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# The Role of Education-Industry Match in College Earnings Premia

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Many states incentivize college students to major in fields aligned with specific, often "in-demand" industries. While their goal is often to raise students' labor market outcomes, little is known about whether matching one's degree with an industry of work improves employment and earnings. We leverage a novel education-industry crosswalk applied to student and worker panel data covering over 295,000 graduates to estimate an education-industry match premium that leverages withinperson variation in earnings. We document which fields have the most and least education-industry matching, how match premia vary across fields, and how match premia evolve over time. We show that workers in industries "matched" with their college degree field experience an average earnings premium of about 5-10%, though these premia vary by gender, field, level of degree, and how long a worker has been working in a matched industry. These findings shed new light on how education, occupation, and industry explain wages and offer important insights for future work and individual investments in higher education.

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**Abstract**
Many states incentivize college students to major in fields aligned with specific, often "in-demand" industries. While their goal is often to raise students' labor market outcomes, little is known about whether matching one's degree with an industry of work improves employment and earnings. We leverage a novel education-industry crosswalk applied to student and worker panel data covering over 295,000 graduates to estimate an education-industry match premium that leverages within-person variation in earnings. We document which fields have the most and least education-industry matching, how match premia vary across fields, and how match premia evolve over time. We show that workers in industries "matched" with their college degree field experience an average earnings premium of about 5-10%, though these premia vary by gender, field, level of degree, and how long a worker has been working in a matched industry. These findings shed new light on how education, occupation, and industry explain wages and offer important insights for future work and individual investments in higher education. (*JEL*: I20, I26, J24, J31)

*Keywords*: college major choice; education-industry match; returns to college degrees; wages

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# The Role of Education-Industry Match in College Earnings Premia

## Introduction

While the benefits of earning a college degree have been well documented (Carneiro et al., 2011; Heckman et al., 2018; Oreopoulos & Petronijevic, 2013), rising tuition and fee rates have renewed a focus on the "return on investment" of credentials. 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 returns by individual ability, race, gender, institution, credential, and more (Grosz, 2020; Jepsen, 2014; Lovenheim & Smith, 2023; 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 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, 2024). Some work has quantified an earnings premium for individuals who match their education and occupation by holding a degree related to the role they perform, a type of "horizontal" match (Cassidy & Gaulke, 2024; Light & Wertz, 2022; Manuel, 2024; Robst, 2007; Yakusheva, 2010). These studies draw 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; Odle & Russell, 2023; Sellami et al., 2018; Silos & Smith, 2015).

Most prior studies that quantify the education-work "match" earnings premia focus narrowly on education-occupation match, an approach that is difficult to replicate or assess with administrative data. State longitudinal data systems, for example, capture workers' *industries* with a North American Industry Classification System (NAICS) code—but typically not their *occupations*. Policymakers and researchers who increasingly rely on these sources to evaluate postsecondary outcomes lack the ability to easily assess education-occupation match. However, they can assess the extent to which students achieve an education-industry match, a potentially valuable indicator of graduates' labor market success. In fact, many states have recently implemented financial aid programs based on education-industry alignment. These programs target grant aid towards students pursuing majors aligned or "matched" with high demand industries in the state. For instance, Kentucky has the Work Ready Kentucky Scholarship, which awards last-dollar aid for programs aimed towards preparing workers for the manufacturing, construction, and healthcare industries.[1] Georgia has HOPE Career Grants, which are awarded to students in select majors aligned with industries the state defines as high demand.[2] Other states with similar programs include Indiana, Kansas, Virginia, Colorado, Idaho, and South Carolina. The underlying premise of these programs is twofold: states benefit from a workforce better equipped to work in key industries, and individuals gain through higher earnings and job prospects. Thus, examining whether graduates in specific majors actually achieve this intended education-industry match—and whether it yields higher earnings—is an important question.

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[1] For more details, see https://workreadykentucky.com/.
[2] For more details, see https://www.gafutures.org/hope-state-aid-programs/hope-zell-miller-grants/hope-career-grant.

In this paper, we conceptualize education-work alignment by focusing on education-industry match: the relationship between a graduate's field of study (i.e., typically their major) and the industry in which they work. Our study leverages panel records from the P20 Connect Tennessee Longitudinal Data System (TN DATA), 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 education records, including credentials received by field, level, and institution. Over 295,000 students in our population 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, which describe a student's major field, and three-digit NAICS codes to identify whether graduates work in a related industry.

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 among the first within-person estimates of an education-industry match premium.[3] In addition to workers' earnings, we also consider whether achieving an education-industry match influences the likelihood of

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

employment in subsequent quarters. Finally, we also document which fields have the most education-industry match/mismatch and how premia evolve over time.

We find that workers with an education-industry match enjoy a meaningful earnings premium of about 5-10% with the exact premium depending on level of degree and time spent in the matched industry. This equates to roughly $1,600-$2,800 more in annual earnings for the average worker. Match wage premia are generally larger for bachelor's degrees (about 10%) than for associate degrees (about 5%) and may be associated with a slightly higher likelihood of continuous employment. Within each level of degree, the importance of match in determining returns varies substantially across fields of study with match particularly important for education, legal, engineering, 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.

In all, our work makes a conceptual contribution to the study of the returns to college degrees alongside several empirical improvements upon prior work. When we remove the role of individual ability through within-worker models, condition on industry of work, and control for a host of omitted variables present in prior works, our heterogeneity robust estimates show that industry-matching is one 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. This 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. Our work lays the foundation for more exploration into the role of education, occupation, and industry in separately explaining earnings.

In what follows, we conceptually define the role of industry in explaining workers' wages and frame our consideration of an education-industry wage premium. We then review prior works examining the returns to college degrees with a particular emphasis on the related, but distinct, education-occupation match. We then present our data, 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.

**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, 2024; Light & Wertz, 2022; Manuel, 2024; 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 rather than only specialized training for the specific *role* one performs. Conceptually, both 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., an accountant with an accounting degree, regardless of where they work], (2) education and industry are closely linked [e.g., a worker with an accounting degree working in finance or related industries, regardless of their role], or (3) education, occupation, and industry are jointly linked [e.g., an accountant with an accounting degree working in finance or a related industry]. Our study focuses on this second, underexplored relationship between education and industry.

***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 that the work in their principal job was "closely related" to the field of their highest degree, while 25% reported performing a "somewhat" related job and 20% reporting work "not related" to their degree. In their update to Robst (2007), Cassidy and Gaulke (2024) 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 role), at least as assessed by workers themselves, may help explain variation in the returns to degrees.

These studies have shown 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 for peers without such a match; conversely, "mismatch" can yield an earnings penalty. Robst (2007) found that men and women experienced a 10-11% wage penalty overall when they reported working in an unrelated field. However, this penalty varied substantially by major, 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 earned 33% less than those who did work in the health field) and 41% for women in computer and information science. Likewise, in their update to Robst (2007), Cassidy and Gaulke (2024) 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 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 focus on education-occupation match premia and mismatch penalties for bachelor's degree holders and rely upon survey measures or cross-sectional records, they consistently point to the role of education-work alignment in explaining earnings.

Our study makes several extensions to this existing body of work. First, no prior works to our knowledge have conditioned earnings differences on industry of work. We empirically define and explore this link between a worker's education and their industry of work in explaining wages. Second, we leverage within-person variation in earnings, where we follow the same worker across matched and unmatched roles, providing some control over concerns for positive selection into matched (mismatched) industries and higher-paying fields. Finally, as noted, many prior works have also almost exclusively focused on estimating premia bachelor's degree holders. We leverage administrative panel data 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."

**Data**

Our administrative records come from TN DATA, which captures the universe of public and private postsecondary enrollments and awards in Tennessee, 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 TN DATA'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.

Our employment records capture individual-quarter workforce participation, including employment status, earnings, and employer characteristics. Our records cover all workers in the state from Q3 2010 through Q4 2020, allowing us to follow a potential 1,672,355 unique individuals over 42 possible quarters. TN DATA'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.[4] 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 Facilities], and more).[5] These fields tell us the industry and subsector within which an individual works, regardless of the role they perform. Like other state administrative datasets, we do not observe workers' occupations.

TN DATA academic records capture whether and when a student earns any 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

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

[5] 0.03% of our quarter-year observations have a "non-specified" NAICS code. We remove these cases.

total college credits earned. We drop any records where the CIP code for a credential is missing or undefined.[6] With TN DATA 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 TN DATA's 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 enrolled and awarded a degree within our sample period. We drop any individuals who had more than one major for their awarded degree.[7] Furthermore, because we are interested in isolating the effect of an education-industry match alone, we do not consider (1) earnings for individuals who are concurrently enrolled in a community college or university 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).[8] 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 community college or a university. 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. These restrictions give us a panel that starts in Q1 2011 and goes through Q4 2020.

