earnings premia from transitioning into education-industry match. Dynamic plots based on matrix completion estimation in Figure 3 show that effects are roughly symmetric. Associates degree holders have earnings that are about 7-8% higher than comparable never treated workers (i.e., never matchers) four to five quarters prior to exiting match; earnings then fall in the quarters immediately prior to exit. By two quarters after exiting match, their earnings are statistically indistinguishable from those who only ever worked in unmatched industries. The pattern is similar for bachelor's degree holders. Four to five quarters prior to exiting match, their earnings are 13-15% higher, consistent with the previously estimated match earnings premium, but then after exit, the earnings difference falls to a precisely estimated zero.

C. Heterogeneity by Major and Industry

To investigate heterogeneity in the importance of education-industry match by major, we categorize CIP codes into 14 broad field categories based on the first two digits of the CIP code: education, legal, engineering/IT/math, business, medical, communications, public administration, arts, physical sciences, production and transport, social sciences, services, humanities, and general studies. Then, for our TWFE estimation, we estimate a version of equation (2) where we interact Match with these 14 field categories—still conditioned on individual and industry fixed effects. These results are shown in Table 5.

Table 5 shows a positive, statistically significant, and economically meaningful match earnings premia for all bachelor's degree fields except "General Studies" which includes CIP codes for liberal arts, general studies, and multidisciplinary studies. Consistent with prior work on occupational match, the estimated industry match premia are relatively larger for education, legal, and medical degrees (Cassidy & Gaulke, 2023; Robst, 2007; Yakusheva, 2010), where the estimated premia for a matched bachelor's degree holder in each of these fields is 30% or higher. Results are more imprecisely estimated for associate degrees, and several of the field categories have very few associate degree CIP codes and graduates. For example, the social science field at the associate degree level only includes one CIP code: 45.0702 [Cartography], and we only have 20 graduates in our sample with this degree. However, we do see similar patterns of returns for fields with larger numbers of graduates, such as for legal and medical associate degrees, which have over 400 and 11,000 graduates respectively.

Table 6 repeats the analysis using the matrix completion counterfactual estimation. For this analysis, we limit the sample to graduates with the indicated degree type and category. Then, we re-estimate the education-industry match premia using matrix completion counterfactual estimation on that subsample and report the ATT three quarters after education-industry match begins to abstract from the temporary job that could be due to job transitions. Estimates are more imprecise than those in Table 5, likely because we must estimate a separate model for each field category in order to use the matrix completion estimator as opposed to one model with interaction terms. Results generally fail to provide conclusive evidence on heterogeneity by field, though it is notable that medical degrees at the both the AA and BA levels have large and statistically significant industry match returns (12% and 24%, respectively).

Taken as a whole, the results indicate that obtaining employment in a related industry is important for wages but that this match is particularly more important for some degrees than others.

D. Limitations

While our study makes conceptual contributions to the study of the returns to college degrees alongside empirical improvements upon prior works in this area, ours is not without notable limitations. First, as previously noted, because we cannot observe workers' occupations in addition to their industry of work implied through our crosswalk, we are (like prior works) unable to fully disentangle an education-occupation match premium from an education-industry match premium.

Second, while we make considerable improvements by leveraging within worker variation in earnings to overcome concerns of endogeneity and improve the precision of prior estimates, it is important to consider whether our sample of "switchers" is representative of the larger population of workers. While any possible positive selection into education-industry matching would not bias our estimates, it is possible our starting population of switchers is relatively unique in that they are more likely to come from "semi-specialized" degree programs (e.g., electronics, culinary arts, management/administration, media and communications) and work in a select group of industries (e.g., hospitals; ambulatory health care services; professional, scientific, and technical services; food services and drinking places).

Finally, because we construct a novel education-industry crosswalk, there are modeling decisions that could influence our results. Namely, we identify a major as mapping to an industry if at least 10% of workers from an occupation linked to that degree are employed in that industry. This occurs because we cannot observe workers' actual education-occupation pairings and link those to industries within our sample. It is therefore possible that our threshold is not restrictive enough—capturing "matches" that are not true or practically meaningful—or, conversely, too restrictive—failing to detect some true matches that are meaningful. However, these would mean our results are understated by saturating our "matched" pool with false matches of low magnitude or inflating our control (unmatched) observation with matches. Across robustness checks, however, we show that our results are largely unchanged when using 5% and 20% thresholds.

V. Conclusion

While earning a college degree generally provides individuals with increased earnings in the labor market, there is substantial variation in this benefit across workers, even among workers who may have earned the same degree from the same institution (Grosz, 2020; Jepsen, 2014; Lovenheim & Smith, 2022; Oreopoulos et al., 2012; Ost et al., 2018). One contributor to this variation is whether a worker's employment is "matched" with their educational training (Cassidy & Gaulke, 2023; Light & Wertz, 2022; Robst, 2007; Yakusheva, 2010). With a novel education-industry crosswalk applied to a 10-year panel covering over 295,000 college graduates, we show that workers in industries "matched" with their associate or bachelor's degree field experience an earnings premium of 3-17% (approximately $800-$3,800 in annual earnings). This match produces significant and economically meaningful returns for graduates who achieve this matching—especially for graduates in specific fields and degree levels.

