Degrees Apart:
Changing Horizontal Stratification in Bachelor's Degrees by Institution and Field in the 21st Century

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Abstract

This study leverages a novel dataset linking U.S. graduates' specific educational credentials—defined as the unique combination of degree level, awarding institution, and field of study—to realized earnings and industry destinations for cohorts from 2001 onward. It offers the first comprehensive estimates of how horizontal stratification across institutions and fields of study shapes earnings inequality among U.S. bachelor's degrees, both from a static perspective and over time across several graduating cohorts. I find that field of study is a stronger predictor of earnings than institutional affiliation, and its importance is growing, though modestly, over time. For both fields of study and institution, the underlying structure behind their importance has been shifting. Field of study's growing importance is largely driven by baseline linkages of certain fields of study to industrial sectors that have seen rising average wages like finance, technology, and professional services. Though variation between universities explains a smaller share of inequality, it is increasingly associated with observable institutional characteristics like test scores and enrollment. Over time, neither shifts in enrollment across institutions and fields nor within-field demographic recomposition meaningfully explain these trends. Likewise, there is no evidence that high-earning credentials have become increasingly concentrated within high-earning institutions. Rather, the findings suggest that as economic returns become increasingly concentrated in a few high-earnings industries, high-earning fields of study already closely tied to those industries have become even more so, reinforcing and consolidating new forms of labor market inequality.

Introduction

The labor market returns to higher education are well documented (for reviews, see Card 1999; Hout 2012; Meghir and Rivkin 2011; Posselt and Grodsky 2017). Yet these returns vary substantially by institution (Zimmerman 2019; Brand 2006; Sekhri 2020), by field of study[1] (Altonji, Kahn, and Speer 2016; Kim, Tamborini, and Sakamoto 2015; Goyette and Mullen 2006; Kirkeboen, Leuven, and Mogstad 2016), and by their intersections, here termed specific education *credentials* to refer to the unique combination of degree level, awarding institution, and field of study.[2] Disparities by such characteristics—what sociologists refer to as horizontal stratification[3]—play an important role in shaping early-career outcomes. Figure 1 provides a stylized representation of these forms of horizontal stratification as compared to vertical stratification.

Prior research has documented large and persistent pay gaps across fields of study and premiums associated with certain institutional characteristics (see Gerber and Cheung 2008; Reimer and Thomsen 2019). Yet this existing research often treats institutional and field of study differences in isolation, even though fields are unevenly distributed across institutions in path-dependent and sometimes idiosyncratic ways, making it diffi-

[1]I use the term "field of study" instead of "college major" to account for variation in degree types (e.g., B.A., B.S.N., B.F.A.) and to allow generalizability across vertical levels of education. "Academic program" might be a suitable alternative, though no term is fully satisfactory.

[2]While this version of the term "credential" differs slightly from its typical usage (see Collins et al. 1979), its usage is precedented. Alternatives like "departments" would not capture that the same department may issue different degree types within the same level of vertical stratification (B.A. vs. B.S.). Like Collins's usage, I do not claim that a credential reliably signals a person's skills or talents. They are rather a form of labor-market currency. Consistent with Collins, a credential is treated as an officially recognized requirement that regulates who may apply for particular jobs and for admission to advanced degree programs. Where I depart from Collins is in scope and granularity. Collins often treats credentials broadly (degrees, certificates, and licenses) as instruments of allocation and closure; here I restrict the term to institution- and field-specific degree designations, leaving out post-degree licensure and other non-degree certifications. The department-specific credentials referenced here are thus nested within Collins's concept: they preserve the gatekeeping/allocative function he emphasizes, but are more specific in being tied to particular institutions and departments, thereby distinguishing, for example, different degrees offered by the same department or the same degree issued by different universities, which may carry different weights for different employers. This is in keeping as well with the conceptualization of specific educational credentials put forward by Brown (2001).

[3]I follow the stratification literature in defining horizontal stratification as variation within a given level of completed education. In this case, that is among individuals who have finished a bachelor's

cult to disentangle the fundamental sources of inequalities. These institutional and field differences also interact with demographic sorting processes, or the uneven distribution of students across fields, institutions, and credentials, necessitating a need for analyses that capture institution-specific path dependencies (Hamilton et al. 2024). The existing literature on horizontal stratification is further limited in its temporal scope, which obscures how the relative importance of institutions, fields, and their intersections has shifted across cohorts. Table 1 highlights exemplary research that addresses vertical stratification and horizontal stratification across fields of study, institutions, and their intersections, both in static contexts and over time. Along with Bleemer and Quincy (2025), the present study is unique in filling an important gap in the literature by jointly analyzing both axes of horizontal stratification, tracing their distinct and combined effects within and across graduating cohorts over time.

The gaps in the extant literature largely reflect artifacts of existing survey data infrastructure. For instance, reliance on the coarsened measures of horizontal stratification inherent to survey data has masked the critical processes that translate specific educational credentials into earnings. These processes include school-to-work linkages by field of study, institutional networks, program-specific recruiting, and peer effects. Horizontally stratified inequality among degree holders therefore reflects not only the skills or prestige a degree endows or signals (more or less what survey data are able to capture) but also how specific programs connect graduates to particular labor market sectors through concrete relational mechanisms (what administrative data may capture) (see Avent-Holt and Tomaskovic-Devey 2014).[4] These relational dynamics between cre-

degree. This usage differs from some strands of higher education research, where the term often refers to variation in experiences, resources, or outcomes during college, including between completers and non-completers. My focus is limited to degree recipients, which makes horizontal and vertical stratification analytically separable. Institutional and field of study-level differences in degree completion, being the result of forces that dictate vertical stratification, are important, but they are outside of the scope of this study.

[4]Examples of such program–industry linkages abound. UC Davis's Department of Viticulture and Enology, for instance, is deeply integrated into California's wine industry through research collabora-

dentials and labor market destinations are essential for understanding why horizontal stratification matters within cohorts and how its consequences have been shifting across successive cohorts. In this vein, prior work shows that school-to-work linkages at the field level shape job placement, unemployment risk, and mobility (DiPrete et al. 2017; Bol et al. 2019). Yet these linkages evolve over time and are influenced by institutional structures beyond fields alone. This evolution is occurring within a rapidly transforming labor market that features shifting wage-setting regimes, changing job quality, and new organizational forms driven by technological change, industry restructuring, and declining unionization (Song et al. 2019; Wilmers and Aeppli 2021; Haltiwanger et al. 2024). By systematically describing inequality between specific institutions, fields of study, and their intersections and demonstrating the co-evolution of educational and labor-market stratification, this study delivers the first comprehensive estimates of how horizontal stratification by field of study and institution produces economic inequality across cohorts.

The methodological and data innovations I propose have implications for theories of horizontal inequality. Effectively Maintained Inequality (EMI, Lucas 2001) offers a compelling explanation for the persistence of horizontal stratification by showing that advantaged groups preserve their positions through access to more desirable programs within the same level of education. Yet EMI pays less attention to the concrete processes through which institutional and field-level characteristics, and their intersections in specific credentials, are translated into labor market returns in the first place. The present analysis addresses this gap by examining how the organization of higher education and labor markets mediates unequal returns to institutions, fields of study, and

tions, internships, and alumni employment pipelines. UCLA's Entertainment Law specialization and its ties to nearby studios, agencies, and media firms exemplify a similar institutional–industrial nexus within the Los Angeles creative economy. These cases illustrate institutionally embedded connections between higher education and specific labor market segments, and while these examples are rather explicit in their linkages to specific industrial sectors, such connections likely exist to some extent between most departments and local labor market destinations.

their intersections across cohorts.

This analysis also carries implications for the view of higher education as a "great equalizer," which has highlighted horizontal variation as central to its core findings but has not engaged with horizontal stratification head-on (Torche 2011; Zhou 2019). As the number of bachelor's degrees conferred has almost doubled since the turn of the 21st century, a proliferation of college-level offerings, both within existing schools and with the creation of new schools, has indubitably radically changed the structuring of opportunity in higher education.[5] Further, since the college–no college earnings gap has leveled off since the turn of the century (Autor et al. 2020), which is coincidentally the temporal beginning of the data used in this analysis, this research offers an unprecedented glimpse into possibly new sources of labor market disparities in an increasingly educationally credentialed society.

To maintain analytical tractability, I focus on a single level of vertical stratification, bachelor's degree holders. This decision is both practical and theoretical. Bachelor's degrees are the most commonly awarded post-secondary credential in the U.S., with roughly two million conferred annually, and they serve as a key gateway to many labor market opportunities. Despite often being treated as a uniform marker of vertical status, outcomes among bachelor's recipients vary widely based on institutional and field-level characteristics, making this a critical site of horizontal differentiation. This focus is especially appropriate in the U.S. liberal arts system, where students often choose or change fields after enrolling, and schools themselves are typically not specialized in one domain of study. Unlike more rigid systems such as Germany's, this flexibility makes it analytically possible and theoretically insightful to ask whether institutional or field-level characteristics matter more for inequality. In my analyses, I analyze outcomes at one, five, and ten years post-graduation in order to study both the direct effect of specific credentials immediately after graduation and their indirect effect as mediated through

[5] https://nces.ed.gov/programs/digest/d12/tables/dt12_310.asp

subsequent continued tertiary education and intervening job moves, though I only report findings for five years of follow-up in the main text. I discuss the implications of this in detail below.

In what follows, I examine the evolving landscape of horizontal stratification among U.S. bachelor's degree recipients and its role in shaping earnings inequality over time using a novel dataset that links educational credentials to labor market outcomes. I quantify the extent to which earnings are structured by (1) fields of study, (2) degree-granting institutions, and (3) their intersections (department-specific education "credentials," or degrees from specific college departments), and I trace the changing importance and distribution of each over successive graduating cohorts. In doing so, I contribute new empirical clarity to a literature that has often treated these axes in isolation, by systematically measuring the distinct and combined effects of each, accounting for previously unmeasured confounding effects caused by university-level differences in field of study offerings. In addition to documenting patterns across the main forms of horizontal stratification, I examine how the major underlying mechanisms shaping each axis have driven these patterns, guided by theory-informed expectations specific to institutions, fields, and credentials, each of which reflects distinct processes of stratification.

In the remainder of the introduction, I begin by reviewing existing research on horizontal stratification by field of study and by institution, highlighting the mechanisms distinctive to each and the challenges of analyzing them separately. I also discuss the importance of measuring specific educational credentials, which allow me to recover effects that are not additive in field of study-only or institution-only designs and mitigates compositional bias from measuring fields without institutional context and vice versa. Finally, I turn to the issue of selection, summarizing evidence on whether differences across institutions and fields reflect causal value added or the preexisting characteristics of individuals who select into specific programs.

*** Figure 1 About Here ***

Horizontal Stratification by Field of Study and Institution

Carnevale, Cheah, and Strohl (2013) show that earnings gaps across fields of study can exceed the overall college versus high school gap. In a human capital view, fields confer different skill bundles with different market premiums, which separates the *general* value of a bachelor's degree from its *specific* forms (Kinsler and Pavan 2015; Kogan et al. 2021; Kambourov and Manovskii 2009; van de Werfhorst et al. 2001). Yet, it is not clear that field of study effects are reducible to skills alone: certain disciplines also carry prestige value, convey signals of skills that may not actually be had, and channel students into occupationally closed or professionally socialized pathways. As Brown (2001) argues, educational credential hierarchies are rooted in status cultures and organizational practices that institutionalize prestige distinctions within education. Fields of study may thus operate as status-bearing credentials as much as ascriptions of skill (see also Bills 2003).