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[6] This results in the loss of records from 37 associate degree recipients and 2,014 bachelor's degree recipients.
[7] 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.
[8] 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.

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 undefined 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.[9] Recall that TN DATA leverage UI records, so quarters without positive earnings reflect actual cases of $0 earnings or a lack of participation in the state labor market—not a case of missing data. We drop 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).

***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.[10,11] The CIP to SOC crosswalk matches postsecondary programs of study (identified by 2020 CIP codes) with

[9] We focus on earnings conditional on employment because if someone is unemployed, they have no industry of employment are not "matched" or "unmatched."
[10] National Center for Education Statistics. (2023). *CIP SOC Crosswalk*. https://nces.ed.gov/ipeds/cipcode/post3.aspx?y=56
[11] 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

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.

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.[12] (We also assess robustness of our education-industry earnings premia results to using a 5% or 20% cutoff and find equivalent results.) This is depicted in Figure 1.

[12] 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].

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 [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 in our crosswalk, the median number of matches 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.[13] Finally, approximately 8% of our quarter-year observations have more than one

[13] 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."

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 38,500 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 distributions are qualitatively similar to Robst (2007) and Cassidy and Gaulke (2024) who observed that roughly half of their workers self-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, 2024; 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; such differences are all statistically significant at the 1% level given our large sample sizes but 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, descriptive cross-sectional regressions that fail to control for individual characteristics likely overstate the returns to education-occupation matches—and would do the same when estimating education-industry match premia. We not only control for individual differences when comparing earnings across workers but also leverage within-worker variation in our preferred specification to provide additional protection against such concerns of selection.

**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 by estimating:

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

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 ($\phi_{\mathrm{t}}$) 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 ($\gamma_j$) and include major-by-college ($\delta_{mc}$) 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 (from the same institution, by level and field) and working in the same industry.[14]

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, total college credits, age polynomials, and a control for being enrolled in a technical college. Here, $\beta$ 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 TN DATA records 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

[14] If a worker has multiple employment records in a quarter, we assign the industry fixed effect based on the record with the highest earnings, as this is likely the earnings from the worker's "primary" job.

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:

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

where the equation is defined similarly to equation (1) but now includes individual worker fixed effects ($\alpha_i$) 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, a control for any technical college enrollment, and cubic polynomials for worker age. We estimate robust standard errors clustered at the individual level.[15] $\beta$ 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 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. We also explore dynamic treatment effects by replacing $\text{Match}_{ijt}$ with leads and lags.

As a complement to our earnings premia results, we also investigate whether education-industry match influences employment in a subsequent quarter. Although our definition of education-industry match is predicated on employment since identifying a match between CIP

[15] Inferences remain unchanged when (1) two-way clustering by college and major and (2) clustering at the major-by-college level.

and NAICS requires an NAICS of an employer, we can estimate models using an employment lead as an outcome of interest, given by:

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

In this model, $y_{ijt+1}$ is a binary indicator for worker $i$ employed in industry $j$ at time $t$ having positive earnings in $t + 1$.

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, we supplement our analysis by leveraging the matrix completion (MC) counterfactual estimator from Liu et al. (2024).[16] The matrix completion counterfactual 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. Here, we also control for age polynomials, highest-earning industry fixed effects, an indicator for any technical college enrollment, and quarters relative to degree receipt. Standard errors are obtained through bootstrapping, clustering at the unit (student/worker) level.[17]

The MC estimator also has the added advantage of using untreated observations to account for potential time-varying confounders semi-parametrically whereas TWFE assumes there are no unobserved time-varying confounders. Conceptually, the idea is that there may exist

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

unobserved unit-time varying confounders, but these can be captured by a few latent common factors interacting with unit-specific loadings. Rather than explicitly modeling the factor structure with parametric loadings and factors as in an interactive fixed effect model, the estimator treats the untreated outcome matrix as approximately low-rank and applies matrix-completion to impute the missing (treated) potential outcomes. This approach effectively controls for unobserved confounders that have a shared temporal structure but where each unit is impacted to different extents (e.g., sector-wide shifts, local economic shocks). However, it cannot adjust for confounders that are idiosyncratic, high-dimensional, or non-shared across units, so person-specific shocks like the birth or a child or need to move for a partner's job would not be controlled for under MC estimation.

## Results

### *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 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]).[18] This lack of education-employment match could explain the relatively weaker

[18] 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].

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.

***Effects of Education-Industry Match on Earnings***

Table 3 presents earnings differences between workers in a matched industry relative to an unmatched industry. Columns 1-4 compare earnings differences across workers (model 1). Since $\text{Match}_{ijt}$ is predicated on the individual working in a particular quarter, these results can be interpreted as earnings, conditional on employment.[19] Adding controls for the CIP code of the degree awarded (column 2) substantially decreases estimated earnings difference 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 by CIP code (column 3), however, does little to alter the estimates. This suggests that there is actually little variation in earnings across institutions in the same sector (i.e., associate, bachelor's) in our sample after accounting for an individual's specific major.

Among Bachelor's degree recipients, 8% have a general studies, liberal arts, or liberal studies degree. Forty percent of Associates degree recipients have one of these "general" degrees.

[19] Appendix Figure A.2 reports the proportion of each sample reporting earnings of $0 in each calendar year and quarter.

As hypothesized, the role of industry does appear important in explaining workers' wages. Conditioning on industry of work fixed effects reduces the estimated premia by over 4 percentage points for bachelor's degree recipients (column 4). This shows that accounting for one's industry of work is an important factor in explaining wages and the college earnings premium. However, we are limited in how much we can learn about an industry-education earnings premia with these cross-sectional comparisons that exploit differences in match status across workers, especially since we find that workers who match are statistically different than those who do not (Table 1).

In columns 5 and 6 of Table 3, we turn our attention to preferred "within" models that add worker fixed effects (model 2). These models allow us to see how earnings evolve for the same worker switching in and out of industries that are matched to their college major. Note that sample sizes are larger for analyses using worker fixed effects because worker fixed effects absorb any time-invariant worker-level covariates, so we can include graduates with missing student covariates data (e.g. ACT score, cumulative GPA upon graduation). We find an earnings premium of about 9% for bachelor's degree holders and 5% for associate degree holders. These estimates are somewhat smaller than those found in previous work for education-occupation match, anywhere between 10% to 42%, though those prior studies did not estimate within worker models (Robst, 2007; Yakusheva, 2010; Cassidy and Gaulke, 2024).

Because industry switches are critical for the within-person identification of an earning premium, we more directly explore the role of industry transitions using an event-study plot and TWFE estimation (Figure 2). For these plots, we examine workers who switch industries, where an industry switch is defined as a change from one quarter to the next in the three-digit NAICS code of the worker's highest earning record in the quarter. We omit $t = -3$ (three quarters before a switch) to account for an Ashenfelter style dip (Ashenfelter, 1978). Note that the grey dots represent differences in log quarterly earnings between workers who will switch industries and workers who will not make an industry transition. We drop any workers who were matched prior to making an industry transition to focus on a group of workers who were in an unmatched and then switch to another unmatched industry (green) or into a matched industry (yellow). This allows us to jointly visualize the impacts of industry switching (overall) and the impacts of switching into a matched industry specifically.

There is evidence of an Ashenfelter style dip that is particularly pronounced for bachelor's degree holders. Although we cannot observe labor supply intensity (i.e., hours of work), we suspect it may be responsible for at least some of this pattern. As people quit or leave their unmatched industry job and begin work in a new industry, 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. The obvious "transition periods" shown in these dynamic plots indicate that it is important to consider only longer-run differences rather than short-run changes in earnings a few quarters prior to match and the first quarter of match. We thus re-estimate models 1 and 2 dropping two quarters prior to match alongside the quarter of match and show the results in Table 4 and find slightly larger estimated industry-match earnings premia: 10% for bachelor's and 7% for associate degree holders. We also find that results are nearly identical if we additionally drop all observations from the year 2020 from our analysis (Appendix Table A.3).

Looking at the post period in Figure 2, we find that earnings gains are significantly larger for workers transitioning into a matched industry both in the associate and bachelor's samples, though the gap is somewhat larger for the bachelor's degree holders. These results are consistent with churn in the labor market, where workers periodically switch jobs and can secure higher earnings by doing so, though these plots suggest that education-industry match is an important predictor of those gains. In the analysis estimating the effect of match specifically (green), the workers experiencing an industry transition from an unmatched industry to a different unmatched industry are part of the control group (untreated workers). This analysis suggests that it is important to include them since their earnings changes are important for understanding the counterfactual. Solely using workers who never transition industries would thus overstate the effects of education-industry match. This allows us to decompose, in part, the effect of switching into an education-industry match on earnings from the effect of a switch alone. Indeed, gaps between switchers who matched (yellow) and those who remained unmatched (green) are qualitatively similar to estimates in Table 4: an approximate 10-point difference for bachelor's degree holders, and 7 points for associate degrees.