Given heightened public and private interests in the return on investment to college degrees (Carnevale et al., 2019; Nietzel, 2023; Vandenbroucke, 2023), our results hold important implications for policy and practice. Namely, our work begs an expansion of conversations around what factors lead to stronger economic returns to degrees to considerations of industry of work. In doing so, colleges and universities may consider supporting students' transitions from majors into occupations, industries, or both occupations and industries closely aligned with their education and training. Our work may help institutions to target specific career supports to students in lower-matching fields or equip students and parents with specific information on what majors are most closely aligned with occupations and industries—and which education-industry pairings yield the highest wage premia. These findings may also be of particular interest to policymakers given ongoing conversations surrounding which degree programs may be economically worthy of additional emphasis or public investment, as well as what policy interventions may be required to ensure all students have equal access to “high” return-on-investment majors (Bleemer et al., 2023).

Our work also extends the debate around human capital acquisition and signaling in explaining wages generally as well as the college earnings premium. Leveraging within-worker variation in employment and earnings, we observe that a worker with a constant “signal” (i.e., the same degree) earns more when they work in an industry closely related to their education and training than when they do not. This suggests that there are, in fact, industry-specific skills or abilities individual acquires through education and training that raise wages. This is true when we also compare earnings across workers from the same college with the same degree and, importantly, even when we condition on industry of work fixed effects that net out the possibility that different industries value general college skills or signals differently.

Our study also broadens the empirical understanding of what explains variation in the economic returns to college degrees and lays an important foundation for future research. We show that prior works have overlooked the important role of industry in explaining workers’ wages both generally and in explaining why returns to even the same degree vary across the population. That is, we empirically show that conditioning on industry of work alone meaningfully changes estimates of the college earnings premium. We also show that a reliance on self-reported matches and/or cross-sectional data paired with workers’ self-selection into majors and occupations has resulted in an overstatement of the wage-premium magnitude. Given that the incidence of matching varies across occupations and industries, subsequent investigations should consider whether the saturation of matching matters. That is, is an education-industry match premium larger in industries where few other workers have a match (i.e., when a worker is “uniquely” trained) or smaller when most other workers also have a match (i.e., when a match is the “norm”)? In addition, since both occupation and industry “matches” matter in explaining variation in workers’ wages, future studies should examine the potential for a joint education-industry-occupation match premium. In all, future works should empirically acknowledge the labor market salience of specialized training in the specific field within which one works alongside specialized training for the specific role one performs.

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Figure 1. *Major to industry crosswalk, linking CIP to SOC codes and SOC to NAICS codes.*