Educational institutions themselves represent the other main axis of horizontal stratification, shaping outcomes through largely other mechanisms altogether. University prestige, for instance, affects returns to a bachelor's degree net of ability or learning (MacLeod et al. 2017); cultural matching in elite labor markets privileges graduates of high-status universities (Rivera 2012); and even randomized exposure to elite peers can enhance long-run outcomes (Michelman, Price, and Zimmerman 2022).

While much of the aforementioned research has focused on estimating the causal effects of fields of study or institutions separately, such estimates are partially inseparable in most survey data due to the unobserved differential distributions of fields of study across institutions. Otherwise put, a causal effect of attending a flagship college may indeed represent a premium in the reduced-form sense, but it may also be mediated through specialized fields of study only available at such institutions, calling into question the extent to which it is truly an institutional effect or a field of study effect. While this paper advances new data and methods that allow them to be disentangled, it is not intended that they be pitted against each other for pure measurement purposes. Rather, they are distinct sites where social and human capital is produced and valued, with implications for the sociological processes that drive their valuation. For instance, although both institutional and field-based effects can operate through prestige signaling, cultural capital, and closure, they do so through different channels of transmission. Institutional prestige signals social exclusivity, network quality, and general status—forms of generic or "portable" cultural capital. Field of study prestige, by contrast, signals domain-specific forms of capital—legitimate knowledge, specialized language, and occupational socialization that carry meaning within particular labor-market segments. What this analysis contributes is an empirical measurement of how these two axes of symbolic and skill-based differentiation and their intersections jointly structure economic returns, opening up avenues for future refinement of the exact mechanisms driving such differentiation.

The aforementioned endogeneity problem inherent to survey-based research is further compounded by how both axes of horizontal stratification are measured in survey data. Institutions are proxied by observed attributes or collapsed into broad groupings (e.g., average test scores or selectivity tiers), while fields of study are recorded crudely and then aggregated into overly broad categories. These strategies obscure meaningful differences across institutions and flattening the closure-generating processes that distinguish specific fields. For example, surveys often collapse computer science, information systems, and electrical engineering into a single "computer-related" major despite sharp differences in training, prestige, and labor market returns; similar flattening occurs within medical and engineering programs, whose subfields have widely divergent outcomes but are too complex for many survey instruments. At the institutional level, treating all flagship publics as equivalent ignores sharp cross-state differences in resources, selectivity, and outcomes, just as collapsing private institutions into a single category erases the gulf between elite research universities (e.g., Ivy League schools) and tuition-dependent regional colleges. Prior work rarely models specific educational credentials directly. Where it does, evidence suggests limited institutional variation net of department effects in a Norwegian context (Borgen and Mastekaasa 2018). Even among elite schools, students' experiences and outcomes vary dramatically. As a result, much of the variation most relevant to horizontal stratification has remained unexplored in prior research.

The value of fields of study and institutions reflects not only the human and social capitals they confer at graduation but also the labor-market destinations they enable. Some credentials channel graduates into high-paying sectors with limited long-run growth (e.g., nursing); others start lower but yield steeper trajectories (e.g., medicine); still others (e.g., technology or consulting) combine high entry pay with long-term mobility (Cheng and Song 2019). These life-course patterns are further stratified by differences in the likelihood of pursuing graduate education, making attention to specific credentials essential. They are also shaped by larger forces: fields, institutions, and credentials evolve with labor-market change as new fields emerge, old ones fade, and programs adjust to shifting occupations, industries, and work forms—often differently so across institutions. Many fields are additionally structured by national academic policies and vocational systems. A large international literature on school-to-work linkages shows that stronger linkages reduce unemployment and improve job outcomes but can limit flexibility and increase mismatch (DiPrete et al. 2017; Bol et al. 2019). This framework situates educational credentials within institutional structures. However, most prior work is cross-national, whereas this study considers variation within a single, large national context. Taken together, this perspective—alongside my analysis—shifts attention away from individual selection and toward institutional and labor-market factors shaping credential outcomes.

The aforementioned measurement difficulties have led to research that has hitherto pursued a narrow agenda. Work on institutional effects in the United States has often focused on elite universities even though they educate a small share of students.[6] However, most bachelor's degrees are awarded by colleges that differ in enrollment patterns, residential versus commuter context, online share, and admissions and advising practices, which conventional metrics such as SAT scores or selectivity do not fully capture (Ciocca Eller 2023). Many students attend nearby colleges or face financial and family constraints, which makes variation among non-elite institutions central. In terms of intergenerational mobility, higher selectivity does not uniformly raise returns because many colleges with the highest mobility rates accept most applicants (Chetty et al. 2017).

Beyond institutional selectivity or quality indicators, organizational features of universities and campus ecologies channel students unevenly by class background, producing divergent trajectories even within the same school (Armstrong and Hamilton 2013) and making an attention to specific institutions and credentials paramount. Crucially, outcomes depend both on where students enroll and on what they study there, because institutions differ in disciplinary strengths and students sort into programs in patterned ways. Among research-intensive elites, program mixes are relatively similar, which can mask this interaction. Among the far larger set of non-elite colleges, the specific fields of studies offered at a given institution are first order.[7] Finally, not all educational credentials express the simple additive effects of a field of study and an institution, departmental quality and program reputation vary. For these reasons, an analysis of inequality broadly amongst the full range of institutional flavors must jointly account for institutions and fields of study to capture how these environments should together structure earnings.

[6] By the author's calculation, 21 Ivy Plus colleges account for 1.8% of bachelor's recipients.

[7] For example, many allied health professions (one of the largest groups of professions comprising laboratory technicians, respiratory therapists, dietitians, etc.) require specialty degrees only available at select universities in each state. Likewise, vocationalized bachelor's degrees for careers as accountants, commercial pilots, and police officers are often geographically limited within a given state.

Selection Effects and Measuring the Value Added of Horizontally Stratified Degrees

In the context of horizontal stratification, I use the term *selection effects* to refer to differences in outcomes across institutions, fields of study, and their intersections that arise because students with different backgrounds, preparation, preferences, or constraints sort into different programs prior to enrollment. Observed earnings gaps may therefore reflect who enters a given credential rather than what that credential does for similarly situated students. This usage is complementary to the concept of *value-added* or causal effects, which capture returns attributable to the training, networks, placement, and other features of the credential itself, holding student characteristics constant. Distinguishing selection effects from values added is central in studies of horizontal and vertical inequality because institutions and fields, and college itself, attract systematically different populations along dimensions correlated with earnings, including academic preparation, socioeconomic background, and labor-market aspirations.

Field of study and institutions differ in demographic makeup and in the forces that channel students into them—including preparation, aspirations, and perceived labor-market risk (Altonji, Blom, and Meghir 2012; Zhou 2019; Brewer, Eide, and Ehrenberg 1999; Loury and Garman 1995; Goyette and Mullen 2006). Crucially, however, differential enrollment by demographic characteristics is not sufficient alone to contaminate causal conclusions from observational data on earnings gaps. It is only when those demographic imbalances are *correlated with unobserved determinants of earnings* (e.g., pre-college academic abilities, productivity, motivation) that travel with students into the labor market or when propensity to choose a specific a field of study or college is correlated with the benefit one is slated to receive from a specific program (treatment effect heterogeneity bias, Zhou and Xie 2020) that they pose problems. When such selection on unobservables into specific credentials is present, cross-credential gaps can reflect sorting rather than credential value added. However, the extent to which institutional differences in earnings reflect underlying selection effects is mixed: some studies attribute differences to selectivity, while others find little effect once unobserved heterogeneity is addressed (Borgen 2014; Bleemer 2021; Manski and Wise 1983; Dale and Krueger 2002; Brand 2006). By contrast, recent work provides limited support for the view that field-of-study pay gaps primarily reflect selection (Dahl et al. 2023; Bleemer and Mehta 2022; Kim et al. 2015). Put differently, demographic segregation matters for the present study only insofar as it generates the earnings differences observed across credentials. Otherwise it is secondary to the task of describing shifting dynamics of earnings inequality over time, though it has implications for whom such inequalities affect the most.

A recent comprehensive study of the college mobility pipeline by Bleemer and Quincy (2025) puts selectivity in perspective in the manner necessary for the present study. Using more than a century of survey data, the authors show that college has become increasingly regressive (i.e., the benefits of vertical stratification in education have shifted toward higher-income groups) since 1960 because of structural changes in higher education. Key shifts include declining institutional quality at public universities most attended by low-income students, diversion into lower-value two-year and for-profit colleges, and growing stratification in major choice. In doing so, the authors quantify the extent to which between-institution and between-field of study earnings differences reflect the "value-added" of a degree—or the value of a degree net of who selects into a degree. They find that selection explains only a small share of earnings differences generally. Their estimates indicate that about 70–80% of earnings differences across institutions and nearly 100% across fields reflect causal effects of credentials rather than preexisting student differences (Bleemer and Quincy 2025). The institutional estimate is consistent with Chetty, Deming, and Friedman (2023).

It is intuitive that selection into institutions and fields accounts for only a limited share of horizontal inequality. Along the vertical margin, such as college versus high school, selection is strong because populations differ in preparation, resources, and aspirations—all of which are correlated with earnings differences even net of college attendance. Along the horizontal margin, differences across schools, fields, and their specific combinations arise from more stochastic forces that do not always track prior ability, at least in a way that is correlated with potential earnings. Xie et al. (2015) document this precise phenomenon with regards to STEM fields: family background and individual characteristics matter for college preparation, but they do not seem to predict the choice to go into a STEM field. What is more likely is that students end up in programs through advising nudges, individual interests, proximity and commuting constraints, tuition and net price, and frictions such as course availability, lotteries, and enrollment priorities. These processes sort students in ways that are noisy with respect to ability, so observed outcome gaps across credentials largely reflect credential value added and the labor-market positions those credentials enable, as summarized in Bleemer and Quincy (2025). Of course, demographic sorting still matters for who enters which programs. However, the earnings attached to credentials appear more sensitive to processes that occur post-sorting into credentials. This does not run contrary to the large literature on horizontal stratification and its relationship to demographic stratification and segregation across horizontally stratified credentials. For instance, Hamilton et al. (2024) document how horizontal stratification coincides with racial, class, and gender inequality in access. Their perspective clarifies who gets in. My analysis focuses on how the value of credentials shifts and how those shifts translate into labor-market outcomes, informing how subsequent stratification across demographic groups comes about.

My analysis is possible even though I do not model selection directly. The findings in Bleemer and Quincy (2025) offer a useful benchmark and help situate my results within broader patterns of inequality. My contribution is to center the structure and evolution of horizontal stratification itself, asking how the value of credentials has shifted over time and how these shifts reflect changes in higher education and the labor market. Unlike survey designs, the dataset I use permits fine-grained analysis at the credential level and makes it possible to separate field effects from institutional effects while tracking their joint evolution. To address concerns that composition alone drives the results, I implement several robustness checks, described below. I now turn to the analytical overview, where I lay out the measurement strategies I use to quantify horizontal stratification across fields of study, institutions, and their intersections and to identify the forces undergirding changes within each stratifying domain.