Plots in Figure 3 show dynamic treatment effects for switching into match using the heterogeneity robust MC estimator and point to qualitatively equivalent findings of a 10% gain for bachelor's degree holders and a 5-7% gain for associate degree holders (Liu et al. 2024). Recall that this estimator avoids any "forbidden comparisons" of a traditional TWFE estimation and controls for non-idiosyncratic, time-varying confounders semi-parametrically. Visually, we again see evidence of an Ashenfelter-style dip for associate degree holders, where earnings decline in the two quarters immediately prior to switching into a matched industry and remain depressed in the first quarter of education-industry match. Among the bachelor's degree sample, we see the depressed earnings in the first quarter of match but find extremely precise zeros for the differences pre-match between actual outcomes for workers who will be treated and their estimated counterfactuals. Then, in quarter two and beyond, there is a statistically significant increase in earnings of 6-13%. Earnings gains for associate degree holders are smaller in magnitude and less precise but remain qualitatively similar and consistent.

Estimates from the MC estimator are not directly comparable to TWFE results in Figure 2 and Table 3 since estimated average treatment effects on the treated (ATTs) are conditioned on the number of periods since match began. Also, unlike a traditional TWFE event study plot, there is no reference time period (Figure 3). Identification comes from estimating counterfactual outcomes for all treated units and all time periods, not from differencing relative to a baseline period, so there is no omitted "baseline" period. However, when reporting a single MC estimate in the analysis that follows (such as in Table 7), we select the ATT from $s = 3$, where the worker has been matched for three quarters. Visual inspection of the dynamic MC plots shows that this allows us to abstract away from temporary transition earnings dips but also provides an estimate from a reasonably large sample of treated individuals shortly after they transition into match.

While leveraging within worker variation in earnings and adopting the MC estimator addresses some concerns of endogeneity, even this preferred approach cannot address all time-varying confounders. Unobserved sources of idiosyncratic time-varying selection such as the birth of a child or a move for a partner's job could prompt a job and industry-education match status change. However, if similar sources of time-varying selection affect industry transitions in general, regardless of whether the switch is into a matched or unmatched industry, larger returns to industry switching when the switch is into a matched industry are suggestive of a positive causal earnings premium from education-industry match specifically.

We also explore whether the earnings penalty from *exiting* education-industry match is comparable to the earnings premium from transitioning into education-industry match (Figure 4). Associate degree holders exiting match experience earnings declines relative to never treated workers (i.e., never matchers) prior to exiting match. After exiting match, their earnings are actually slightly higher than those who only ever worked in unmatched industries. The patterns are different for bachelor's degree holders. Their earnings are 5-10% higher in the 4-6 quarters prior to exiting match then never matchers. They experience falling earnings prior to the transition, and then after exit, the earnings difference falls to a precisely estimated zero.

***Effects of Education-Industry Match on Employment***

Results shown so far have been effects for earnings conditional on employment. We next investigate whether an education-industry match is associated with continued employment. Table 5 displays results for model 3 using TWFE. We find that education-industry match is predictive of having positive earnings in the next subsequent quarter, both for bachelor's and associate degree holders, but the magnitude of this association is small: no more than 2 percentage points.

***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. We drop two quarters prior to match and the quarter of match to abstract away from temporary transition effects. Results are shown in Table 6.

Table 6 shows a positive, statistically significant, and economically meaningful match earnings premia for almost 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 and medical degrees (Cassidy & Gaulke, 2024; 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 engineering and medical associate degrees.

Table 7 repeats the analysis using the MC 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 premium using matrix completion on that subsample and report the ATT three quarters after education-industry match begins to abstract from temporary changes that could be due to job or industry transitions. Estimates are more imprecise than those in Table 6, likely because we must estimate a separate model for each field category 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 associate and bachelor's levels have large and statistically significant match returns. Taken as a whole, the results indicate that obtaining employment in a related industry is important for wages but that this match is more important for some degrees than others.

***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, 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 separate 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. 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. This is, however, not possible in our data or in available federal data, such as the American Community Survey.[20] This remains an area ripe for future work and believe our CIP-NAICS crosswalk represents an important step for researchers and policymakers alike interested in examining education-work alignment with UI records.

Second, while we make considerable improvements by leveraging within worker variation in earnings to address some concerns of endogeneity and improve the precision of prior estimates, our work is clearly descriptive in nature due to our inability to control for time-varying confounders which could lead to some bias in the estimation of the education-industry match premium. Relatedly, it is important to consider whether our sample of "switchers" is representative of the larger population of workers. 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).

[20] Although the ACS contains worker-level earnings information with occupation (SOC) and industry (NAICS) identifiers, the lack of CIP codes for field of degree makes it impossible to map our CIP-NAICS crosswalk onto these data to assess the separate contributions of occupation-education and industry-education match. Even if we created new education-occupation and education-industry crosswalks using ACS field of study codes (which are less detailed than CIP codes), we could not estimate education-occupation match or education-industry match premia for associate degree holders since field of degree is reported for bachelor's degree holders only, nor could we estimate worker fixed effects models due to the cross-sectional structure of the ACS.

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 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 results are largely unchanged when using 5% and 20% thresholds (Appendix Table A.1 and Appendix Table A.2, respectively).

**Discussion**

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, 2023; 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, 2024; Light & Wertz, 2022; Manuel, 2024; Robst, 2007; Yakusheva, 2010). With a novel education-industry crosswalk applied to a 10-year panel covering over 295,000 college graduates, we define a new education-industry match premia and show that workers in industries "matched" with their associate or bachelor's degree field experience statistically significant earnings gains of about 5-10% and may be slightly more likely to remain employed.

Our findings on education-industry match complement and provide partially overlapping evidence on the same underlying mechanism as prior work exploring education-occupational match. Estimates of education-occupation match premia range from roughly 10 to 40%, with the exact estimate depending on the estimation strategy, type of postsecondary study, population, and data source (Robst, 2007; Yakusheva, 2010; Cassidy & Gaulke, 2024). The fact that both education-occupation alignment (ignoring industry) and education-industry alignment (ignoring occupation) are associated with statistically significant earnings differences indicate that the same underlying mechanisms may be at work: human capital specificity and/or signaling. Our results also point to education-industry match as a potentially meaningful evaluative metric for policymakers hoping to ensure students can maximize their return on investment for postsecondary degrees. Industry identifiers are a practical, scalable, and informative proxy for alignment between education and work, even if occupational identifiers are unavailable.

Given heightened public and private interests in the return on investment to college degrees and education-industry alignment (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—beyond occupational choice to similar 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 specifically identifies which fields of study are most likely to enjoy these premia—allowing institutions to target specific career supports to students in lower-matching fields or equipping students and parents with specific information on what majors are most closely aligned with industries. These findings may also be of particular interest to policymakers given public subsidies for higher education, concerns for why the returns to degrees vary across graduates, and considerations of policy interventions that may help ensure equal access to “high” return-on-investment majors (Bleemer et al., 2023).

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 industry-specific skills or abilities individuals acquire 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 industry has been an overlooked factor in explaining workers’ wages both generally and in explaining why returns to even the same degree vary across the population. We also show that prior reliance on self-reported matches and/or cross-sectional data paired with workers’ self-selection into majors and occupations could have resulted in an overstatement of the wage-premium magnitude. An ideal extension of our work would identify education-occupation match premia conditional on industry of work—or education-industry match premia conditional on occupation—to further disentangle the relationship between education, occupation, and industry matching in explaining wages. Given that the incidence of matching varies across occupations and industries, subsequent investigations should also 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 all, future works should empirically acknowledge the labor market salience of specialized training in the specific field within which one works.