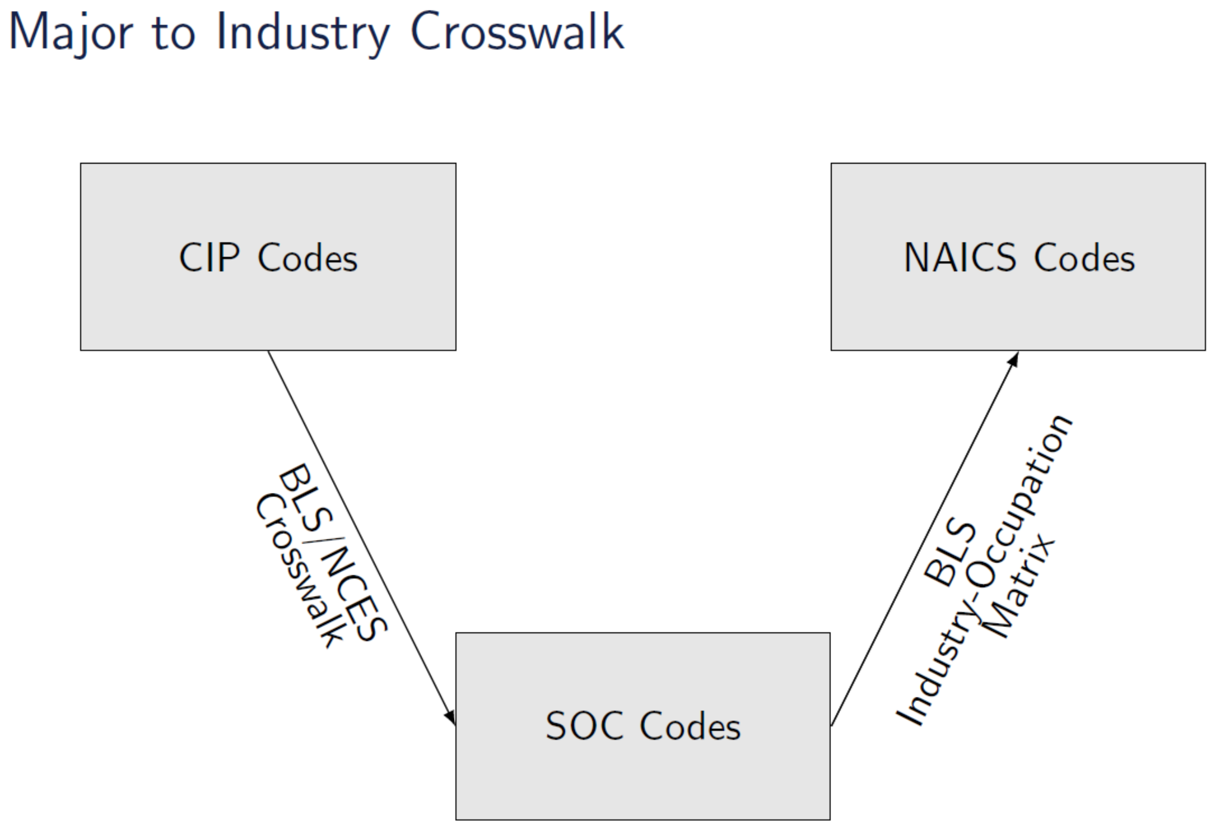
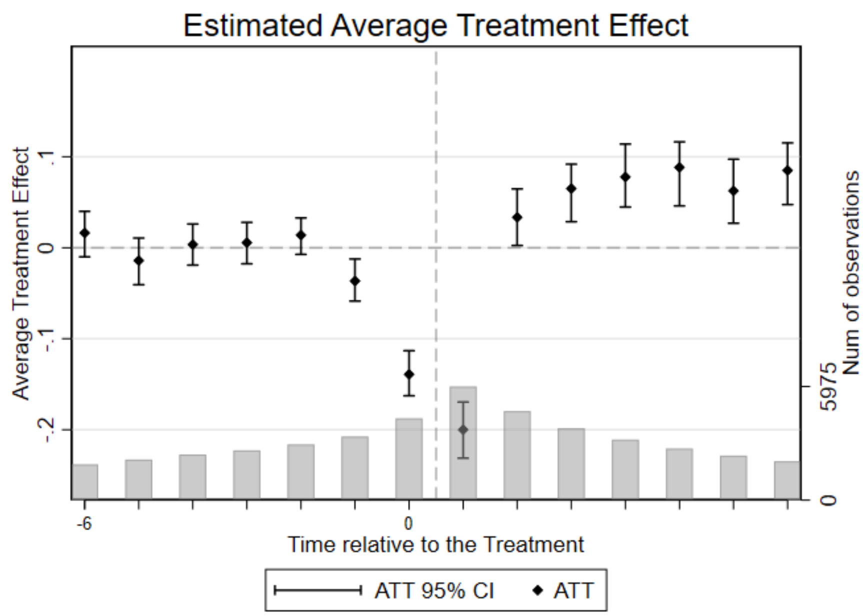
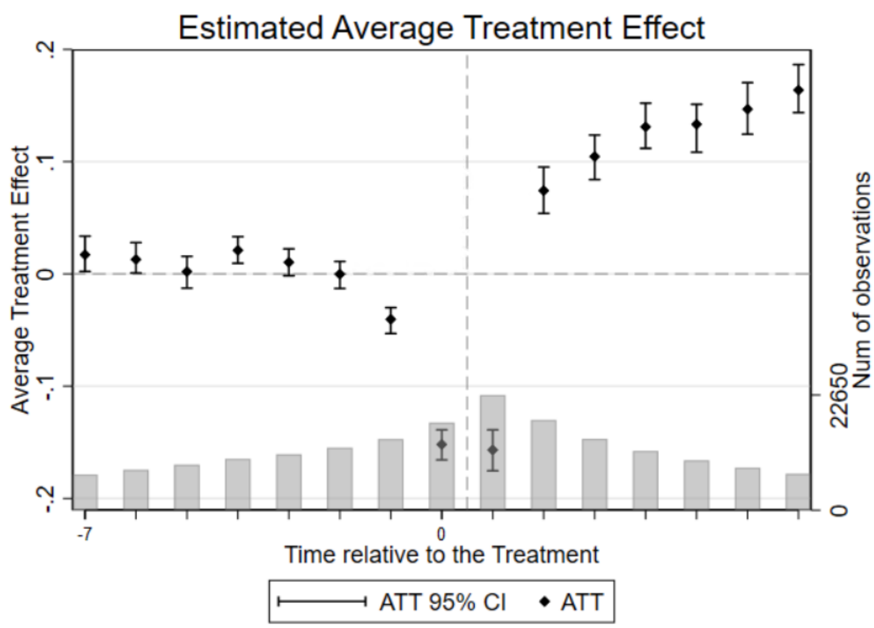


Figure 2. *Dynamic treatment effects plots: Entering education-industry match.*

(a) Associate Degree Sample:



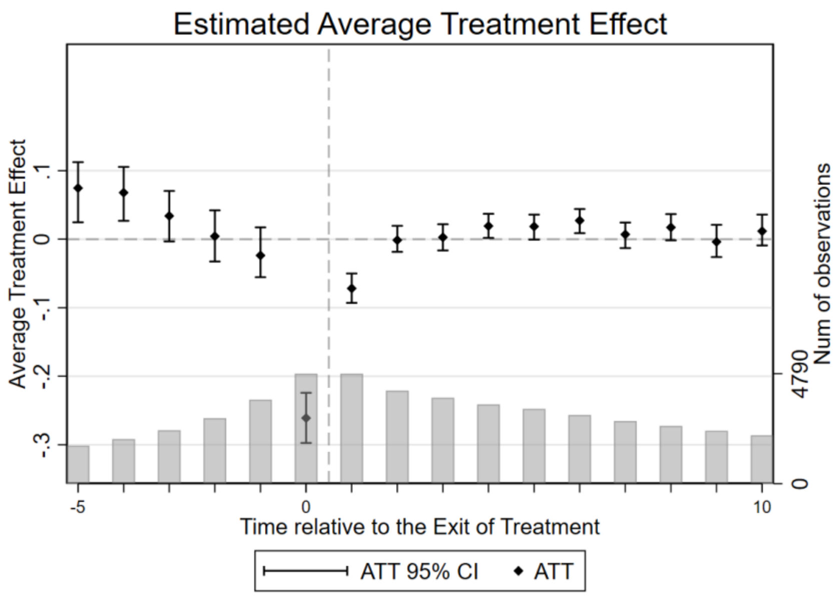
(b) Bachelor's Degree Sample:



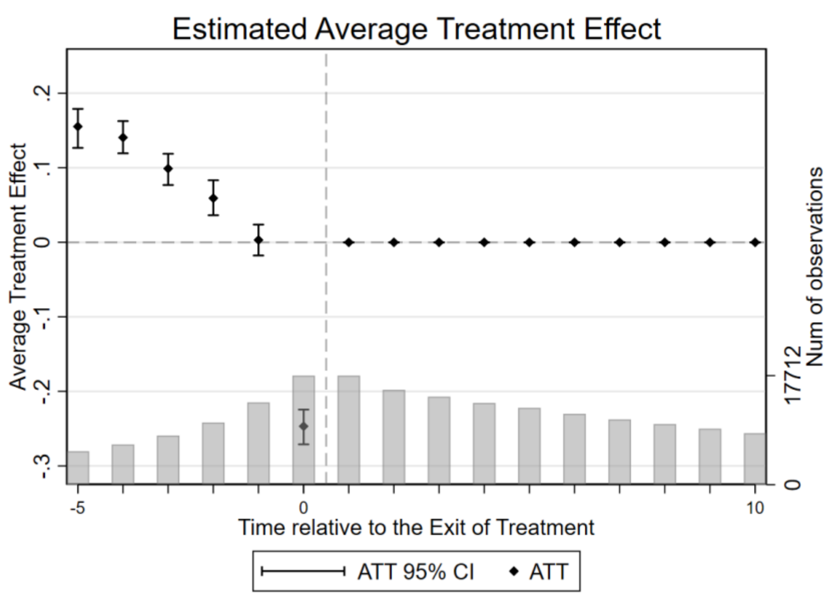
Notes: Estimation based on the matrix completion estimator of Liu et al. (2024). Dependent variable is the natural log of quarterly earnings CPI adjusted to 2020 dollars. The dependent variable is missing for any quarters with 0 earnings. Estimated model includes industry fixed effects, individual fixed effects, age polynomials, quarter relative to degree receipt, and year-quarter fixed effects. Error bars plot 95% confidence intervals using bootstrapped standard errors..

Figure 3. *Dynamic treatment effects plots: Exiting education-industry match.*

(a) Associate Degree Sample:



(b) Bachelor's Degree Sample:



Notes: Estimation based on the matrix completion estimator of Liu et al. (2024). Dependent variable is the natural log of quarterly earnings CPI adjusted to 2020 dollars. The dependent variable is missing for any quarters with 0 earnings. Estimated model includes industry fixed effects, individual fixed effects, age polynomials, quarter relative to degree receipt, and year-quarter fixed effects. Error bars plot 95% confidence intervals using bootstrapped standard errors. In panel (b), confidence intervals are so narrow that lower and upper bound brackets appear visually on top of the diamond point estimate markers.

Table 1. *Descriptive statistics for associate and bachelor's degree analysis samples.*

	Associate				Bachelor's			
	All	Only Ever Matched	Never Matched	Switcher	All	Only Ever Matched	Never Matched	Switcher
	N=38,457 (100.0%)	N=9,684 (25.2%)	N=22,039 (57.3%)	N=6,734 (17.5%)	N=115,348 (100.0%)	N=29,311 (25.4%)	N=58,958 (51.1%)	N=27,079 (23.5%)
Characteristics								
Age at Degree Receipt	29.6	31.8	28.2	30.9	25.6	26.1	25.6	25.2
Female	0.64	0.76	0.57	0.69	0.56	0.66	0.51	0.55
Race: African American	0.10	0.08	0.10	0.12	0.15	0.10	0.16	0.17
Race: Am. Indian or AK Native	0.003	0.003	0.003	0.003	0.003	0.002	0.003	0.003
Race: Asian	0.01	0.01	0.01	0.01	0.02	0.02	0.03	0.02
Race: White	0.82	0.85	0.81	0.81	0.75	0.81	0.73	0.74
Race: Multiple or Other	0.07	0.05	0.07	0.06	0.07	0.07	0.08	0.06
ACT Score	20.1	20.5	20.0	19.9	22.5	22.9	22.4	22.3
College GPA	3.16	3.25	3.11	3.17	3.16	3.34	3.10	3.11
Labor Market Outcomes								
Quarters Post-Degree	25.8	25.3	24.8	28.4	26.2	24.9	25.9	28.0
Employed	0.787	0.833	0.744	0.839	0.708	0.736	0.650	0.787
Ln(Earnings>0) (2020$)	9.014	9.240	8.895	9.022	9.069	9.241	9.012	9.020
Earnings (2020$)	$8,231	$10,073	$7,100	$8,916	$7,918	$9,048	$7,076	$8,463
N (Individual-Quarter)	719,664	173,653	382,306	163,705	2,271,884	519,497	1,111,821	640,566

Notes: Table reports means for graduates with either an associate or bachelor's degree in the analysis sample. Means for the characteristics are from person-level data. Means for the labor market outcomes are from quarter-year data.