*** Table 1 About Here ***

Analytical Overview

This paper treats field of study, institution, and their intersection as analytically distinct yet interdependent dimensions of horizontal stratification. Each represents a categorical form of differentiation within a single level of education but operates through different underlying mechanisms. Together, they constitute the primary ways in which educational differentiation structures labor market outcomes among bachelor's degree recipients.

Fields of study shape earnings primarily through differential flows to labor-market destinations that vary in work content. Their effects arise from how programs channel graduates into specific industries and occupations, which are themselves characterized by distinct wage-setting regimes, internal labor markets, and opportunities for advancement (DiPrete et al. 2017; Bol et al. 2019; Kalleberg and Lincoln 1988; Tomaskovic-Devey et al. 2020). As between-industry and between-firm dispersion in wages has grown (Song et al. 2019; Wilmers and Aeppli 2021; Haltiwanger et al. 2024), the labor market destinations associated with a field have become an increasingly consequential determinant of its average returns. Therefore, the analyses that follow seek to disentangle the extent to which horizontal stratification by fields of study is due to changes in fields of study, changes in labor markets, and changes in how they are linked to one another.

Institutions, in contrast, influence labor market outcomes largely through prestige signaling, resource endowments, and social capital formation. Institutional prestige conveys general status and exclusivity that may operate independently of any particular field of study, and institutional environments vary in peer composition, advising quality, and access to employer networks, all of which shape post-graduation opportunities (Rivera 2012; MacLeod et al. 2017; Michelman et al. 2022; Ciocca Eller 2023; Armstrong and Hamilton 2013). While selectivity and observable characteristics such as tuition or test scores proxy parts of these mechanisms, a substantial portion of institutional value remains embedded in organizational practices and campus cultures that produce portable but often intangible advantages. A key task of this analysis is to measure how much of variation in institutional outcomes is due to observable differences in institutions as opposed to unobservable differences in institutions.

The intersections of field and institution, institution- and field of study-specific educational credentials, combine these mechanisms in distinctive ways. Certain departments at particular universities possess well-developed linkages to specific employers or industries, creating pipelines that cannot be explained by either institutional prestige or field-level skill specificity alone. Such credential-level linkages can consolidate new forms of inequality by directing graduates toward high- or low-wage sectors in systematically different ways. For this reason, I take the institution-by-field of study combination as an operative unit alongside its margins. In addition to measuring how such combinations systematically dictate earnings in college graduates, I also seek to understand how fields of study are differentially distributed across institutions in patterned ways to see if certain colleges and universities have been better able to adapt their course offerings in a changing labor market.

The empirical design I employ below follows from these mechanisms. In the first part of the analysis, I reconstruct individual-level earnings from aggregated PSEO credential statistics to recover within-credential dispersion and decompose total earnings inequality across cohorts into components attributable to institutions, fields of study, and their intersections. This approach also distinguishes changes arising from shifts in credential-specific earnings premiums from those due changes in overall enrollment patterns. In the second part, I disentangle each major axis of horizontal stratification independently. For fields of study, I analyze changes in average earnings through field-to-industry flows and the earnings structures of destination industries, decomposing whether trends are driven by reallocation across industries or by changes in industry pay. I also benchmark these changes against what would be expected from demographic recomposition within fields. For institutions, I assess the extent to which observable characteristics such as selectivity, size, tuition, and enrollment explain variation in outcomes net of field composition and how these associations evolve over time. For credentials, I examine whether field–institution pairings have become more stratified—specifically, whether high-earning fields have become increasingly concentrated in high-earning institutions—thereby indicating consolidation of advantage at the intersection of prestige and field-specific specialization.

Data

Across both parts of the analysis, this study draws primarily on the U.S. Census Bureau's experimental Post-Secondary Employment Outcomes (PSEO) dataset, which links college graduation records to employer-reported earnings via the Longitudinal Employer–Household Dynamics (LEHD) system. To my knowledge, this study represents the first use of these data in sociology research. The LEHD provides near-complete coverage of annual earnings reported for unemployment insurance purposes in participating states, and the PSEO links these earnings to graduates by institution, field of study (four-digit CIP code), and graduation year. The result is a dataset that captures labor market outcomes at the credential level for up to ten years after graduation. This structure enables direct measurement of horizontal stratification along the dimensions outlined in the introduction.

The PSEO contains two core components. The "earnings" dataset reports average earnings for each credential one, five, and ten years after graduation, alongside the 25th and 75th percentiles of the earnings distribution. The "flows" dataset tracks the number of graduates from each credential entering different industries, aggregated at the two-digit NAICS level, at the same intervals. The data also include counts at the credential level of workers not employed in the workforce, based on the observed gap between the number of graduates and the number of workers found in the LEHD. Although the data are aggregated, they allow partial reconstruction of earnings distributions and analysis of how field–industry linkages evolve over time, which I discuss below. I focus on five-year post-graduation outcomes, which reflect earnings after one has established their career and avoid the limited cohort coverage in the ten-year data. Five-year post-graduation data includes earnings even for individuals who have continued their education, so long as they are in the workforce at the time of follow-up. Otherwise put, the effects shown here represent the *reduced form effect* of a bachelor's degree or the total effect of a bachelor's degree, even if it is mediated by continued education within five years of graduation. While a number of students may not have finished their schooling five years after they graduate with a bachelor's degree, most have if they are going to. For comparison's sake, one- and ten-year outcomes are used in supplementary analyses that double as robustness checks to the extent that these results are mediated by continued graduate education. Because of this decision, results in the main analyses are only available for cohorts up to 2013–2015, as they must be observed five years after graduation, and the raw underlying data extend through 2019. More recent results are available in the appendix for a one year time horizon.

Because the PSEO is based on voluntary state and institution agreements, its coverage is incomplete but diverse, spanning public and private universities, community colleges, online colleges, and flagship state institutions. While not nationally representative on their own, the breadth of institutions allows for rich analyses of variation in credential outcomes. The fact that many states' participating institutions represent over 80% of these states' total graduates allows the sample to credibly reflect a representative sample nationwide of college graduates after reweighting.[8] I adjust for imbalances in institutional representation in the original data using an entropy balancing reweighting method discussed in the supplementary appendix, and I revisit these limitations later in the paper. Appendix Figure A1 maps institutional coverage.

One important limitation is that the PSEO does not report earnings by industry at the credential level. While I observe the average earnings for each credential and the distribution of its graduates across industries, I cannot observe earnings within industries conditional on credential. To approximate this, I supplement with industry-level earnings data from the American Community Survey (ACS), which reports average annual earnings by industry for bachelor's degree holders. These estimates are used only in analyses where industry flows and sectoral average wages are central, which are just a subset of all analyses. The PSEO data also do not disaggregate credential-level earnings by demographic characteristics: race, ethnicity, and gender. I undertake a sensitivity analysis using NCES data, which contain cohort-by-cohort credential-level statistics of degrees conferred by race/ethnicity and gender.

Finally, I incorporate data from the Department of Education's College Scorecard to characterize institutional attributes such as mean SAT scores, tuition, undergraduate enrollment, and selectivity. These variables are used to evaluate whether observable institutional traits help explain differences in graduate earnings net of field composition. They are also used in the reweighting of the data to ensure representativeness. The Scorecard covers nearly all institutions in the PSEO, though some variables are missing

[8] https://lehd.ces.census.gov/data/pseo_experimental.html

for a subset of schools. As with the ACS data described in the previous paragraph, these data are used in supplementary analyses that examine institutional-level variation and are not central to the paper's headline findings.

Part I - Decomposing Variation in Earnings Inequality Amongst College Graduates

Methods

Generating Income Distributions From Observed and Scenario-Based Credential-Level Earnings Summary Statistics

I begin by simulating individual-level income data from specific educational credential-specific and cohort-specific earnings distributions. This allows me to contextualize categorical distinctions within the broader earnings distribution and compare inequality between credentials to inequality among individuals within the same credential. To do so, I simulate individual-level income data from the aggregate statistics provided in the PSEO dataset.[9] This allows the importance of between-field, -institution, and -credential variation to be compared relative to variation within these groupings.

In the earnings dataset, for each specific credential (field of study-by-school combination) and graduation cohort combination, four statistical moments are known: the number of graduates, and the 25th, 50th, and 75th earnings percentiles (π). Graduation cohorts are grouped into three-year spans for bachelor's degrees (e.g. 2001–2003, 2004–2006, 2007–2009, etc.). This aggregation is necessary to protect individual privacy as many credentials only graduate a few individuals each year, and sample sizes for each cohort-credential observation must be large enough to protect graduates' privacy. Con-

[9] While a parametric variance decomposition is possible when distributions are presumed to be log-normal, it provides similar results to the approach taken here and is less flexible than a simulation-based approach. The simulation-based approach allows for flexibility in specifying the robustness tests, in particular varying distributional forms and adding in non-earners, as specified later in the methods section.

versely, this allows the inclusion of even small fields of study.[10] Using these points of information, one can recover a simulation of the original microdata that produced them. To do so, I assume that within each cell (specific educational credential–graduation cohort combination), incomes are distributed log-normally. For each cell, the density function of the distribution is calculated as is shown below in equation 1, which calculates a singular standard deviation (equation 3) from the 25th and 75th percentiles. As incomes are assumed to be log normal, the logged median and logged mean are assumed to be the same (equation 2).

$$f(x) \sim \mathcal{N}(\mu, \sigma^2) \sim \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\ln(\mu))^2}{2\sigma^2}} \tag{1}$$

$$\mu = \pi_{50}(X) \tag{2}$$

$$\sigma = \frac{\ln(\pi_{75}(X)) - \ln(\pi_{25}(X))}{2 \times 0.674} \tag{3}$$

Using the above functional forms, I simulate individual earnings from the reconstructed distribution for each credential, generating a dataset that approximates the original underlying microdata. This simulated dataset serves as the basis for most subsequent analyses. The method carries limitations: most notably, it assumes log-normality and no skew within each distribution. While deviations from log-normality could affect the tail behavior, this assumption is well supported in the literature (Gibrat 1931; Battistin, Blundell, and Lewbel 2009). To ensure the robustness of this assumption, I implement an alternative specification using a piecewise log-normal/Pareto distribution, assigning a Pareto tail to the top 2% of the distribution, capturing greater income inequality among high earners in line with previous work. These approaches assume that individuals within each credential are interchangeable. Given that my analysis relies exclusively on aggregated data and not individual characteristics, this assumption is analytically appropriate.

[10] Noise is also added to the data to keep them differentially private, though it is not expected that this process will substantively affect my results.

In addition to simulating observed distributions, I generate counterfactual, scenario-based datasets that allow me to isolate the drivers of inequality over time. In creating simulated datasets of individuals for each credential, I hold constant at the earliest observation either the number of individuals in each credential or the credential-specific distribution of income across cohorts in what amounts to effectively a "Das Gupta" decomposition (1993). Using these simulated scenario-based datasets in the following sections allows me to determine whether it is shifting allocation of individuals across institutions, fields of study, and specific credentials that may be driving changes in stratification or if it is simply different average earnings attached to each that are driving the effects.