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

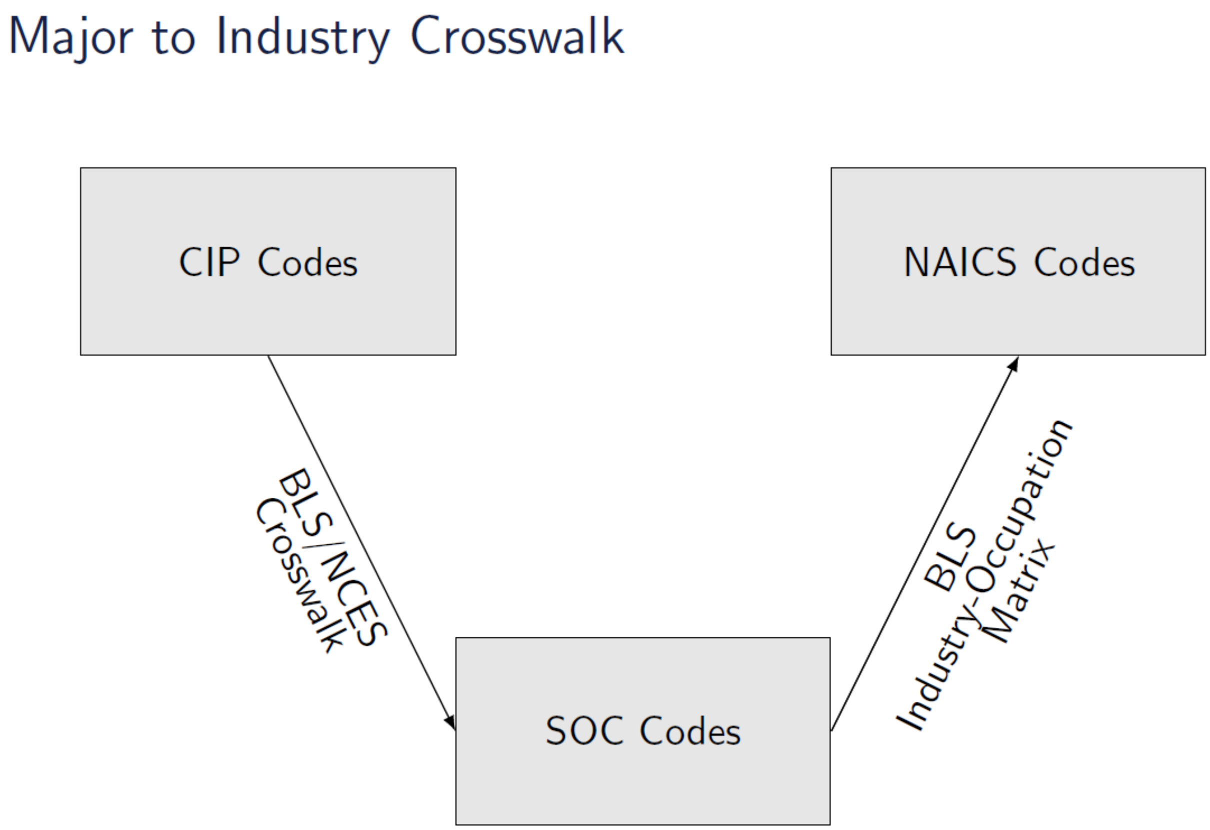
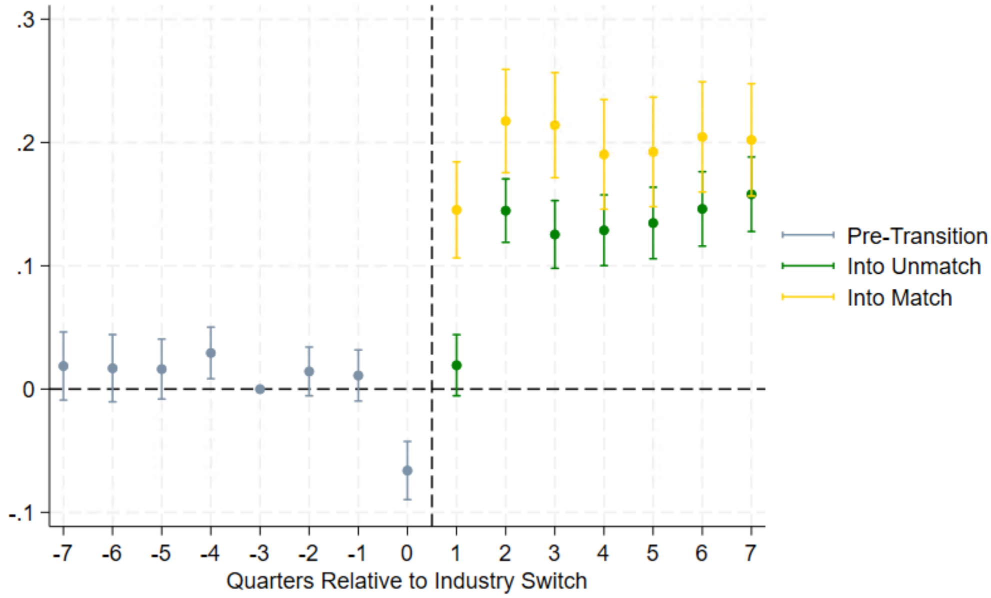
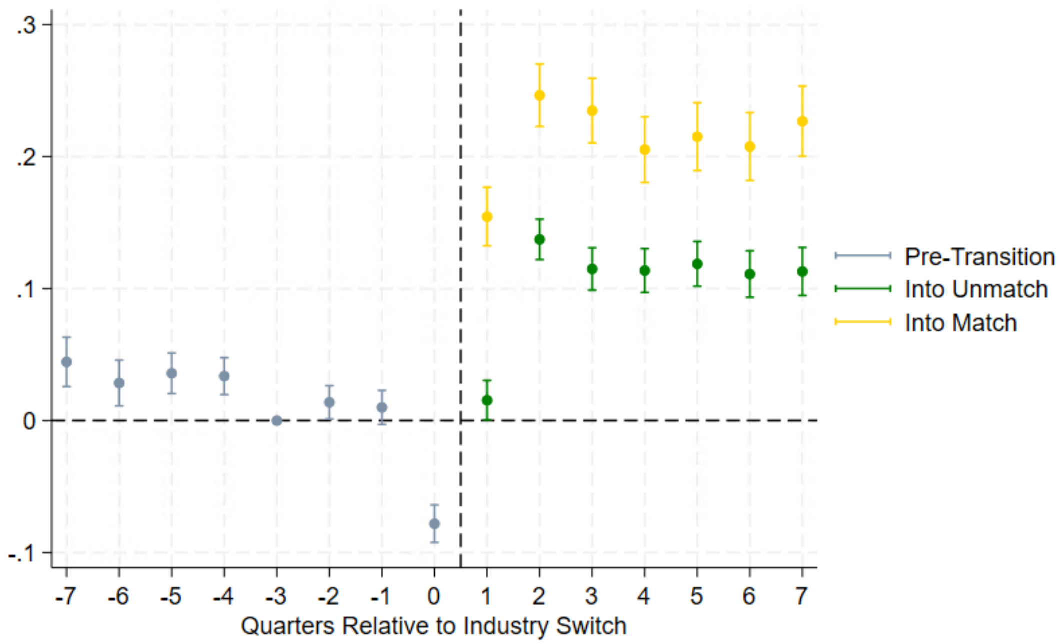


**Figure 2**. *Two-way fixed effects dynamic treatment effects plots: Industry transition*.

(a) Associate Degree Sample:



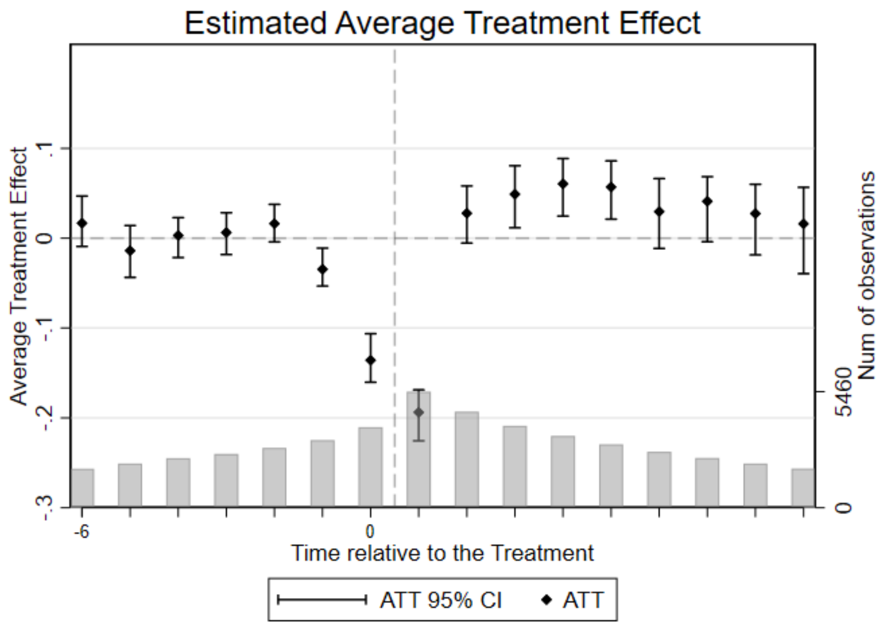

(b) Bachelor's Degree Sample:



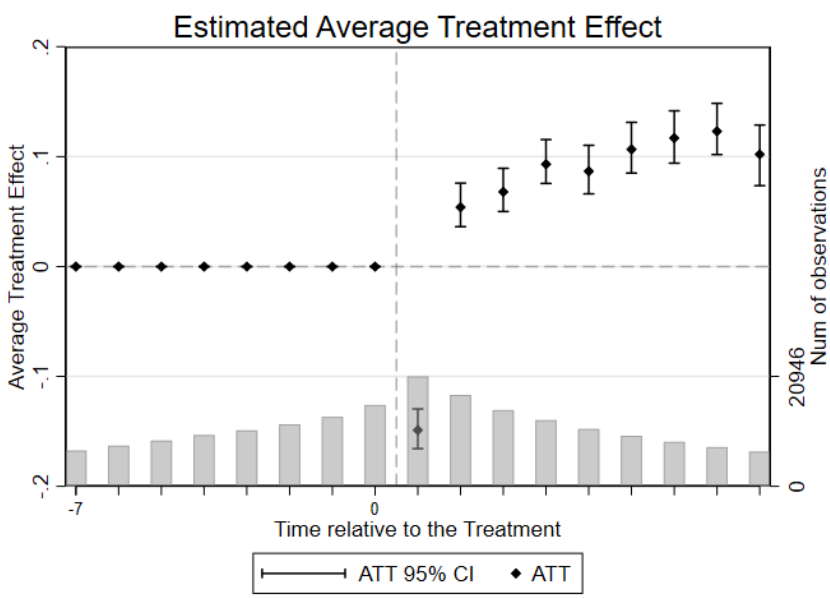

Notes: Estimation based on two-way fixed effects models with individual fixed effects, industry fixed effects (based on employment record with highest earnings in the quarter), age polynomials, control for technical college enrollment, quarter relative to degree receipt, and calendar year-quarter fixed effects. Dependent variable is the natural log of quarterly earnings CPI adjusted to 2020 dollars. Error bars plot 95% confidence intervals using standard errors clustered on worker. Sample is limited to the first industry switch event where a switch is defined based on the industry in which the individual has the highest earnings in the quarter.

**Figure 3.** *Matrix completion estimator dynamic treatment effects plots: Entering education-industry match.*

(a) Associate Degree Sample:



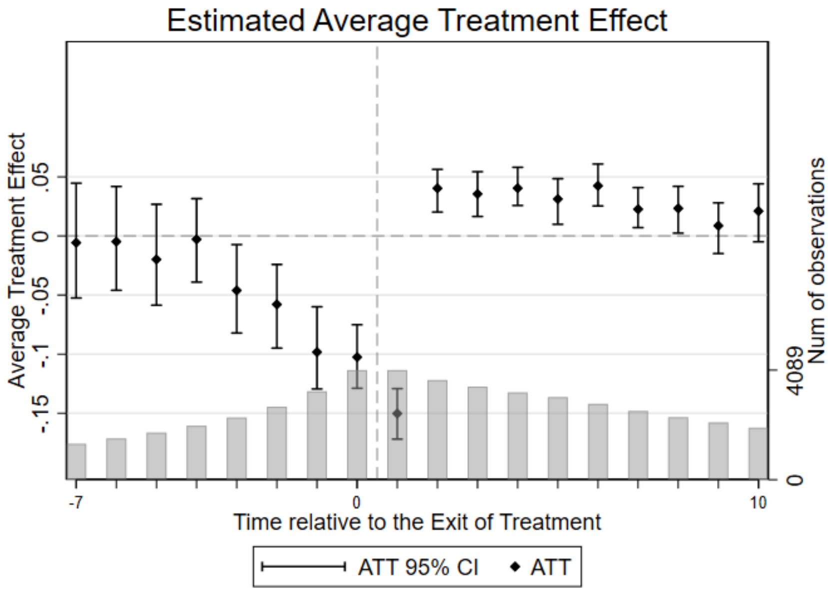

(b) Bachelor’s Degree Sample:



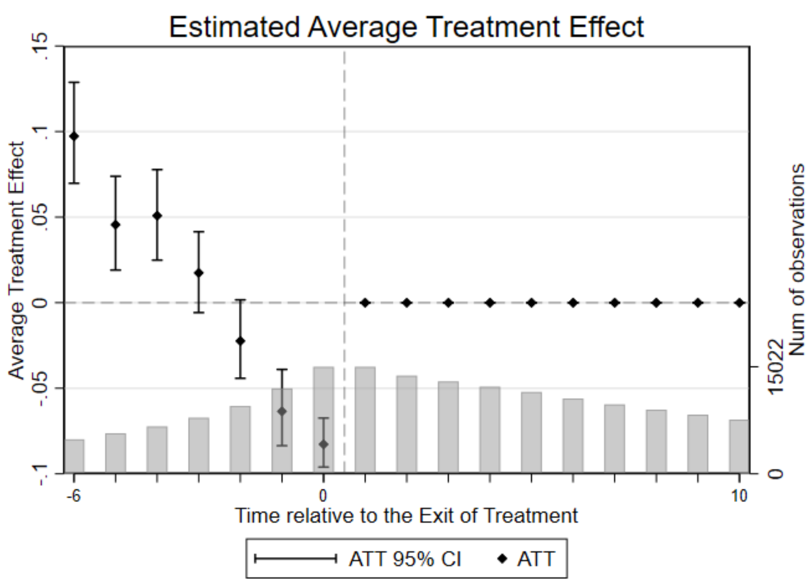

Notes: Estimation based on the matrix completion estimator of Liu et al. (2024). Dependent variable is the natural log of quarterly earnings CPI adjusted to 2020 dollars. The dependent variable is undefined for any quarters with 0 earnings. Estimated model includes industry fixed effects, individual 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.

**Figure 4.** *Matrix completion estimator 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 undefined 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. Differences in characteristics and labor market outcomes between the three groups (only ever matched, never matched, and switcher) are statistically significant at the 1% level for all characteristics except Race: American Indian or Alaskan Native (BA & AA sample) and Race: Asian (BA sample only).

**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*** | 0.119*** | 0.115*** | 0.069*** | 0.133*** | 0.085*** |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.005) |
| N | 1,374,621 | 1,374,621 | 1,374,620 | 1,374,621 | 1,601,357 | 1,601,357 |
| *Panel B: Bachelor's - Women* | | | | | | |
| Matched | 0.221*** | 0.143*** | 0.139*** | 0.072*** | 0.163*** | 0.097*** |
| | (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*** | 0.088*** | 0.055*** | 0.096*** | 0.070*** |
| | (0.006) | (0.005) | (0.005) | (0.007) | (0.007) | (0.008) |
| N | 618,356 | 618,356 | 618,353 | 618,356 | 706,754 | 706,754 |
| *Panel D: Associate - All* | | | | | | |
| Matched | 0.303*** | 0.041*** | 0.035*** | 0.030*** | 0.089*** | 0.054*** |
| | (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 | 0.333*** | 0.003 | -0.004 | 0.008 | 0.079*** | 0.034*** |
| | (0.010) | (0.015) | (0.015) | (0.015) | (0.012) | (0.013) |
| N | 214,548 | 214,548 | 214,548 | 214,548 | 362,330 | 362,330 |
| *Panel F: Associate - Men* | | | | | | |
| Matched | 0.231*** | 0.108*** | 0.101*** | 0.053*** | 0.107*** | 0.089*** |
| | (0.014) | (0.017) | (0.016) | (0.018) | (0.014) | (0.016) |
| N | 125,327 | 125,327 | 125,327 | 125,327 | 201,989 | 201,989 |
| Student Covariates | Yes | Yes | Yes | Yes | - | - |
| CIP FE | No | Yes | - | - | - | - |
| College x CIP 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. If the worker has multiple employers in a quarter, the industry fixed effect is for the one for which they had the highest earnings. The dependent variable is undefined for any quarters with 0 earnings, so earnings outcomes are conditional on employment. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Table reports coefficients and robust standard errors (in parentheses) clustered at the student/worker level. Inferences unchanged with two-way clustering (individual and industry) and clustering at the major-by-college level. Ns are Individual-Quarter observations. Same sizes increase in individual FE models (columns 5-6) given missing time-varying covariates (columns 1-4).