Table 2. *Degree fields with highest and lowest rates of education-industry match, by match status and degree level.*

	CIP Code	CIP Title	Share of Awardees
Panel A: Only Ever Work in Matched Industry			
Associate	51.0904	Emergency Medical Technology/Technician	0.892
	51.0909	Surgical Technology/Technologist	0.824
	51.0907	Medical Radiologic Tech/Science – Radiation Therapist	0.815
	51.0803	Occupational Therapist Assistant	0.747
	51.0601	Dental Assisting/Assistant	0.744
Bachelor’s	13.1202	Elementary Education and Teaching	0.886
	51.0911	Radiologic Technology/Science – Radiographer	0.859
	51.3801	Registered Nursing/Registered Nurse	0.794
	51.0602	Dental Hygiene/Hygienist	0.792
	51.3801	Nursing	0.715
Panel B: Never Work in Matched Industry			
Associate	51.1004	Clinical/Medical Laboratory Technician	0.967
	15.0403	Electromechanical Tech/Electromechanical Engineering Tech	0.905
	24.0102	General Studies	0.901
	24.0101	Liberal Arts and Sciences/Liberal Studies	0.899
	15.0613	Manufacturing Engineering Technology/Technician	0.898
Bachelor’s	49.0101	Aeronautics/Aviation/Aerospace Science and Tech, General	0.983
	10.0304	Animation, Interactive Tech, Video Graphics and Special Effects	0.946
	19.0901	Apparel and Textiles, General	0.933
	19.0402	Consumer Economics	0.929
	51.1005	Clinical Laboratory Science/Medical Technology/Technologist	0.919
Panel C: Switchers (Some Quarters Matched, Some Unmatched)			
Associate	26.1201	Biotechnology	0.485
	12.0503	Culinary Arts/Chef Training	0.477
	47.0101	Electrical/Electronics Equipment Installation/Repair, General	0.462
	52.0904	Hotel/Motel Administration/Management	0.438
	11.0901	Computer Systems and Telecommunications	0.425
Bachelor’s	52.1001	Human Resources Management/Personnel Admin, General	0.453
	15.0612	Industrial Technology/Technician	0.444
	42.2804	Industrial Organizational Psychology	0.442
	51.0706	Health Information/Medical Records Admin/Administrator	0.433
	11.0801	Web Page, Digital/Multimedia, Information Resources Design	0.423

Notes: Excludes any CIP codes with fewer than 25 graduates and any CIP codes that do not appear in the CIP-NAICS crosswalk (i.e., any CIP codes where no match is possible.) Table reports top 5 CIP codes ranked by share of awardees who only ever work in a matched industry (Panel A), share never work in matched industry (Panel B), and share of awardees who work in a matched industry at least one quarter and in an unmatched industry at least one quarter (Panel C).

Table 3. *Estimated education-industry match earnings premia, by degree level and gender, using two-way fixed effects estimation.*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Bachelor's - All						
Matched	0.197***	0.120***	0.119***	0.104***	0.133***	0.128***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
N	1,374,621	1,374,621	1,374,621	1,374,621	1,601,357	1,601,357
Panel B: Bachelor's - Women						
Matched	0.221***	0.143***	0.144***	0.118***	0.164***	0.151***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
N	756,281	756,280	756,280	756,280	894,603	894,603
Panel C: Bachelor's - Men						
Matched	0.166***	0.093***	0.091***	0.078***	0.096***	0.099***
	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)	(0.008)
N	618,356	618,356	618,356	618,356	706,754	706,754
Panel D: Associate - All						
Matched	0.363***	0.045***	0.043***	0.074***	0.092***	0.085***
	(0.008)	(0.011)	(0.011)	(0.012)	(0.010)	(0.010)
N	339,875	339,875	339,875	339,875	564,319	564,319
Panel E: Associate - Women						
Matched	0.401***	0.007	0.004	0.074***	0.081***	0.076***
	(0.010)	(0.015)	(0.015)	(0.016)	(0.012)	(0.013)
N	214,548	214,548	214,548	214,548	362,330	362,330
Panel F: Associate - Men						
Matched	0.278***	0.112***	0.110***	0.059***	0.110***	0.103***
	(0.014)	(0.017)	(0.017)	(0.019)	(0.015)	(0.017)
N	125,327	125,327	125,327	125,327	201,989	201,989
Student Covariates	Yes	Yes	Yes	Yes	-	-
CIP FE	No	Yes	Yes	Yes	-	-
College FE	No	No	Yes	Yes	-	-
Industry FE	No	No	No	Yes	No	Yes
Individual FE	No	No	No	No	Yes	Yes
Estimator	OLS	TWFE	TWFE	TWFE	TWFE	TWFE

Notes: Student covariates are gender, race indicators, cumulative college GPA and ACT admission test score. Dependent variable is the natural log of quarterly earnings CPI adjusted to 2020 dollars. The dependent variable is missing for any quarters with 0 earnings. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Table reports coefficients and robust standard errors (in parentheses) clustered at the student/worker level. Columns 1-4 correspond to equation (1); columns 5-6 to equation (2). Ns are Individual-Quarter observations.

Table 4. *Estimated education-industry match earnings premia, by degree level and gender, using matrix completion counterfactual estimation.*