Variance Decomposition

With these simulated individual-level earnings data in hand, I next decompose the total variance in earnings to estimate how much is attributable to different forms of horizontal stratification: field of study, institution, and specific credentials. This variance decomposition approach allows me to assess the relative importance of each component and track how their contributions to inequality evolve across cohorts. I perform a variance decomposition of logged annual earnings at the individual level $ln(\omega_{i,u,f}|Y)$ wherein I, separately for each graduation cohort (y) and year of followup (X), iteratively add fixed effects for field of study (F_f), institution/university (U_u), and institution-field of study interactions $\Big(\gamma(U_u \times F_f)\Big)$. The differential increase in R^2 is the percent of the total variance explained by each additional term with respect to all previous terms. In comparing these estimates over time and across cohorts, one can recover the extent to which each axis of horizontal stratification matters among degree holders in determining annual earnings. The model specification is as follows, and fixed effects components are added step-wise from left to right in equation 4[11]:

[11]The full model with field of study, institution, and their intersection fixed effects is not technically identifiable because the interaction term is nested within its main effects. This does not pose a problem

$$ln(\omega_{i,u,f}|Y = y + X) = F_{f,y} + U_{u,y} + \gamma(U_{u,y} \times F_{f,y}) + \epsilon_{i,y} \tag{4}$$

While the order of the components will affect the results, particularly given that fields of study are unevenly distributed across universities and change over time, I address this concern through a sensitivity analysis in the supplementary appendix by reversing the order in which fixed effects are entered. Alternative approaches to this issue do exist, though they are generally designed either for settings with more than two primary fixed effects or for contexts where the primary object of interest is a single "main" regression coefficient (see, for example, Xie and Zhou 2014; Gelbach 2016). In contrast, my approach provides a transparent set of bounds: one in which field of study premiums precede institutional premiums in importance, and one in which the reverse is true. I present the former in the main text, while also discussing the latter in the results section and presenting its results in the supplementary appendix. However, the ordering I have chosen for the main results is not arbitrary; it reflects the reasonable view that institutional wage premiums are layered on top of, rather than independent from, field of study premiums, such that an institutional premium is meaningfully interpreted in relation to a given field of study premium. Otherwise put, a credential is associated with three additive premiums: one based on field of study and the skills and capital conferred with it, one based on institutional prestige and the various forms of capital that come with it (net of field of study), and one based on specific departmental- or credential-level traits (net of the prior two premiums).

*** Figure 2 About Here ***

for the present analysis because the variance of each component and its contribution to total explained variance are identified. The decomposition relies on the incremental change in R^2 as each set of fixed effects is added rather than on the absolute value of the coefficients themselves.

Results

Data Coverage, Representativeness, and Descriptive Statistics

Figure A1 shows the geographic distribution of degree-granting institutions in the PSEO data. Inclusion is not based on a probabilistic sample but on voluntary partnerships between states, institutions, and the federal government. Figure 2 further illustrates this selectivity by plotting all U.S. universities by 2016 undergraduate enrollment, with in-state tuition, average SAT scores, and admission rates where available. Included and omitted schools are distinguished by color. While many private universities are missing, this is not a major concern: within public and private sectors, included schools largely mirror the full population in their institutional characteristics, though coverage varies. In this sense, the data are structurally representative, though compositional reweighting is necessary. One exception is the underrepresentation of Ivy League and similarly selective private colleges, which appear as outliers in the lower portions of the facets on selectivity and size. Given their small enrollments relative to large public institutions, their exclusion likely has limited effect on overall trends, though it constrains generalizability at the very top of the institutional earnings hierarchy, as discussed in the discussion.

*** Table 2 About Here ***

To make the data more closely reflect the actual target population of all U.S. institutions granting bachelor's degrees, I reweight the included PSEO institutions using an entropy balancing technique so that, on observables, the weighted PSEO sample more closely matches the full universe of colleges and universities. Specifically, drawing covariates from the College Scorecard (public/private, enrollment, tuition, selectivity, and average SAT scores), I calculate weights to match first moments of these covariates in the target population while minimizing divergence from uniform weights. I apply the resulting weights in all analyses in this paper where appropriate. Covariate balance before/after weighting is shown in Table 2. Balance is largely achieved, but there is a slight mismatch in in-state tuition due to missingness of the most prestigious private colleges. Though highly selective publics like the University of Michigan are present in the data, these have lower tuition rates, making achieving perfect balance infeasible. For full details of these methods, see the supplementary appendix. To qualify and foreshadow further results below, many results are not changed dramatically by this reweighting exercise, and so imperfect balance is not much cause for alarm. This likely reflects three stylized facts: 1) Most students attend public schools (which are well represented in the PSEO data); 2) Even when they attend private schools, they are non-elite private schools (which are well represented in the PSEO data); and most importantly 3) Much meaningful variation between schools transcends typical metrics of school prestige and selectivity and comes down to more nuanced variation based on instruction type, resources, school environment, and advising structures, which makes rebalancing the data on these characteristics not have much impact.

*** Table 3 About Here ***

Table 3 shows the number of included units in the data, stratified by cohort. Because the PSEO aggregates credential-cohort combinations into into multi-year credential-cohort combinations, the data are reported in three-year spans for bachelor's degrees (2001–2003, 2004–2006, etc.). In 2014, roughly 1.8 million individuals earned a bachelor's degree in the United States.[12] By comparison, my cumulative sample size of earnings five years post-graduation for the 2013–2015 graduating cohorts is 1,309,057, which represents slightly less than one-quarter of all U.S. bachelor's recipients. This shortfall reflects both the non-coverage of certain institutions (as discussed above) and the fact that not all graduates are observed with earnings in the LEHD system. The PSEO

[12] https://nces.ed.gov/programs/digest/d12/tables/dt12_310.asp

does not track unemployment directly, but it does report the gap between the number of degrees conferred and the number of graduates with matched earnings records. This discrepancy reflects all individuals not linked to the LEHD as employees—a group that may include the unemployed, those out of the labor force (e.g., those engaged in full-time caregiving, pursuing further schooling, or working in informal workor work abroad), and those working in uncovered sectors. Because these individuals have no observed earnings, the analyses in the main text implicitly condition on labor-force attachment. As a result, my main estimates potentially mismeasure total inequality across all graduates if unemployment is considered. I account for this by simulating non-attached workers, as reported by the PSEO data for each specific credential-cohort combination, as having zero annual earnings in a sensitivity analysis, even though it is likely that many non-workers are not employed by choice. These results are presented in supplementary appendix Figure A4 and are discussed where appropriate below.

In Table 3, it is clear that the number of individuals, fields of study, schools, and their intersections are increasing over the time period shown in the data, however colleges also begin being represented in the data at different points in time. To accommodate this, most of my analyses use a restricted set of institutions that appear in the data every year, amounting to 270 degree-granting institutions in total. In the restricted set, the number of college graduates increases by over 50% in the observed time period, which is commensurate with the growth of college attendance and population growth in this time period. As the number of fields of study at the four-digit level is increasing over time, I also conduct sensitivity analyses using two-digit CIP codes, the number of which does not increase similarly over the period in question, and I use a middle ground between two- and four-digit CIP codes, which is detailed in the supplementary appendix. Furthermore, the Das Gupta-inspired analysis holds constant enrollments, allowing me to ensure that the creation and elimination of fields of study are not driving the results.

*** Table 4 About Here ***

*** Figure 3 About Here ***

Finally, to orient the reader to the structure of the original data before proceeding to my analytical results, Table 4 shows the top and bottom ten credentials in terms of earnings five years post-graduation for the bachelor's degrees graduating cohorts 2001–2003 and 2013–2015, the earliest and most recent cohorts of the sample. Even from this simple summary table alone, several notable phenomena stand out. For both sets of cohorts, the level of structured horizontal stratification is staggering. The lowest-earning credentials earn less than one-fifth of what the highest earning credentials earn. While the interquartile range of pay within each credential is large, it is dwarfed by this between-credential variability in earnings. For earlier cohorts, engineering and pharmacy majors monopolized the highest earning credentials, while in later time periods it is dominated by a mixture of computer science, health professions, engineering and pharmacy. Also, the highest earning credentials appear to be much larger than the highest earning credentials in the earlier time period, with larger cohort sizes. Finally, the righthand-most column shows the percent of workers in the largest industry as a function of each credential. This is a simplified way of rendering the industry share distribution for each credential since there are 20 possible industries, but it shows that the highest earning credentials appear to have stronger credential-to-work linkages than the lowest-earning credentials. Figure 3 shows this variation in an alternative manner across the entire distribution of credentials, displaying each credential as a point on the graphs, stratified by the two-digit field of study.

*** Figure 4 About Here ***

Earnings Variance Decomposition Analysis

Results for the variance decomposition are shown in the left-most panel of Figure 4. The first finding is that over the relatively short time period in question, the percent of overall variance explained (R^2) increased from 25% to 30% for earnings one year after graduation. Mechanically, this means that within institutions and fields of study, the role of individual variation decreased from explaining 75% to 70% of total variance in log earnings. Otherwise put, conditional on having a bachelor's degree, the importance of observable degree characteristics for earnings is increasing and individual variation in outcomes net of one's degree characteristics is decreasing proportionally.

Several striking findings emerge. First, most of the variation in earnings is explained by what people study—not where they study. This pattern likely reflects both a response to exogenous technological change, as in RBTC, and an endogenous restructuring of opportunity that runs through educational credentials, but more study is needed to understand the causes of changing industry flows and industry average earnings. Still, the magnitude is notable: for the 2013–2015 cohorts, 21% of variation is attributable to field of study, compared to just 5% for institution, and 4% for specific credentials. Second, the rising importance of degree characteristics is primarily driven by the growing influence of field of study. There is also slight evidence of increasing institutional importance, though to a much smaller extent. Third, the contribution of specific credentials has remained largely stable over time. That is, changing characteristics of individual departments, net of school and field effects, are not driving the results. These findings are robust to multiple sensitivity tests. Appendix Figure A4 shows consistent results across alternative specifications: using two-digit CIP codes, including non-earners as zeroes, applying a piecewise log-normal/Pareto distribution, estimating models without log transformation, estimating unweighted models, and using different weights to upweight only private institutions to match the national bachelor's degree-holding population. Across all approaches, field of study remains the dominant and increasingly important predictor of earnings. I draw the reader's attention specifically to the robustness check that reorders the fixed effects to allow institutions to come before fields of study. Even here, where the institutional effect is measured first, allowing it to include the effect caused by institution-level differences in fields of study offered, the explanatory power of field of study prevails. Indeed, it is impossible to fully disentangle the two, but the main effect and this robustness check provide the lower and upper bounds of the importance of field of study and institution, with both scenarios highlighting the explanatory power of field of study.

*** Table 5 About Here ***

A natural follow-up to the previous results is whether observed changes are driven by changing enrollments across credentials or by shifts in credential-specific average annual earnings. To address this, I decompose the results from the left-most panel of Figure 4 using two counterfactual scenarios: one holding credential-specific earnings constant at their earliest observation, and another holding constant the size of graduating cohorts by credential. This Das Gupta-style decomposition shows that most of the change is due to shifting average earnings across credentials, not changing enrollments. In fact, such allocative forces appear to slightly offset the earnings-based trend across the first four cohorts observed. That is, students have not disproportionately moved into high- or low-earning credentials in ways that would explain the increasing inequality, nor has the creation or disappearance of specific credentials driven the results. Instead, the credentials themselves have changed in what they yield in the labor market. The causes of these shifts are unclear but are taken up in later sections. Table 5 shows that the flight from high-earning fields of study like business and computer science (discussed further below) is likely partially to blame for this. Appendix Figure A2 replicates the decomposition at both one and ten years post-graduation, with consistent findings at both intervals. The trend of growing explanatory power, as driven by fields of study, also holds for one–year outcomes. While only three cohorts allow ten–year follow-up, these results show no deviations that would call earlier findings into question, and the consistent findings between the three different periods of follow-up indicate that the primary findings are likely not mediated by graduate schooling.