**Table 4.** *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*** | 0.150*** | 0.102*** | 0.146*** | 0.101*** |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.006) | (0.006) |
| N | 1,277,178 | 1,277,176 | 1,277,174 | 1,277,174 | 1,485,853 | 1,485,853 |
| *Panel B: Bachelor's - Women* | | | | | | |
| Matched | 0.249*** | 0.176*** | 0.173*** | 0.105*** | 0.171*** | 0.108*** |
| | (0.005) | (0.006) | (0.006) | (0.007) | (0.008) | (0.009) |
| N | 698,615 | 698,614 | 698,613 | 698,613 | 825,148 | 825,148 |
| *Panel C: Bachelor's - Men* | | | | | | |
| Matched | 0.203*** | 0.128*** | 0.124*** | 0.090*** | 0.116*** | 0.093*** |
| | (0.006) | (0.006) | (0.006) | (0.008) | (0.007) | (0.009) |
| N | 578,563 | 578,560 | 578,555 | 578,555 | 660,705 | 660,705 |
| *Panel D: Associate - All* | | | | | | |
| Matched | 0.338*** | 0.080*** | 0.074*** | 0.067*** | 0.097*** | 0.066*** |
| | (0.008) | (0.011) | (0.011) | (0.012) | (0.011) | (0.011) |
| N | 321,668 | 321,667 | 321,664 | 321,664 | 531,329 | 531,329 |
| *Panel E: Associate - Women* | | | | | | |
| Matched | 0.370*** | 0.043*** | 0.037*** | 0.046*** | 0.082*** | 0.039*** |
| | (0.011) | (0.015) | (0.015) | (0.016) | (0.014) | (0.014) |
| N | 201,450 | 201,448 | 201,445 | 201,445 | 338,474 | 338,474 |
| *Panel F: Associate - Men* | | | | | | |
| Matched | 0.263*** | 0.145*** | 0.138*** | 0.087*** | 0.125*** | 0.116*** |
| | (0.014) | (0.017) | (0.017) | (0.019) | (0.016) | (0.018) |
| N | 120,218 | 120,217 | 120,212 | 120,212 | 192,855 | 192,855 |
| Student Covariates | Yes | Yes | Yes | Yes | - | - |
| CIP FE | No | Yes | - | - | - | - |
| College x CIP 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 undefined for any quarters with 0 earnings, so earnings outcomes are conditional on employment. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Table reports coefficients and robust standard errors (in parentheses) clustered at the student level. Inferences unchanged with two-way clustering (individual and industry) and clustering at the major-by-college level. Columns 1-4 correspond to equation (1); columns 5-6 to equation (2). Ns are Individual-Quarter observations. Same sizes increase in individual FE models (columns 5-6) given missing time-varying covariates (columns 1-4).

**Table 5.** *Estimated effect of education-industry match on employment in t+1, by degree level and gender, using two-way fixed effects estimation.*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Panel A: Bachelor's - All* | | | | | | |
| Matched | 0.017*** | 0.014*** | 0.013*** | 0.012*** | 0.017*** | 0.015*** |
| | (<0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| N | 1,304,534 | 1,304,534 | 1,304,534 | 1,304,534 | 1,515,844 | 1,515,844 |
| *Panel B: Bachelor's - Women* | | | | | | |
| Matched | 0.019*** | 0.017*** | 0.016*** | 0.013*** | 0.020*** | 0.016*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| N | 717,514 | 717,513 | 717,513 | 717,514 | 846,457 | 846,457 |
| *Panel C: Bachelor's - Men* | | | | | | |
| Matched | 0.014*** | 0.0.11*** | 0.010*** | 0.011*** | 0.014*** | 0.013*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) |
| N | 587,020 | 587,019 | 587,019 | 587,020 | 669,387 | 669,387 |
| *Panel D: Associate - All* | | | | | | |
| Matched | 0.017*** | 0.007*** | 0.007*** | 0.005*** | 0.008*** | 0.007*** |
| | (0.001) | (0.001) | (0.005) | (0.001) | (0.002) | (0.002) |
| N | 320,587 | 320,586 | 320,586 | 320,586 | 532,414 | 532,414 |
| *Panel E: Associate - Women* | | | | | | |
| Matched | 0.018*** | 0.007*** | 0.007*** | 0.004*** | 0.008*** | 0.006*** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| N | 202,572 | 202,569 | 202,569 | 202,572 | 342,009 | 342,009 |
| *Panel F: Associate - Men* | | | | | | |
| Matched | 0.013*** | 0.007*** | 0.006*** | 0.006*** | 0.008*** | 0.010*** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) |
| N | 118,015 | 118,013 | 118,013 | 118,013 | 190,405 | 190,405 |
| Student Covariates | Yes | Yes | Yes | Yes | - | - |
| CIP FE | No | Yes | - | - | - | - |
| College x CIP 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 a lead for being employed in the following quarter (t+1). The dependent variable is undefined for any quarters with 0 earnings, so earnings outcomes are conditional on employment. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Table reports coefficients and robust standard errors (in parentheses) clustered at the student/worker level. Inferences unchanged with two-way clustering (individual and industry) and clustering at the major-by-college level. Columns 1-4 correspond to equation (1); columns 5-6 to equation (2). Ns are Individual-Quarter observations. Same sizes increase in individual FE models (columns 5-6) given missing time-varying covariates (columns 1-4).

**Table 6.** *Heterogeneity in education-industry match earnings premia, dropping two quarters prior to match and quarter of match, 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 | 0.543** | 0.602*** | -0.272* | 0.381*** | 0.345*** | 0.418*** |
| | (0.216) | (0.232) | (0.156) | (0.028) | (0.031) | (0.062) |
| Match x Legal | 0.130** | 0.073 | 0.778** | 0.197 | 0.250* | -0.131 |
| | (0.064) | (0.064) | (0.394) | (0.122) | (0.141) | (0.212) |
| Match x Eng/IT/Math | 0.079*** | 0.075 | 0.082*** | 0.114*** | 0.222*** | 0.105*** |
| | (0.023) | (0.063) | (0.024) | (0.015) | (0.053) | (0.015) |
| Match x Business | -0.006 | -0.019 | 0.036 | 0.026*** | 0.039*** | 0.025*** |
| | (0.020) | (0.023) | (0.036) | (0.010) | (0.016) | (0.012) |
| Match x Medical | 0.136*** | 0.105*** | 0.258*** | 0.255*** | 0.230*** | 0.311*** |
| | (0.019) | (0.021) | (0.047) | (0.025) | (0.027) | (0.070) |
| Match x Communication | 0.109 | 0.098 | 0.147* | 0.042** | 0.063** | 0.033 |
| | (0.080) | (0.138) | (0.078) | (0.020) | (0.025) | (0.034) |
| Match x Pub Admin | 0.117 | 0.097 | 0.198*** | 0.261*** | 0.239*** | 0.260** |
| | (0.103) | (0.118) | (0.051) | (0.043) | (0.045) | (0.127) |
| Match x Arts | 0.153 | 0.127 | 0.191 | 0.095*** | 0.065* | 0.178*** |
| | (0.098) | (0.142) | (0.135) | (0.029) | (0.036) | (0.047) |
| Match x Phys Science | 0.215* | 0.195 | 0.221 | 0.140*** | 0.117*** | 0.181*** |
| | (0.122) | (0.154) | (0.159) | (0.026) | (0.036) | (0.036) |
| Match x Manual | -0.131 | - | -0.097 | 0.054* | 0.058 | 0.061* |
| | (0.092) | - | (0.089) | (0.028) | (0.047) | (0.034) |
| Match x Soc Science | -0.405*** | -0.384*** | - | 0.072*** | 0.049*** | 0.126*** |
| | (0.016) | (0.020) | - | (0.016) | (0.019) | (0.028) |
| Match x Service | 0.229*** | 0.223*** | 0.264*** | 0.091*** | 0.071*** | 0.125*** |
| | (0.052) | (0.067) | (0.086) | (0.020) | (0.026) | (0.029) |
| Match x Humanities | - | - | - | 0.098*** | 0.068** | 0.155*** |
| | - | - | - | (0.024) | (0.031) | (0.037) |
| Match x Gen Studies | -0.140*** | -0.177*** | -0.012 | -0.042 | -0.117** | 0.100 |
| | (0.043) | (0.054) | (0.065) | (0.039) | (0.051) | (0.061) |
| N (Individual-Quarter) | 531,329 | 338,474 | 192,855 | 1,485,853 | 825,148 | 660,705 |

Notes: Dependent variable is the natural log of quarterly earnings CPI adjusted to 2020 dollars. The dependent variable is undefined for any quarters with 0 earnings, so earnings outcomes are conditional on employment. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. 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, control for enrolled in a technical college, quarter relative to degree receipt, and year-quarter fixed effects. Empty entries appear for samples where there are an insufficient number of graduates to estimate an education-industry match.