	(1)	(2)	(3)	(4)	(5)	(6)
		Associate			Bachelor's	
	All	Women	Men	All	Women	Men
Average Treatment Effects						
Two Quarters	0.033*	0.012	0.089***	0.074***	0.076***	0.068***
	(0.017)	(0.022)	(0.025)	(0.010)	(0.012)	(0.014)
N	4,683	3,256	1,427	17,736	9,767	7,969
Three Quarters	0.065***	0.046**	0.109***	0.105***	0.108***	0.096***
	(0.017)	(0.023)	(0.026)	(0.010)	(0.013)	(0.013)
N	3,779	2,624	1,155	14,017	7,732	6,285
Four Quarters	0.078***	0.061**	0.115***	0.131***	0.140***	0.116***
	(0.017)	(0.025)	(0.028)	(0.010)	(0.014)	(0.014)
N	3,184	2,196	988	11,642	6,399	5,243
Five Quarters	0.088***	0.066***	0.140***	0.133***	0.142***	0.121***
	(0.018)	(0.024)	(0.028)	(0.010)	(0.015)	(0.016)
N	2,719	1,886	833	9,807	5,377	4,430
Six Quarters	0.063***	0.044*	0.107***	0.147***	0.154***	0.135***
	(0.019)	(0.027)	(0.031)	(0.011)	(0.015)	(0.016)
N	2,347	1,622	725	8,358	4,573	3,785
Seven Quarters	0.085***	0.060**	0.141***	0.164***	0.189***	0.131***
	(0.019)	(0.026)	(0.032)	(0.011)	(0.016)	(0.016)
N	2,050	1,421	629	7,151	3,905	3,246
Eight Quarters	0.073***	0.050**	0.128***	0.163***	0.176***	0.143***
	(0.019)	(0.025)	(0.33)	(0.012)	(0.015)	(0.016)
N	1,768	1,421	532	6,080	3,323	2,757
Nine Quarters	0.070***	0.045*	0.133***	0.149***	0.165***	0.123***
	(0.021)	(0.027)	(0.033)	(0.12)	(0.015)	(0.017)
N	1,505	1,045	460	5,242	2,859	2,383
Ten Quarters	0.067***	0.052*	0.106***	0.169***	0.190***	0.138***
	(0.021)	(0.028)	(0.038)	(0.013)	(0.016)	(0.017)
N	1,295	895	400	4,470	2,415	2,055

Notes: Dependent variable is the natural log of quarterly earnings CPI adjusted to 2020 dollars. The dependent variable is missing for any quarters with 0 earnings. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Controls include age polynomials, indicators for quarters relative to degree receipt, and industry fixed effects. Table reports estimated ATTs and bootstrapped standard errors (in parentheses). Ns are the number of treated individuals used in the counterfactual estimation.

Table 5. *Heterogeneity in education-industry match earnings premia, by field of degree, using two-way fixed effects estimation.*

	(1)	(2)	(3)	(4)	(5)	(6)
		Associate			Bachelor's	
	All	Women	Men	All	Women	Men
Match x Education	0.619***	0.692***	0.052	0.461***	0.452***	0.422***
	(0.191)	(0.206)	(0.312)	(0.024)	(0.027)	(0.052)
Match x Legal	0.135***	0.095	0.504**	0.299***	0.372***	-0.010
	(0.058)	(0.059)	(0.250)	(0.109)	(0.124)	(0.157)
Match x Eng/IT/Math	0.080***	0.146***	0.071***	0.151***	0.243***	0.137***
	(0.020)	(0.058)	(0.022)	(0.013)	(0.045)	(0.014)
Match x Business	-0.005	-0.004	0.005	0.040***	0.055***	0.034***
	(0.018)	(0.022)	(0.033)	(0.008)	(0.013)	(0.011)
Match x Medical	0.164***	0.143***	0.249***	0.320***	0.309***	0.343***
	(0.017)	(0.019)	(0.041)	(0.022)	(0.023)	(0.059)
Match x Communication	0.023	-0.015	0.075	0.045***	0.087***	0.003
	(0.061)	(0.103)	(0.064)	(0.018)	(0.022)	(0.028)
Match x Pub Admin	-0.014	-0.088	0.465***	0.282***	0.263***	0.329***
	(0.156)	(0.170)	(0.078)	(0.036)	(0.038)	(0.117)
Match x Arts	0.059	0.066	0.068	0.107***	0.097***	0.142***
	(0.084)	(0.113)	(0.126)	(0.025)	(0.031)	(0.041)
Match x Phys Science	0.175	0.147	0.197	0.147***	0.123***	0.182***
	(0.110)	(0.146)	(0.134)	(0.022)	(0.031)	(0.032)
Match x Manual	-0.099		-0.053	0.079***	0.109***	0.065**
	(0.082)		(0.079)	(0.025)	(0.042)	(0.030)
Match x Soc Science	-1.147	-0.423***	-3.381***	0.095***	0.094***	0.108***
	(0.768)	(0.020)	(0.073)	(0.014)	(0.016)	(0.024)
Match x Service	0.197***	0.162***	0.271***	0.118***	0.110***	0.133***
	(0.044)	(0.059)	(0.067)	(0.016)	(0.022)	(0.024)
Match x Humanities				0.101***	0.096***	0.118***
				(0.021)	(0.028)	(0.032)
Match x Gen Studies	-0.043	-0.069	-0.005	-0.016	-0.068	0.075
	(0.037)	(0.046)	(0.057)	(0.033)	(0.043)	(0.050)
N (Individual-Quarter)	564,319	362,330	201,989	1,601,357	894,603	706,754

Notes: Dependent variable is the natural log of quarterly earnings CPI adjusted to 2020 dollars. The dependent variable is missing for any quarters with 0 earnings. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Table reports coefficients and robust standard errors (in parentheses) clustered at the student/worker level. Estimated model for columns (1) and (2) matches equation (2) in the text and includes industry fixed effects, individual fixed effects, age polynomials, quarter relative to degree receipt, and year-quarter fixed effects.