While these results do not necessarily reflect the causal "premium" offered by specific fields of study, institutions, and credentials, or the "value added" of choosing one credential over another, prior studies of the causal effects of institutions and fields of study can benchmark the findings reported here. As mentioned in the introduction, Bleemer and Quincy (2025) synthesized the evidence on this subject and found that earnings differences in fields of study reflect 100% of the value added of attending different majors. For institutions, earnings differences may be attenuated by 20% when accounting for selection effects. Otherwise put, accounting for differential selection into fields of studies and institutions only would attenuate the findings reported here for institutions, and the importance of fields of study would remain, strengthening my main finding of the increased importance of field of study. There are no causal studies at the credential level on earnings differences, but they are likely somewhere between fields of study and institutions in representing the "value added" effect of credentials. This strengthens the findings reported here, as fields of study already explain the bulk of variation in horizontal stratification.

Finally, one might worry that the results are mechanistic as there are many more fields of study than one might expect. Even when repeating the analysis at the 2 digit CIP code level, which juxtaposes 36 fields of study against 270 institutions, fields of study retain their explanatory power (supplementary appendix Figure A4), though its power is slightly attenuated.

*** Figure 5 About Here ***

Part II - Understanding the Drivers of Each Axis of Horizontal Stratification

The methods and results described up to this point have enabled me to paint an overview of the relative importance of each kind of horizontal stratification in driving earnings inequality among college graduates over time. However, the fundamental forces driving these changes require further study. The following methods will tackle each source of horizontal stratification—field of study, degree-granting institution, and specific credentials—one at a time to understand the underlying forces dictating the importance of each.

Methods

Analyzing Changing Average Annual Earnings by Field of Study Over Time

To understand how and why and how field of study-based inequality in earnings is changing, I examine the shifting relationship between fields of study and industries. As argued in the introduction, field-to-industry flows are central to understanding horizontal stratification in the modern labor market. This section uses decomposition techniques to assess whether changes in average earnings by field of study are driven by where graduates end up (industry placement), how well those industries pay, or both. For legibility, and because flow data are only available for aggregated fields of study, this is done at the two-digit CIP code level.

While the earlier decomposition shows how much fields, institutions, and their intersections contribute to overall inequality, identifying what drives those changes requires an additional step. As discussed in the introduction, industry dynamics are central to understanding horizontal stratification over time. To examine this, I analyze flows from fields of study into industries, alongside changes in industry-level earnings for college graduates. Because the PSEO data do not report earnings by industry, I use ACS data on industry-level earnings among college-educated 27–29-year-olds, in combination with average earnings by field and field-to-industry flows. Assuming additivity in logged components, this enables estimation of average earnings by field net of industry, and by industry net of field. Further methodological detail fo deriving these estimates is provided in the supplementary appendix.

These estimates may then be used to estimate expected field of study average wages based on changing industry flows. Moving beyond such simple comparisons and to formally disentangle the contributions of changing industry composition and changing industry-specific average earnings to field of study-level earnings trends, I decompose changes in $ln(\omega_{f,y})$, logged average earnings for each graduating cohort in a given field of study, using an extended version of a Kitagawa-Oaxaca-Blinder Decomposition (Oaxaca and Sierminska 2023; Kitagawa 1955). The following equation (equation 5) describes a basic Kitagawa-Oaxaca-Blinder Decomposition using two time points, y_1 and y_2, which are equivalent to the earliest and most recent cohorts in my sample. Average shares and average annual earnings (equations 6 and 7, respectively) are based on the simple means of the two time points. There is also an residual component reflecting the difference in the observed change in field of study-specific average annual earnings and what is predicted by industry shifts and changing industry premiums alone (equation 8).

$$\Delta \ln(\omega'_f) = \sum_{ind} \overbrace{S^*_{ind,f}\left(\ln(\omega_{ind,f,y_2}) - \ln(\omega_{ind,f,y_1})\right)}^{\substack{\Delta \text{ due to changing} \\ \text{industry annual earnings}}} + \overbrace{\ln(\omega^*_{ind,f})\left(S_{ind,f,y_2} - S_{ind,f,y_1}\right)}^{\substack{\Delta \text{ due to changing} \\ \text{industry shares}}} \tag{5}$$

$$S^*_{ind,f} = \frac{S_{ind,f,y_1} + S_{ind,f,y_2}}{2} \tag{6}$$

$$\ln(\omega^*_{ind,f}) = \frac{\ln(\omega_{ind,f,y_1}) + \ln(\omega_{ind,f,y_2})}{2} \tag{7}$$

$$\Delta \ln(\omega_f) = \Delta \ln(\omega'_f) + \varepsilon_f \tag{8}$$

Holding shares at their average amount between the two time points $S^*_{ind,f}$ and annual earnings at the average level between the two time points $\ln(\omega^*_{ind,f})$, one can decompose the extent to which overall changes in average annual earnings by field of study are due to each component. However, since industry changes are affecting the entire labor market to some extent, I further decompose the change due to industry shares to a "global" and a "local" effect, where the former is the shift due to industry growth in the overall labor market of college graduates, and the latter is any industry shifts net of that.

Expanding the second term in equation 5, I arrive at the following expression:

$$\ln(\omega^*_{ind,f})\left(\overbrace{(S_{ind,y_2} - S_{ind,y_1})}^{\text{Global effect}} + \overbrace{[(S_{ind,f,y_2} - S_{ind,f,y_1}) - (S_{ind,y_2} - S_{ind,y_1})]}^{\text{Local effect}}\right) \tag{9}$$

In sum, the above "extended" Kitagawa-Oaxaca-Blinder Decomposition allows me to decompose the extent to which changes in observed field of study average annual earnings are due to three components: global growth and decreases in industry representation of working college graduates, local field of study-specific growth and decreases in industry flows, and changes to average industry-specific average annual earnings among college graduates. Any residual differences (ε_f) between observed and predicted changes in annual earnings over the time period in question are presumed to be due to interactive effects between fields of study and industry, within-field heterogeneity in four-digit CIP codes since CIP codes are measured at the two-digit level, or due to individual variation. None of these sources of variation can be modeled directly using the data, but the magnitude of the residual changes in total are shown for comparison.

Just because industry flows may predict field of study-level earnings, does not mean it is the primary cause. While this research is in not causal, it is important to acknowledge that changing field of study average earnings may simply reflect demographic compositional change within fields of study. Even if this were the case, it would not invalidate these methods and any findings that come about because of them, but it would be a prudent way to qualify my results. In order to test this possibility, I devise a simple test to predict cohort-to-cohort changes in average wages based on within-field of study demographic composition as opposed to industry flows. I employ within-field of study and within-credential fixed effects models wherein the predictors are alternatively demographic composition (which is available at the field of study and credential level in the NCES data) or industry flows and use the within-unit predictive power to understand how well each phenomenon describes changing earnings. I present these robustness checks as additional methods and results in the supplementary appendix, and I discuss these results in the main paper's results section below. I also directly compare predicted earnings changes based on each method to realized changes in earnings in the supplementary appendix.

The primary decomposition methods presented in this section highlight how much of field-based earnings change is driven by industrial flows and average wages. However, the same logic may not apply to institutions. Whereas field of study stratification is often closely linked to occupational closure and industry placement, institutional stratification may reflect different mechanisms, such as prestige signaling, resource disparities, and social capital, that are less directly tied to specific sectors. As a result, changes in institutional earnings may follow a different pattern than those observed for fields. In the following section, I examine whether and how institutions have changed position within the earnings hierarchy over time.

Analyzing Changing Average Annual Earnings by Degree-Granting Institution Over Time

Because institutional stratification operates through mechanisms largely distinct from those of field of study, such as prestige, teaching quality, resources, and student composition, it requires a different analytic approach. Net of the distribution of fields of study within a degree-granting institution, there are several variables along which institutions may be stratified: commuter vs. non-commuter schools, flagship vs. other state universities, private vs. public universities, average SAT score, tuition fees, and more. To understand changes in institution-specific average earnings over time, I assess whether observable characteristics, such as selectivity or size, predict institutional differences in earnings, net of field of study, and I assess these changing relationships over time.

With College Scorecard data, I use average SAT scores at the institution level, logged undergraduate tuition, the logged number of graduate students, the logged number of undergraduate students, and the undergraduate admission rate as indicators of college quality and prestige. As all variables are continuous in nature, they likely explain more variation in the data than do binary or categorical indicators representing institutional characteristics. To assess the degree to which they are associated with earnings after graduation, I regress them on adjusted average annual earnings for each university in a given year, $\Omega_{u,y}$, which are normalized for the distribution of fields of study within that institution. Otherwise put, $\Omega_{u,y}$ represents the average earnings of all graduates from a given university, adjusting for field of study level differences in earnings. It is calculated as follows:[13]

$$\Omega_{u,y} = \sum_{i} \frac{N_{f,u,y}}{N_{u,y}} \left(\omega_{i,f,u,y} - \overline{\omega}_{f,y}\right) \tag{10}$$

Estimates of $\Omega_{u,y}$ are then regressed separately against each institutional characteristic, stratified by different graduation cohorts. The R^2, or the percentage of overall variance explained by the predictor variables, is then used to determine the extent to which inequality on the basis of measurable institution-level characteristics, net of fields of study, is changing over time. This approach provides insight into whether institutional stratification is increasingly shaped by quantifiable dimensions of prestige or status. I now turn to the credential level—the intersection of field and institution—to examine how their joint distribution is evolving.

Analyzing Changing Average Annual Earnings by Credential Over Time

The final component of horizontal stratification I examine is the credential itself. While earlier sections analyzed how each axis contributes independently to inequality, this section addresses a distinct but related question: are high-earning fields of study increasingly concentrated in high-earning institutions? This form of consolidation would suggest a deepening structural alignment between educational sorting and labor market

[13]This is actually the same result as the university-level fixed effects from a two-way fixed effects regression such as that described in equation 4. It is simply rewritten here in this manner for clarity.

inequality, and would echo recently described phenomena in the labor market wherein high-earnings occupations are more concentrated in high-earnings firms (Wilmers and Aeppli 2021) and high-earnings workers are more concentrated in high-earnings firms (Song et al. 2019).

While the decomposition analysis in the first part of the analysis tests whether individuals are shifting across fields of study and institutions by recovering the level of overall variation due to the interaction effect of these two axes of horizontal stratification, that is a slightly different question from what this proposed analysis addresses. This analysis analyzes whether fields of study themselves are differentially distributed across schools over time. Moving from having the analytical unit be at the level of the individual to having it be at the level of the specific educational credential tests a distinct concept of institutional consolidation as opposed to more basic allocative and distributional forces.

To test the consolidation of high-earnings fields of study in high-earnings institutions and the co-location of low-earnings fields in low-earnings institutions, and how this is changing over time, I again return to the basic earnings equation in which credential-specific average annual earnings are operationalized as the additive effects of field of study-specific effects, institution-specific effects, and an interaction effect (equation 4). Using the fixed effects estimated for each field of study $F_{f,y}$ and institution $U_{u,y}$, I measure the changing correlation and covariance of each over time, weighted by cell size. By assessing the changing covariance of institutional and field-specific earnings effects, this analysis reveals whether horizontal stratification at the credential level is becoming more concentrated, creating a novel variety of inequality at a structural level, which is net of the other forms of inequality described in this paper.