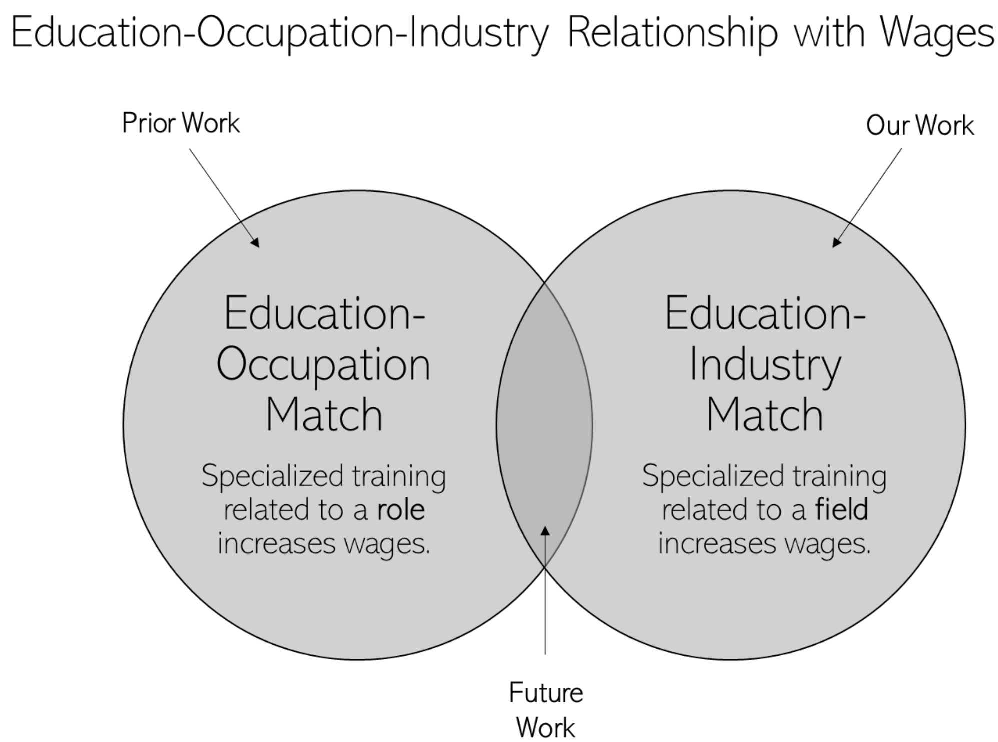
**Table 7.** *Heterogeneity in education-industry match earnings premia, by field of degree, using matrix completion matrix completion counterfactual estimation.*

| | (1) Associate | (2) Bachelor's |
|---|---|---|
| Match for Education | 0.618 | 0.198 |
| | (0.867) | (0.561) |
| | [18] | [867] |
| Match for Legal | 0.243 | 0.136 |
| | (0.211) | (4.141) |
| | [73] | [12] |
| Match for Engineering/IT/Math | 0.141*** | 0.182 |
| | (0.032) | (0.128) |
| | [510] | [1268] |
| Match for Business | 0.053 | 0.059 |
| | (0.044) | (0.076) |
| | [828] | [3777] |
| Match for Medical | 0.128*** | 0.161*** |
| | (0.039) | (0.055) |
| | [1596] | [836] |
| Match for Communications | 0.084 | -0.106 |
| | (0.173) | (0.078) |
| | [67] | [1055] |
| Match for Public Administration | 0.613 | -0.018 |
| | (1.284) | (0.465) |
| | [8] | [291] |
| Match for Arts | 0.417** | 0.125 |
| | (0.163) | (0.098) |
| | [39] | [596] |
| Match for Physical Science | 1.511 | 0.423 |
| | (3.590) | (0.506) |
| | [11] | [620] |
| Match for Manual | 0.186 | 0.068 |
| | (0.383) | (0.061) |
| | [19] | [479] |
| Match for Social Science | - | 0.159 |
| | | (0.109) |
| | | [1806] |
| Match for Service | -0.031 | 0.081* |
| | (0.129) | (0.042) |
| | [213] | [1249] |
| Match for Humanities | - | 0.139 |
| | | (0.177) |
| | | [819] |
| Match for General Studies | -0.239*** | -0.047 |
| | (0.068) | (0.060) |
| | [495] | [342] |

Notes: Dependent variable is the natural log of quarterly earnings CPI adjusted to 2020 dollars. The dependent variable is undefined for any quarters with 0 earnings, so earnings outcomes are conditional on employment. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. 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.

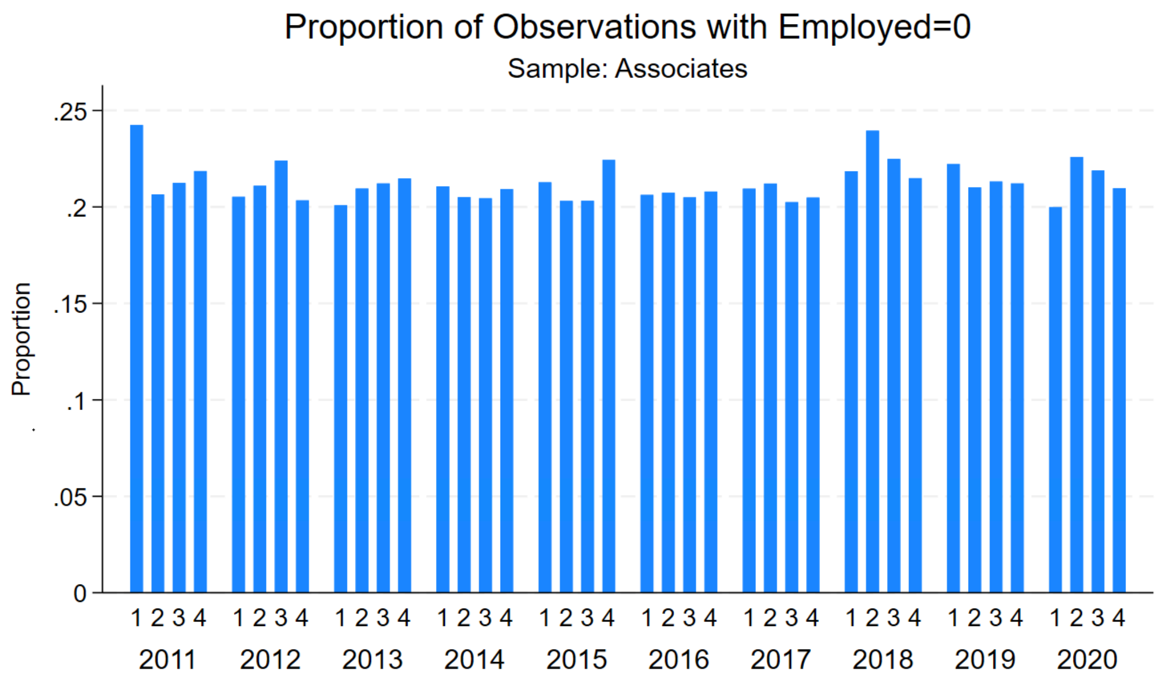
# APPENDIX

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



**Appendix Figure A.2.** *Proportion of sample in each quarter-year with no reported earnings.*

(a) Associate Degree Sample:




(b) Bachelor's Degree Sample:

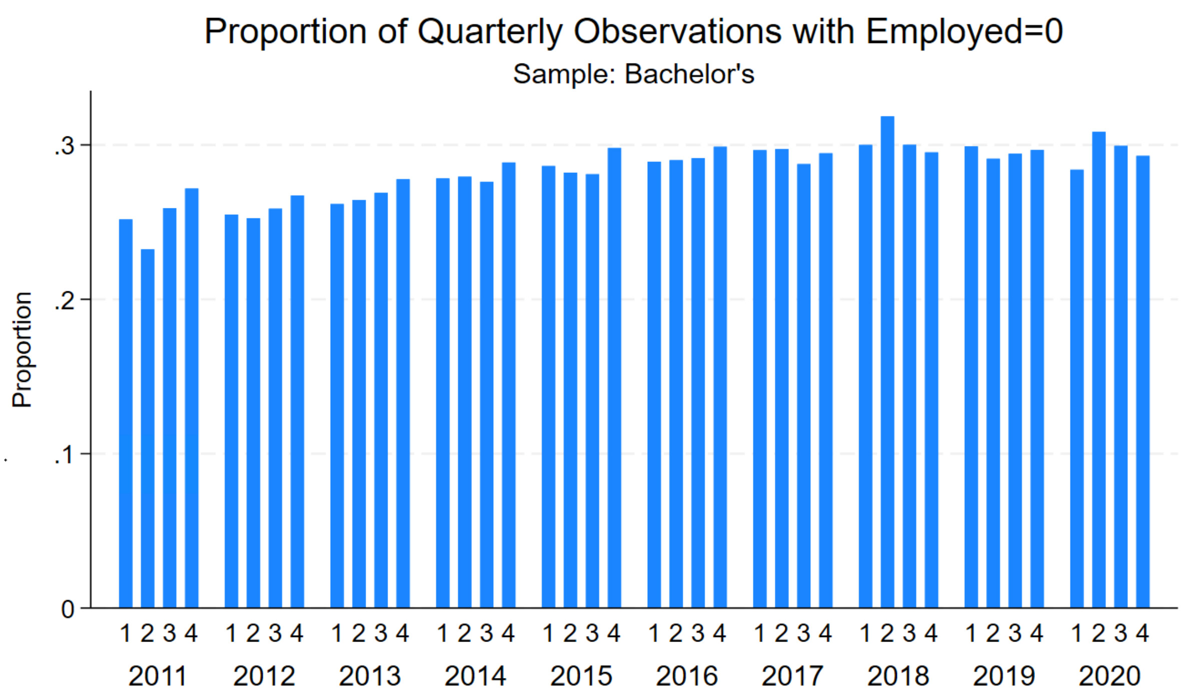


**Table A.1.** *Robustness of estimated education-industry match earnings premia to using alternate 5% occupation share crosswalk cutoff.*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Panel A: Bachelor's - All* | | | | | | |
| Matched | 0.231*** | 0.135*** | 0.132*** | 0.074*** | 0.150*** | 0.098*** |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.005) |
| N | 1,374,621 | 1,374,621 | 1,374,620 | 1,374,620 | 1,601,357 | 1,601,357 |
| *Panel B: Bachelor's - Women* | | | | | | |
| Matched | 0.239*** | 0.154*** | 0.151*** | 0.083*** | 0.182*** | 0.114*** |
| | (0.005) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) |
| N | 756,265 | 756,264 | 756,262 | 756,262 | 894,603 | 894,603 |
| *Panel C: Bachelor's - Men* | | | | | | |
| Matched | 0.221*** | 0.113*** | 0.109*** | 0.059*** | 0.114*** | 0.082*** |
| | (0.005) | (0.005) | (0.005) | (0.007) | (0.006) | (0.007) |
| N | 618,356 | 618,356 | 618,353 | 618,353 | 706,754 | 706,754 |
| *Panel D: Associate - All* | | | | | | |
| Matched | 0.342*** | 0.095*** | 0.088*** | 0.054*** | 0.117*** | 0.065*** |
| | (0.008) | (0.012) | (0.012) | (0.012) | (0.010) | (0.010) |
| N | 339,875 | 339,875 | 339,872 | 339,872 | 564,319 | 564,319 |
| *Panel E: Associate - Women* | | | | | | |
| Matched | 0.381*** | 0.053*** | 0.044*** | 0.044*** | 0.120*** | 0.060*** |
| | (0.010) | (0.017) | (0.017) | (0.017) | (0.015) | (0.014) |
| N | 214,548 | 214,546 | 214,543 | 214,543 | 362,330 | 362,330 |
| *Panel F: Associate - Men* | | | | | | |
| Matched | 0.263*** | 0.149*** | 0.142*** | 0.059*** | 0.109*** | 0.069*** |
| | (0.013) | (0.015) | (0.015) | (0.016) | (0.014) | (0.014) |
| N | 125,327 | 125,327 | 125,322 | 125,322 | 201,989 | 201,989 |
| Student Covariates | Yes | Yes | Yes | Yes | - | - |
| CIP FE | No | Yes | Yes | - | - | - |
| College x CIP 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 undefined for any quarters with 0 earnings, so earnings outcomes are conditional on employment. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Table reports coefficients and robust standard errors (in parentheses) clustered at the student level. Inferences unchanged with two-way clustering (individual and industry) and clustering at the major-by-college level. Columns 1-4 correspond to equation (1); columns 5-6 to equation (2). Ns are Individual-Quarter observations. Same sizes increase in individual FE models (columns 5-6) given missing time-varying covariates (columns 1-4).

**Table A.2.** *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*** | 0.096*** | 0.080*** | 0.127*** | 0.099*** |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.005) |
| N | 1,374,621 | 1,374,621 | 1,374,620 | 1,374,620 | 1,601,357 | 1,601,357 |
| *Panel B: Bachelor's - Women* | | | | | | |
| Matched | 0.206*** | 0.126*** | 0.122*** | 0.083*** | 0.156*** | 0.106*** |
| | (0.005) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) |
| N | 756,265 | 756,264 | 756,262 | 756,262 | 894,603 | 894,603 |
| *Panel C: Bachelor's - Men* | | | | | | |
| Matched | 0.140*** | 0.068*** | 0.063*** | 0.063*** | 0.085*** | 0.083*** |
| | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.008) |
| N | 618,356 | 618,356 | 618,353 | 618,353 | 706,754 | 706,754 |
| *Panel D: Associate - All* | | | | | | |
| Matched | 0.278*** | 0.023** | 0.018 | 0.039*** | 0.083*** | 0.072*** |
| | (0.009) | (0.011) | (0.011) | (0.012) | (0.009) | (0.010) |
| N | 339,875 | 339,875 | 339,872 | 339,872 | 564,319 | 564,319 |
| *Panel E: Associate - Women* | | | | | | |
| Matched | 0.295*** | -0.016 | -0.018 | 0.008 | 0.069*** | 0.050*** |
| | (0.011) | (0.014) | (0.014) | (0.016) | (0.011) | (0.012) |
| N | 214,548 | 214,546 | 214,543 | 214,543 | 362,330 | 362,330 |
| *Panel F: Associate - Men* | | | | | | |
| Matched | 0.229*** | 0.105*** | 0.093*** | 0.078*** | 0.105*** | 0.104*** |
| | (0.014) | (0.018) | (0.018) | (0.019) | (0.015) | (0.016) |
| N | 125,327 | 125,327 | 125,322 | 125,322 | 201,989 | 201,989 |
| Student Covariates | Yes | Yes | Yes | Yes | - | - |
| CIP FE | No | Yes | Yes | - | - | - |
| College x CIP 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 undefined for any quarters with 0 earnings, so earnings outcomes are conditional on employment. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Table reports coefficients and robust standard errors (in parentheses) clustered at the student level. Inferences unchanged with two-way clustering (individual and industry) and clustering at the major-by-college level. Columns 1-4 correspond to equation (1); columns 5-6 to equation (2). Ns are Individual-Quarter observations. Same sizes increase in individual FE models (columns 5-6) given missing time-varying covariates (columns 1-4).

**Table A.3.** *Robustness of estimated education-industry match earnings premia after dropping two quarters prior to match, first quarter of match, and quarters from 2020.*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Panel A: Bachelor's - All* | | | | | | |
| Matched | 0.230*** | 0.153*** | 0.149*** | 0.097*** | 0.145*** | 0.097*** |
| | (0.004) | (0.004) | (0.004) | (0.006) | (0.006) | (0.007) |
| N | 1,021,601 | 1,021,598 | 1,021,598 | 1,021,598 | 1,189,802 | 1,189,802 |
| *Panel B: Bachelor's - Women* | | | | | | |
| Matched | 0.251*** | 0.174*** | 0.171*** | 0.099*** | 0.168*** | 0.103*** |
| | (0.006) | (0.007) | (0.007) | (0.008) | (0.009) | (0.010) |
| N | 557,939 | 557,938 | 557,937 | 557,937 | 660,030 | 660,030 |
| *Panel C: Bachelor's - Men* | | | | | | |
| Matched | 0.205*** | 0.128*** | 0.124*** | 0.085*** | 0.118*** | 0.092*** |
| | (0.006) | (0.006) | (0.006) | (0.008) | (0.008) | (0.010) |
| N | 463,662 | 463,658 | 463,658 | 463,658 | 529,772 | 529,772 |
| *Panel D: Associate - All* | | | | | | |
| Matched | 0.346*** | 0.079*** | 0.074*** | 0.062*** | 0.095*** | 0.068*** |
| | (0.009) | (0.013) | (0.012) | (0.013) | (0.012) | (0.012) |
| N | 252,002 | 252,001 | 251,996 | 251,996 | 422,828 | 422,828 |
| *Panel E: Associate - Women* | | | | | | |
| Matched | 0.378*** | 0.042*** | 0.036*** | 0.041*** | 0.080*** | 0.042*** |
| | (0.011) | (0.016) | (0.016) | (0.018) | (0.015) | (0.016) |
| N | 158,403 | 158,399 | 158,392 | 158,392 | 269,785 | 269,785 |
| *Panel F: Associate - Men* | | | | | | |
| Matched | 0.270*** | 0.145*** | 0.138*** | 0.080*** | 0.122*** | 0.116*** |
| | (0.015) | (0.019) | (0.019) | (0.021) | (0.018) | (0.020) |
| N | 93,599 | 93,599 | 93,594 | 93,594 | 153,043 | 153,043 |
| Student Covariates | Yes | Yes | Yes | Yes | - | - |
| CIP FE | No | Yes | Yes | - | - | - |
| College x CIP 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 undefined for any quarters with 0 earnings, so earnings outcomes are conditional on employment. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Table reports coefficients and robust standard errors (in parentheses) clustered at the student level. Inferences unchanged with two-way clustering (individual and industry) and clustering at the major-by-college level. Columns 1-4 correspond to equation (1); columns 5-6 to equation (2). Ns are Individual-Quarter observations. Same sizes increase in individual FE models (columns 5-6) given missing time-varying covariates (columns 1-4).