Table 6. *Heterogeneity in education-industry match earnings premia, by field of degree, using matrix completion matrix completion counterfactual estimation.*

	(1) Associate	(2) Bachelor's
Match for Education	0.359	0.314
	(1.403)	(0.612)
	[18]	[867]
Match for Legal	0.434	1.169
	(1.127)	(10.123)
	[73]	[12]
Match for Engineering/IT/Math	-0.175**	0.352
	(0.080)	(0.205)
	[510]	[1268]
Match for Business	0.093	0.076
	(0.063)	(0.102)
	[828]	[3777]
Match for Medical	0.123***	0.236***
	(0.043)	(0.049)
	[1596]	[836]
Match for Communications	-1.675	-0.049
	(0.967)	(0.078)
	[67]	[1055]
Match for Public Administration	4.236	0.234
	(1.572)	(0.656)
	[8]	[291]
Match for Arts	0.454	0.164
	(0.284)	(0.101)
	[39]	[596]
Match for Physical Science	0.062	0.557
	(4.679)	(1.324)
	[11]	[620]
Match for Manual	0.047	0.077
	(0.318)	(0.056)
	[19]	[479]
Match for Social Science		0.028
		(0.161)
		[1806]
Match for Service	0.028	0.129***
	(0.134)	(0.036)
	[213]	[1249]
Match for Humanities		-0.064
		(0.269)
		[819]
Match for General Studies	-0.081	0.004
	(0.088)	(0.056)
	[495]	[342]

Notes: Dependent variable is the natural log of quarterly earnings CPI adjusted to 2020 dollars. The dependent variable is missing for any quarters with 0 earnings. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Controls include age polynomials, indicators for quarters relative to degree receipt, and industry fixed effects. Table reports matrix completion counterfactual estimator ATT three quarters after education-industry match and bootstrapped standard errors (in parentheses). Brackets report number of treated graduates in counterfactual estimation.

APPENDIX

Appendix Figure A.1 *Conceptual relationship between education, occupation, and industry with wages.*

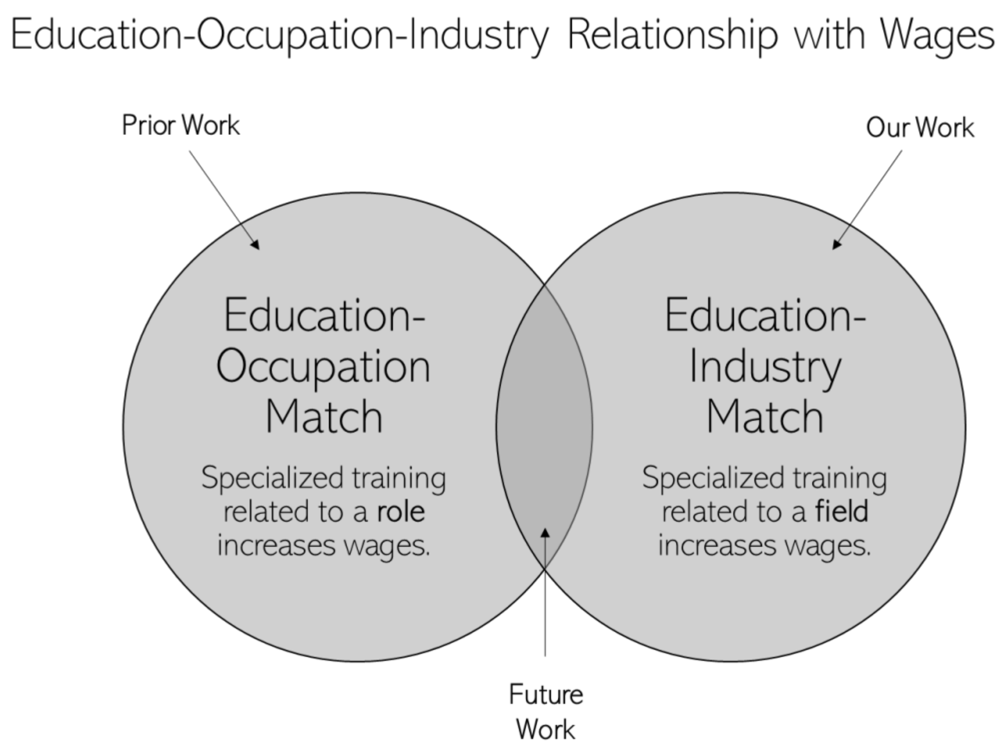


Table A.1. *Robustness of estimated education-industry match earnings premia after dropping two quarters prior to match and quarter of match*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Bachelor's - All						
Matched	0.228***	0.154***	0.153***	0.132***	0.146***	0.140***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)
N	1,277,178	1,277,176	1,277,176	1,277,176	1,485,853	1,485,853
Panel B: Bachelor's - Women						
Matched	0.249***	0.176***	0.177***	0.144***	0.171***	0.159***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)
N	698,615	698,614	698,614	698,614	825,148	825,148
Panel C: Bachelor's - Men						
Matched	0.203***	0.128***	0.126***	0.109***	0.117***	0.119***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.009)
N	578,563	578,560	578,560	578,560	660,705	660,705
Panel D: Associate - All						
Matched	0.398***	0.084***	0.081***	0.101***	0.101***	0.091***
	(0.008)	(0.012)	(0.011)	(0.013)	(0.011)	(0.011)
N	321,668	321,667	321,667	321,667	531,329	531,329
Panel E: Associate - Women						
Matched	0.438***	0.046***	0.043***	0.101***	0.083***	0.075***
	(0.010)	(0.015)	(0.015)	(0.016)	(0.014)	(0.014)
N	201,450	201,448	201,448	201,448	338,474	338,474
Panel F: Associate - Men						
Matched	0.310***	0.149***	0.146***	0.086***	0.129***	0.120***
	(0.014)	(0.017)	(0.017)	(0.020)	(0.017)	(0.019)
N	120,218	120,217	120,217	120,217	192,855	192,855
Student Covariates	Yes	Yes	Yes	Yes	-	-
CIP FE	No	Yes	Yes	Yes	-	-
College FE	No	No	Yes	Yes	-	-
Industry FE	No	No	No	Yes	No	Yes
Individual FE	No	No	No	No	Yes	Yes
Estimator	OLS	TWFE	TWFE	TWFE	TWFE	TWFE