Results

Understanding Changing Average Annual Earnings by Field of Study

The previous analysis showed two major findings: field of study is the primary axis of horizontal stratification with regards to annual earnings after five years of graduation, and its impact appears to be growing for successive graduation cohorts. Further, this finding is also driven by changes in credential average annual earnings and not distributional changes across fields of study. So the question remains: what is causing changing average annual earnings by field of study to lead to greater between-field inequality?

Figure 5 shows the observed changes in the average annual earnings, adjusted for inflation, of bachelor's degree-holders five years after graduation, by field of study. There are clearly large discrepancies in which fields of study have secured earnings gains, with "Computer & Information Sciences" and "Mathematics and Statistics" capturing over $20,000 and $10,000 in earnings increases, respectively. Likewise, fields of study like "Liberal Arts," "Homeland Security & Law," and "Education" have seen more modest decreases in average annual earnings. In this figure, I also show predicted changes in field of study average annual earnings based on changing field of study-to-industry flows alone, as measured in the data. As the figure shows, these predictions largely line up with observed changes in average annual earnings, indicating changing industry flows and changing industry-level average annual earnings play a potentially large role in explaining observed changes in average annual earnings by field of study. Importantly, the two fields of study "Computer & Information Sciences" and "Mathematics and Statistics" with the largest observed growth in average annual earnings are well-explained by industry. Likewise, "Liberal Arts," "English," and "Protective Services," with the largest decreases in average earnings are also well-explained by industry. Some larger fields of study such as "Health Professions," "Education," and "Psychology" do not fit as perfectly, though it is worth noting that the direction of the change in earnings is correct for all but one field of study, “Architecture.”

*** Figure 6 About Here ***

These changes reflect a mixture of changing industry composition within the entire labor market sector composed of students with bachelor’s degrees, shifting industry flows within fields of study, and changing average annual earnings by industry for college graduates. An extended Kitagawa-Oaxaca-Blinder decomposition, shown in Figure 6, parses these differences in the predicted earnings changes. The re-composition of flows from fields of study to industry due to global shifts in industry representation among college-educated workers has little bearing on overall changes in field of study average annual earnings, as gains in certain industries are often offset by losses in others. Nevertheless, some findings are striking. Globally, there is clearly a shift away from “Educational Services” and “Public Services” towards “Professional, Scientific, and Technical Services,” “Information,” “Health Care and Social Assistance,” and “Management of Companies and Enterprises.” There is also consolidation of lucrative industries net of overall shifts in industry flows for specific fields of study. “Professional, Scientific, and Technical Services,” “Information,” and “Finance and Insurance” industries are increasingly industry destinations for bachelor’s degree-holders with degrees like “Computer Science/IT Support,” “Mathematics and Statistics,” and “Business.” These same industries are less represented as destinations for degree holders coming from “Engineering,” “Engineering Technologies,” and “Liberal Arts” fields of study, among others. Otherwise, put, not only are there global changes in flows from school to industry for all Bachelor’s degree-holders that reflect a shift to a service economy rooted in white-collar industry, high-tech, and management services, but there is also a consolidation of these lucrative industries among a select subset of fields of study. This does not follow the typical RBTC and STEM/non-STEM split, as fields of study like “Engineering,” “Health Professions,” and “Biology” have been largely left in the lurch.

Moving away from changes in field of study-to-industry flows, it is clear that baseline flows to industries has contributed most meaningfully to changing average annual earnings by field of study. Fields of study with preexisting greater flows to industries that saw large increases in earnings obviously benefited more. Thus, once again "Computer Science/IT Support," "Mathematics and Statistics," and "Business" saw increased average annual earnings due to simple baseline connections to these industries, notwithstanding the global and local shifts towards these industries that they also saw.

Of course, changes in average annual earnings by field of study are not fully explained by shifts in industry placement or industry-level average wages; the decomposition leaves a relatively small amount of earnings change unaccounted for by these factors alone. These may be due heterogeneity within two-digit CIP codes within smaller, more specific fields of study. For instance, the two-digit CIP code encompassing "Health Professions" contains a wide variety of programs, with widely differing post-college outcomes and levels of perceived prestige. Likewise, there are certainly some synergistic earnings effects between fields of study and industry that cannot be captured here, due to the lack of industry-by-field of study specific wages. Nevertheless, the residuals, for the most part, are much smaller than the overall changes, indicating that an industry-level explanation is a decent analytical lens for describing such changes over time.

In sum, several industries saw large increases in average annual earnings for college graduates over the period in question. Fields of study, due to baseline school-to-work linkages to these industries also saw large gains in average annual earnings by field of study. This complements global shifts among bachelor's degree-holders into more lucrative industries and field of study-specific shifts into these lucrative industries. Of course, as this is an observational analysis, it is difficult to say that this effect is causal. Indeed, there may be large shifts in sorting into universities and field of study, complemented by a preference for these higher-quality workers by certain industries, resulting in increased compensation owing to levels of skills. However, such speculation and analyses are far beyond the scope of this paper. Nevertheless, I undertake an additional set of analyses (described and reported in the Appendix) to test whether the observed changes in field of study-level average earnings are better explained by shifting demographic composition within majors or by evolving industry flows. These models show that demographic change accounts for only a modest share of the observed trends (28%), whereas industry-based measures consistently explain the bulk (86%) of the variation (supplementary appendix Table A1). I also report predicted field of study-specific average earnings based on the two sets of predictors as a modified version of Figure 5 in supplementary appendix Figure A5. These findings reinforce the conclusion that the rising salience of field of study reflects the importance of field of study-to-industry linkages and industry wage structures, with demographic compositional shifts in who enters particular fields being secondary.

*** Figure 7 About Here ***

Understanding Changing Average Annual Earnings by Degree-Granting Institution

Though between-university stratification only explains a small amount of overall variation in annual earnings among bachelor's degree-holders, it remains the first line of stratification for many high school students as they choose where to attend university. Figure 7 shows institution-level average annual earnings, after adjusting for the distribution of fields of study within educational institutions, regressed against five different continuous characteristics of degree-granting institutions for graduating cohorts 2001–2003 and 2013–2015. Remarkably, school characteristics associated with student quality and instruction like average SAT scores and the number of graduate and undergraduate students show stronger and steeper relationships with earnings over time. The relationship with indicators that may be more closely linked to concepts of prestige, like tuition fees for in-state students and the admission rate, do not show the same patterns. While all of these characteristics reflect both latent concepts of quality and prestige to some extent, these patterns are suggestive and merit further exploration in future research.

The strongest and most dynamic relationship is that of average SAT Score and institution-level average annual earnings, with the R^2 increasing from 0.12 to 0.35 between the two cohort spans. Likewise, the variance explained by the logged number of graduate students increased from 0.05 to 0.12 and the logged number of undergraduates increased from 0.01 to 0.05. Of course, these relationships are associational only, and there is no causal component to this part of the analysis. However, it could easily be proposed that degree-granting institutions are becoming more stratified along observable characteristics. While between-school disparities in outcomes is not a main driver of overall inequality, it is nevertheless striking that the institutional differences we can observe are becoming more tightly aligned with dimensions that sociologists have long associated with stratification. Further, this relationship is not mechanically caused by the inflation of university characteristics over time and changing leverage of certain data points. Repeating the analysis holding constant university characteristics by taking their mean value across all cohorts and simply allowing university premiums to change shows substantively similar results (Appendix Figure A3).

Finally, this evidence of the changing interrelationship of the characteristics of educational institutions and institutions' average outcomes calls into the standard practice of grouping educational institutions based on observable characteristics. Although the relationship between observable characteristics and institutional earnings has grown stronger over time, these features still explain only a modest share of the variation. Most of the inequality in institutional outcomes remains unexplained by commonly used metrics, suggesting that the deeper sources of institutional stratification lie in less visible organizational processes, historical positioning, and localized industry linkages. This final point should also give researchers pause when using survey data to assess horizontal inequality among institutions, as it is clear that outcomes are highly variable even among nominally similar institutions.

*** Table 6 About Here ***

Understanding Changing Average Annual Earnings by Credential

The final research question moves beyond the analysis of field of study effects and institution effects in isolation to look at their intersection. Specifically, this analysis answers the question of whether high- or low-earning fields of study are increasingly consolidated in high- or low-earning institutions. Table 6 shows that this is not the case. To begin with, both the correlation and covariance of institutional effects and field of study effects are close to zero, indicating there is little baseline consolidation. Furthermore, there is no discernible pattern over time in either of these indicators. Thus, while specific credentials from specific academic departments explain 3–4 percent of overall earnings variation, there is little evidence that the dynamics of how it comes about are being dramatically reorganized.

Discussion

This study provides new evidence on how horizontal stratification among bachelor's degree recipients has evolved over time. Strikingly, variation in pay is becoming more explainable by degree characteristics over time, meaning that college and field of study choice are becoming more and more consequential. Of the three primary axes examined—field of study, institution, and their intersection—field of study stands out as the most consequential for earnings inequality. From graduating cohorts from 2001 to 2015, it explains a growing share of post-graduation earnings variation, while institutional and credential effects remain smaller and more stable. While the measurement of the relative importance of different axes of horizontal stratification represents an important contribution in its own right, it also raises further questions about the forces driving these patterns. To address this, the analysis turns to each axis in detail, drawing on existing literature to examine the structural and institutional mechanisms that may be shaping their evolving relationship to labor market outcomes.

The growing importance of field of study as a source of horizontal stratification is not explained by the reallocation of students across majors or institutions, nor by changes in the number or composition of credentials alone. It also appears not to be primarily a function of changing demographics within fields. Fixed effects models in the supplementary appendix show that within-field shifts in gender and racial composition explain only a modest share of the observed change in field-level premiums, whereas industry-linked measures account for substantially more of the within-field variation over time. This does not invalidate ample research showing that fields of study are gendered and racialized, impacting their value on the labor market, especially in the patterned ways that they lead to gendered or racialized occupations (e.g., England et al. 2007; Alon and DiPrete 2015; Goyette and Mullen 2006). Rather, it indicates that the changing importance of degree characteristics described in this paper are not driven by changes in these forces. Substantively, the results suggest that broader structural shifts in the labor market, particularly the expansion of high-wage service industries like technology, finance, and professional services, may be contributing to the rising returns associated with certain fields of study. Notably, this transformation does not uniformly reward traditionally "technical" majors like engineering or health sciences. Fields such as business, social sciences, and communications/journalism, which are often peripheral in frameworks based on RBTC, have experienced substantial earnings growth, largely due to their alignment with high-paying sectors whose wage structures continue to diverge from the rest of the labor market. These patterns imply that credentials increasingly derive value from where they are positioned in an evolving industrial wage structure, not simply from changes in student composition.

These patterns are visible due to the recency and granularity of the data, which capture labor market outcomes through 2020. This extended temporal scope is critical, as it allows the analysis to include the post-recession period, a time marked by deep restructuring in the labor market, the maturation of the tech sector, and growing divergence in industrial wage structures. Unlike earlier periods shaped by the initial waves of changes due to computers, the post-2008 landscape reflects a new stage of labor market change, in which a narrower set of industries increasingly concentrates economic returns. In most cases, observed earnings gains reflect rising wages within industries already associated with particular fields of study; in others, they stem from a tighter clustering of lucrative sectors around a smaller subset of fields of study. This dynamic suggests that education policy, career advising, and labor market interventions must grapple with a world in which the labor market value of a degree is increasingly determined not by content alone, but by how credentials are absorbed into an evolving and uneven industrial structure.

Universities themselves account for only a small amount of variation in annual earnings, and yet this variation is increasingly explainable based on observable university characteristics. This finding contrasts with the findings of Borgen and Mastekaasa (2018), who finds that universities play no role in dictating labor market outcomes in excess of the individual department (specific educational credential). This discrepancy is likely linked to comparative differences in the U.S. and Norwegian context and motivates future work on school-to-work linkages in a comparative setting. Though their analyses include individual-level characteristics, they report supplementary analyses that omit such characteristics that are consistent with the key assumptions of this research based on the synthesis of Bleemer and Quincy (2025): individual sorting into programs does not attenuate effects of fields of study, and it only slightly attenuates the effects of institutions.

The two-pronged increase in stratification along the axes of fields of study and institutions makes salient an increasingly important source of inequality in society—what and where one studies during their bachelor's degree—but this increasing stratification in outcomes opens doors for increased inequality to come about due to other, allocative factors. For instance, differential sorting into different fields of study on gendered and racialized lines (e.g., Lepage, Li, and Zafar 2025) would exacerbate known sources of horizontal stratification based on selection into fields of study and institutions. Further, research has documented a pattern of an increased prevalence of GPA-restricted majors within colleges, and these internal gatekeeping mechanisms limit access to high-return fields, often along lines of prior preparation and social background, reinforcing inequality even within institutions (Bleemer and Mehta 2024). Increasingly divergent returns across fields of study only heighten the stakes of such mechanisms, as access to lucrative majors then becomes an additional channel through which educational systems reproduce broader social inequalities.

Although specific credentials account for a similar share of overall earnings inequality as educational institutions, there is no clear evidence that high- or low-earning fields of study are becoming increasingly concentrated within correspondingly high- or low-earning institutions, respectively. The overall distribution of majors across institutions has remained remarkably stable, suggesting that the growing influence of field of study is not being driven by credential-level consolidation. Nor do patterns of field emergence and obsolescence appear confined to particular types of institutions. Instead, the rise in horizontal stratification reflects broader changes in the economic value of fields themselves, shaped by evolving industrial wage structures and shifting pathways from education to work. These findings not only clarify the empirical contours of horizontal stratification but also raise important questions for how sociologists conceptualize the education–labor market relationship moving forward.

Finally, an enduring concern is selection: to what extent do the observed differences in fields of study, institutions, and credentials reflect value added versus sorting by ability, preferences, or background? While the design here does not identify causal effects, three pieces of evidence help calibrate interpretation. First, the demographic fixed-effects analyses in the supplementary appendix indicate that within-field shifts in gender and race/ethnicity explain only a modest share of changes in field premiums, whereas industry-linked measures account for substantially more variation over time. Second, robustness checks that reweight institutions and reorder fixed effects suggest that the growing role of fields is not an just an artifact of compositional shifts in the mix of majors across campuses. Third, recent causal evidence implies that field-of-study differences largely represent value added (on the order of 100%), while institutional differences are attenuated by selection but still predominantly causal (roughly 80%), with estimates for institutions consistent with Chetty et al. (2023) and Bleemer and Quincy (2025). Finally, recent qualitative work by Moss-Pech (2025) also finds that within-institution stratification by field of study at a major Midwestern flagship university does not represent differences in ambition or talent, but that most of the between-field differences in employment outcomes are mediated largely by ties to specific sectors of work. While the evidence in support of the key assumptions employed in my analyses is robust to multiple specifications across several papers, more evidence using large scale administrative data like what is used in this paper would be welcome, especially since the importance of selection may change over time. Nevertheless for the time being, the decomposition results should be read as nearly equal to the causal importance of fields of study and as an upper bound for institutions. Substantively, selection concerns do not overturn the main conclusion: the dominant driver of horizontal inequality lies in field-linked positioning within an evolving industrial wage structure; institutional effects remain secondary, and their interpretation should be tempered slightly by concerns over selection processes and by the underrepresentation of the most selective private institutions in these data.

Implications for Research on Education and Labor Market Inequality

These findings suggest that sociological research on education and labor markets must further integrate perspectives from the school-to-work literature and the literature on labor market polarization. The increasing differentiation of field of study-based average annual earnings aligns with research on firm segregation and industry polarization (Wilmers and Aeppli 2021; Godechot et al. 2024; Haltiwanger et al. 2024). These findings highlight the importance of considering how industry-level transformations may interact with educational credentials. Rather than treating industry and education as separate domains, future research should consider how the stratification of earnings across credentials and across industries may be increasingly intertwined.

Evidence that industry dynamics are driving changes in horizontal stratification underscores the need to examine the institutional mechanisms that reinforce or mitigate these trends. This study documents a form of sectoral stratification: a macro-level shift in which earnings inequality is shaped by the consolidation of capital, wage growth, and economic power within a small set of high-value industries (Haltiwanger et al. 2024). These industries likely encode patterns of occupational closure and firm-level compensation differences that also operate via field-to-industry linkages, positioning fields of study as conduits into evolving configurations of work. This pattern reflects not only a response to exogenous technological change, as in the RBTC literature, but also an endogenous restructuring of opportunity through educational credentials. As wage gaps between industries widen, access to high-paying sectors may become increasingly dependent on specific credentials or fields of study, narrowing mobility and deepening inequality. Understanding how universities, employers, occupations, and policy shape these linkages is critical. Relational inequality theory (Tomaskovic-Devey and Avent-Holt 2019) offers a framework for analyzing how these patterns are maintained at both the meso level, through ties between academic departments and firms, and the macro level, through the institutional alignment of higher education and labor markets. While this study cannot observe these mechanisms directly, access to linked credential and firm-level microdata would significantly advance this research agenda. Beyond empirical trends, these results invite a reconsideration of dominant theoretical frameworks in the for contending with labor market change in the contemporary period.

Connections to Theories of Educational Stratification

This study also suggests that sociologists must further refine theories of educational stratification to account for the increasing importance of horizontal distinctions. Much of the literature on education and inequality has focused on vertical stratification (e.g., high school versus college, or bachelor's versus master's degrees). However, this study provides further evidence that horizontal distinctions—especially field of study—are becoming just as important as, if not more important than, vertical distinctions in shaping labor market outcomes.

These results partially align with the Effectively Maintained Inequality (EMI) framework (Lucas 2001), which emphasizes how educational expansion leads advantaged groups to secure qualitatively better credentials. EMI focuses primarily on educational sorting and how families respond to changes in access, with less emphasis on the role of labor market dynamics in shaping the value of those credentials. The findings here suggest that growing differentiation in earnings outcomes is influenced not only by patterns of sorting into fields and institutions, but also by structural shifts in the labor market. In particular, the link between fields of study and industries with diverging wage trajectories appears to be a key driver of horizontal stratification. At the same time, the increasing correlation between institutional earnings and characteristics such as selectivity and graduate enrollment is consistent with the patterns that EMI anticipates. A more direct test of the framework would require data on family background and its relationship to enrollment decisions in response to changes in labor market returns, and the findings presented here of increasing horizontal stratification do beg the question of how individuals and families respond to changing inequality dynamics. Further, although some institutional characteristics, such as selectivity and graduate enrollment, are increasingly associated with graduates' earnings, a substantial amount of variation across institutions remains unexplained. This suggests that the labor market value of institutional credentials may depend on broader organizational dynamics or embedded institutional roles that are not captured by conventional indicators like prestige or test scores. These findings underscore the need to theorize horizontal stratification not only in terms of credential content but also in terms of how colleges are positioned within larger systems of economic and organizational inequality.

The increasing salience of horizontal stratification also raises pressing policy concerns. As earnings gaps across fields widen, expanding access to college alone may not reduce inequality unless students from marginalized backgrounds also gain access to higher-earning fields and more prestigious colleges. For instance, existing research suggests that students from lower socioeconomic backgrounds are less likely to enroll in or persist in high-earning STEM and business majors (Bleemer and Mehta 2022; Monaghan and Jang 2017). Addressing these disparities could involve targeted recruitment into certain fields of study, firm-credential partnerships to alter flows into certain industries, and changed advising and student support structures. Finally, the growing correlation between institutional characteristics, such as SAT scores or graduate enrollment, and graduate earnings raises concerns about increasing prestige-driven exclusion. If labor market returns are increasingly tied to institutional reputation rather than skills imparted, opportunities may diverge sharply across college types. Even when these patterns reflect sorting by student ability, they raise normative questions about the role of higher education as a public institution committed to expanding opportunity.

Limitations

To contextualize my findings and guide future research, it is important to acknowledge several limitations, some of which have been discussed in earlier sections. First, the analyses rely on summary statistics rather than individual-level data. Although these statistics are highly granular, capturing credential-cohort combinations with as few as 30 graduates, they necessarily obscure within-cell variation and do not allow for the identification of micro-level selection mechanisms or causal pathways related to individual characteristics such as race, gender, parental education, or academic preparation. Nonetheless, sensitivity checks (Appendix Figure A4) suggest that the patterns identified are robust across specifications that may be related to such mechanisms. Moreover, this design tradeoff is what enables the study to provide a rare, macro-level perspective on how horizontal stratification unfolds across institutions and fields of study over time.

Second, this analysis focuses on three analytically tractable forms of horizontal stratification: institution, field of study, and their intersection. Other important dimensions such as intra-field specialization, co-curricular experiences, and informal academic tracking are not examined here, though they likely shape labor market outcomes and interact with the patterns observed. Rather than cataloging all forms of horizontal inequality, this paper traces how credentials have become increasingly differentiated in economic value amid structural labor market change. Future research should explore these finer-grained dynamics as richer data become available.

Third, as noted in the results, Ivy League and similarly highly-selective private institutions are underrepresented in the dataset. While the broader underrepresentation of private universities is addressed through compositional reweighting and sensitivity checks, the absence of Ivy League and their peer institutions poses a distinct limitation. Nevertheless, these schools enroll relatively few students compared to large public universities, so their exclusion likely has minimal impact on overall trends. However, it does constrain generalizability at the top of the institutional earnings distribution, where the labor market returns to elite prestige may be most pronounced. As a result, this study may understate the extent of institutional stratification at the highest levels of the college hierarchy.

Focusing on annual earnings five years after graduation has limitations. While robustness checks (Appendix Figure A2) show similar patterns of horizontal stratification at one and ten years and comparable dynamic trends at one year, income is an imperfect proxy for social position, well-being, and long-term mobility. Still, it remains a uniquely valuable measure: it reflects actual economic standing, avoids measurement bias, and is especially relevant for recent graduates navigating economic precarity. For many, particularly those from non-elite backgrounds, earnings serve as a proxy for broader labor market outcomes. Early-career income also aligns with experiences common to this key life stage, such as student loan repayment and household formation, making it a salient indicator of inequality. Other dimensions of stratification like non-monetary compensation, occupational prestige, or long-term growth are harder to measure (Cheng 2014; Cheng and Song 2019) and likely correlate with earnings, suggesting my results may understate overall horizontal stratification. The data also exclude individuals still in school. Those who later complete graduate degrees enter the analysis only upon labor market participation, making it difficult to isolate the effects mediated through the pursuit of an advanced degree. Nevertheless, sensitivity checks affirm that the main findings are robust to different periods of follow-up post-graduation. Future research with richer labor market indicators and linked microdata would help clarify these mechanisms.