Notes: Student covariates are gender, race indicators, cumulative college GPA and ACT admission test score. Dependent variable is the natural log of quarterly earnings CPI adjusted to 2020 dollars. The dependent variable is missing for any quarters with 0 earnings. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Table reports coefficients and robust standard errors (in parentheses) clustered at the student level. Columns 1-4 correspond to equation (1); columns 5-6 to equation (2). Ns are Individual-Quarter observations.

Table A.2. *Robustness of estimated education-industry match earnings premia to using alternate 5% occupation share crosswalk cutoff.*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Bachelor's - All						
Matched	0.231***	0.135***	0.134***	0.106***	0.150***	0.139***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
N	1,374,621	1,374,621	1,374,621	1,374,621	1,601,357	1,601,357
Panel B: Bachelor's - Women						
Matched	0.239***	0.155***	0.155***	0.128***	0.182***	0.167***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
N	756,281	756,280	756,280	756,280	894,603	894,603
Panel C: Bachelor's - Men						
Matched	0.221***	0.113***	0.111***	0.079***	0.115***	0.108***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)	(0.007)
N	618,356	618,356	618,356	618,356	706,754	706,754
Panel D: Associate - All						
Matched	0.402***	0.103***	0.100***	0.102***	0.122***	0.101***
	(0.008)	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)
N	339,875	339,875	339,875	339,875	564,319	564,319
Panel E: Associate - Women						
Matched	0.452***	0.062***	0.056***	0.120***	0.123***	0.107***
	(0.010)	(0.017)	(0.017)	(0.017)	(0.015)	(0.014)
N	214,548	214,548	214,548	214,548	362,330	362,330
Panel F: Associate - Men						
Matched	0.303***	0.155***	0.153***	0.072***	0.116***	0.094***
	(0.013)	(0.016)	(0.016)	(0.017)	(0.014)	(0.015)
N	125,327	125,327	125,327	125,327	201,989	201,989
Student Covariates	Yes	Yes	Yes	Yes	-	-
CIP FE	No	Yes	Yes	Yes	-	-
College FE	No	No	Yes	Yes	-	-
Industry FE	No	No	No	Yes	No	Yes
Individual FE	No	No	No	No	Yes	Yes
Estimator	OLS	TWFE	TWFE	TWFE	TWFE	TWFE

Notes: Student covariates are gender, race indicators, cumulative college GPA and ACT admission test score. Dependent variable is the natural log of quarterly earnings CPI adjusted to 2020 dollars. The dependent variable is missing for any quarters with 0 earnings. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Table reports coefficients and robust standard errors (in parentheses) clustered at the student level. Columns 1-4 correspond to equation (1); columns 5-6 to equation (2). Ns are Individual-Quarter observations.

Table A.3. *Robustness of estimated education-industry match earnings premia to using alternate 20% occupation share crosswalk cutoff.*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Bachelor's - All						
Matched	0.178***	0.100***	0.100***	0.110***	0.127***	0.136***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
N	1,374,621	1,374,621	1,374,621	1,374,621	1,601,357	1,601,357
Panel B: Bachelor's - Women						
Matched	0.206***	0.127***	0.127***	0.124***	0.156***	0.155***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
N	756,281	756,280	756,280	756,280	894,603	894,603
Panel C: Bachelor's - Men						
Matched	0.140***	0.068***	0.066***	0.082***	0.086***	0.106***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)
N	618,356	618,356	618,356	618,356	706,754	706,754
Panel D: Associate - All						
Matched	0.336***	0.027**	0.024**	0.073***	0.087***	0.092***
	(0.008)	(0.011)	(0.011)	(0.012)	(0.009)	(0.010)
N	339,875	339,875	339,875	339,875	564,319	564,319
Panel E: Associate - Women						
Matched	0.359***	-0.012	-0.015	0.057***	0.071***	0.078***
	(0.010)	(0.014)	(0.014)	(0.015)	(0.011)	(0.012)
N	214,548	214,548	214,548	214,548	362,330	362,330
Panel F: Associate - Men						
Matched	0.279***	0.109***	0.104***	0.083***	0.111***	0.115***
	(0.014)	(0.018)	(0.018)	(0.020)	(0.016)	(0.017)
N	125,327	125,327	125,327	125,327	201,989	201,989
Student Covariates	Yes	Yes	Yes	Yes	-	-
CIP FE	No	Yes	Yes	Yes	-	-
College FE	No	No	Yes	Yes	-	-
Industry FE	No	No	No	Yes	No	Yes
Individual FE	No	No	No	No	Yes	Yes
Estimator	OLS	TWFE	TWFE	TWFE	TWFE	TWFE

Notes: Student covariates are gender, race indicators, cumulative college GPA and ACT admission test score. Dependent variable is the natural log of quarterly earnings CPI adjusted to 2020 dollars. The dependent variable is missing for any quarters with 0 earnings. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Table reports coefficients and robust standard errors (in parentheses) clustered at the student level. Columns 1-4 correspond to equation (1); columns 5-6 to equation (2). Ns are Individual-Quarter observations.