Additionally, this analysis cannot disentangle how much of the observed stratification reflects worker–firm sorting. Because firms are nested within industries, rising industry premiums could partly reflect shifts toward higher-paying firms within those industries rather than changes common to all firms. And since the PSEO data used in these analyses do not include firm identifiers or characteristics, one cannot analyze firm-level phenomena such as wage-setting or recruiting pipelines. Access to microdata linking education records to employer-level data would clarify the extent to which horizontal stratification reflects institutional value added versus sorting into higher-wage firms.

In addition, this analysis necessarily excludes individuals who begin but do not complete a bachelor's degree. As noted earlier, the study defines horizontal stratification as variation within the population of bachelor's degree recipients, which allows for clear analytical separation from vertical processes such as degree attainment. As a result, the findings reflect patterns of inequality among graduates only, and do not capture the potentially large disparities generated by differential rates of completion by field of study and institution. Because non-completion is strongly patterned by background characteristics and institutional context, the earnings differences reported here are likely conservative. Future research should examine how institutional and field-level differences in retention and completion interact with vertical stratification and shape access to the types of credentials studied here.

Finally, there is question of industry as the appropriate labor market indicator to explain the stratification described here. Other indicators, like RBTC at the occupation level or deindustrialization more broadly are alternative lenses through which this analysis could have been performed. While the data limit me to focusing on industrial change, I believe this is also a principled choice. Other research has pointed out the realignment of industries in the labor market as a primary source of changing dynamics of inequality (Wilmers and Aeppli 2021; Haltiwanger et al. 2024). Wilmers and Aeppli (2021) in particular outline how changing occupational dynamics coincide with changing industry dynamics, though the question of which precedes the other remains an open question that should be addressed with further research.

Future Research Directions

While this study provides a broad overview of the changing landscape of horizontal stratification in higher education, it also raises several key questions that future research should address. One of the most pressing concerns is the causal mechanism behind the school-to-work linkages discussed here, and their knock-on effects for selection into college and fields of study in the first place. This study demonstrates that industry-level dynamics play a crucial role in shaping earnings stratification across fields of study, but it does not pinpoint whether these effects stem from employer preferences, student self-selection, or institutional steering.

Future work should examine how these trends vary across demographic groups. Prior research suggests that access to high-return majors like STEM and finance is stratified by race, gender, and class (Xie and Shauman 2003; Gaddis 2015). If these fields increasingly shape earnings, horizontal stratification may reinforce existing inequalities. Investigating whether industry practices or educational interventions can offset this stratification is a key next step.

An additional avenue for future research involves examining the role of school-to-work linkages within a single national context. Prior work has shown that stronger linkage systems, typically analyzed in cross-national comparisons, shape employment outcomes by more tightly connecting educational credentials to specific labor market destinations (DiPrete et al. 2017; Bol et al. 2019). While this study does not center on linkage strength, the fine-grained credential-level structure of the data, combined with detailed information on industry destinations, offers a novel opportunity to do so. This creates the possibility of extending the original framework to examine variation in linkage strength across institutions, fields of study, and credentials within the U.S. context. Such an approach would allow researchers to test whether more tightly coupled credentials produce more stable or more unequal outcomes in a causal framework, and to investigate how linkage strength itself evolves alongside changes in industrial structure and institutional positioning.

Graduate education also warrants closer attention. While this study focuses on bachelor's degree holders, similar patterns in horizontal stratification may be simultaneously occurring, or even intensifying, at the master's and doctoral levels. As advanced degrees are often viewed as mobility pathways, understanding whether certain graduate credentials are consolidating economic advantages while others lag is critical. In addition, future research should explore how post-baccalaureate education moderates the patterns observed here, particularly for those whose earnings outcomes reflect the combined value of undergraduate and graduate training.

Finally, a comparative perspective is necessary to assess to what extent these trends are unique to the United States. The U.S. higher education system is characterized by its flexibility and relatively weak school-to-work linkages compared to other nations, where vocational training and credentialing structures may create different trajectories for students. If similar patterns of growing horizontal stratification are observed in other countries, it may suggest a global strengthening of school-to-work linkages due to specific industrial relations rather than being due to the specific institutional features of U.S. higher education. Indeed the only study remotely comparable to this, which was conducted in a Norwegian context, found that there was no effect of educational institutions in excess of credential-specific effects, highlighting the importance of national context (Borgen and Mastekaasa 2018). Future research should explore cross-national comparisons to determine whether the increasing importance of field of study and institutional prestige in shaping earnings outcomes is a universal phenomenon or whether it is shaped by national policies, labor market structures, and educational institutions.

Conclusion

In sum, this study provides new evidence that horizontal stratification in higher education—particularly stratification by field of study—plays a large and increasingly important role in shaping economic inequality, as measured by earnings inequality after entry into the labor market. Unlike prior research, which has primarily examined horizontal stratification in a static framework, this study takes a longitudinal approach and finds that the role of horizontal stratification is growing over time. Further, these trends are largely driven by shifting industry structures and to a lesser extent changing patterns of school-to-work linkages. While institutions also contribute to earnings disparities among graduates, their importance remains secondary to that of field of study. Nevertheless, their effects are increasingly structured by observable characteristics.

Although increasing horizontal stratification by field of study raises concerns about inequality, it could plausibly also be interpreted as reflecting a labor market that rewards acquired skills and productive specialization more directly than one centered on institutional prestige or individual characteristics. In this sense, the rising importance of what graduates study relative to where they study may indicate that economic outcomes increasingly track substantive competencies and human capital rather than reputational advantages. If this interpretation holds, the growth of field of study-based stratification could represent a partial shift toward a more meritocratic linkage between education and work, where skill-based differentiation outweighs credential-based gatekeeping. Further study of the mechanisms conferring field of study-level differences in earnings is needed, however.

A central contribution of this study lies in its use of temporally rich, credential-level data that span over fifteen years and include nearly a variety of U.S. higher educational institutions. Prior research has often been limited to single cohorts, broad institutional groupings, or narrow timeframes. By contrast, this study captures how stratification unfolds dynamically, in tandem with structural shifts in the labor market. This level of temporal and institutional granularity allows for a more empirically grounded account of how educational inequality is produced and reproduce, not just through individual sorting, but through evolving relationships between education and work.

These findings suggest that higher education researchers must integrate insights from the literature on industrial change, firm segregation, and relational inequality to better understand the shifting landscape of educational stratification. The job market for bachelor's recipients is no longer characterized by guaranteed job security, as earned income is increasingly dependent on from where one received their degree and what they studied. Likewise, industry shifts to a knowledge-intensive economy have benefited some fields of study more than others, though in ways that defy typical frameworks of RBTC or deindustrialization.

These findings point to the need for a reconceptualization of how educational stratification interacts with broader processes of labor market change. Horizontal and vertical stratification cannot be understood merely as a reflection of individual preferences or institutional sorting mechanisms, but as parts of a dynamic system in which educational and economic structures co-evolve. As the boundaries between educational categories and labor market positions become increasingly structured by industry-level transformations, the conceptual frameworks used to study stratification must evolve in kind. Attending to these shifting alignments will be essential for advancing theories of education, stratification, and inequality.

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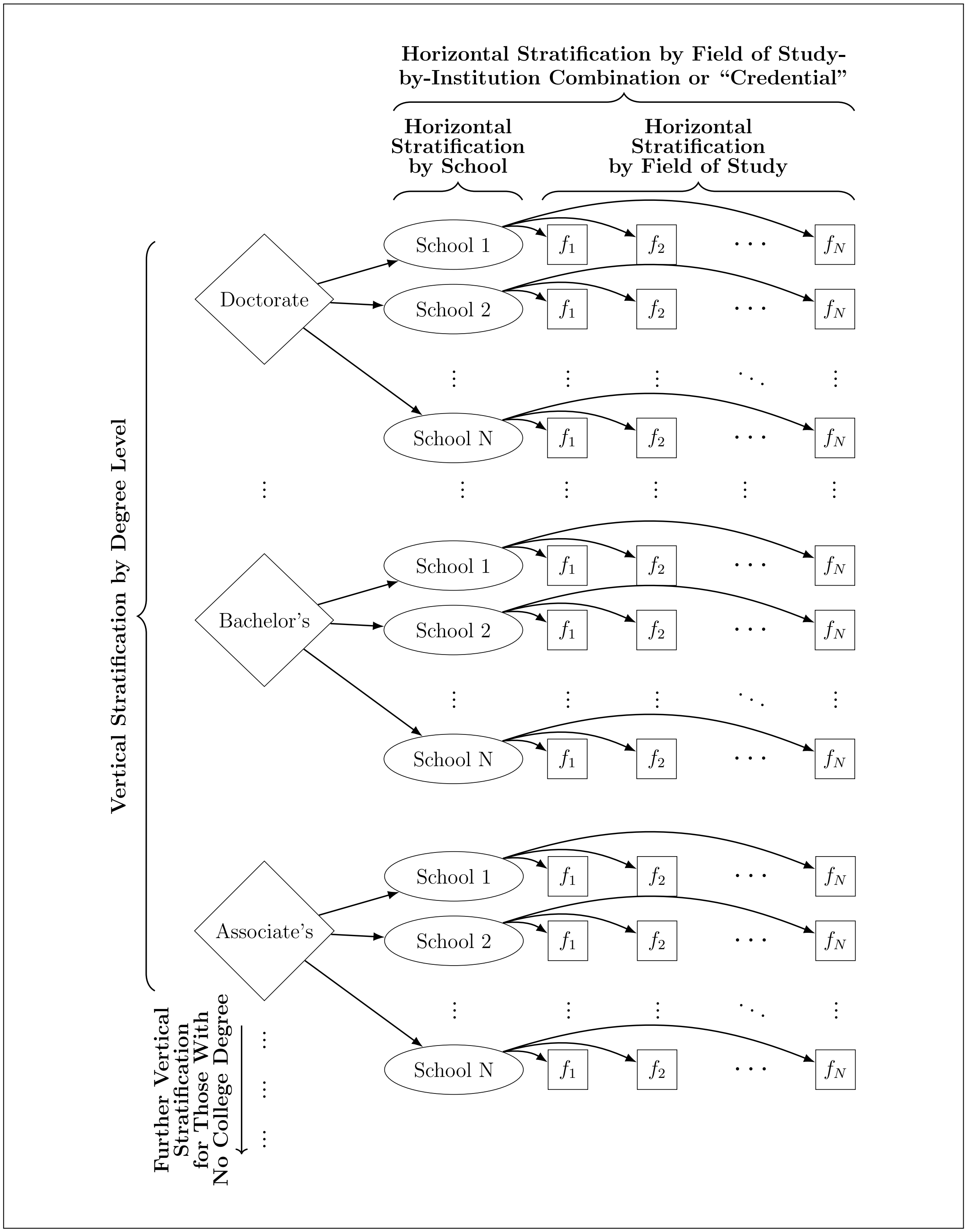

Figure 1: Schematic Showing Vertical Stratification and Horizontal Stratification by Both School and Field of Study

Notes: Only vertical stratification at the two-year college level and above is shown. There is unshown vertical stratification for those with high school, less than high school, and no schooling. Whether or not these exhibit meaningful horizontal stratification by school is unknown, and there is no field of study specialization below the college level.

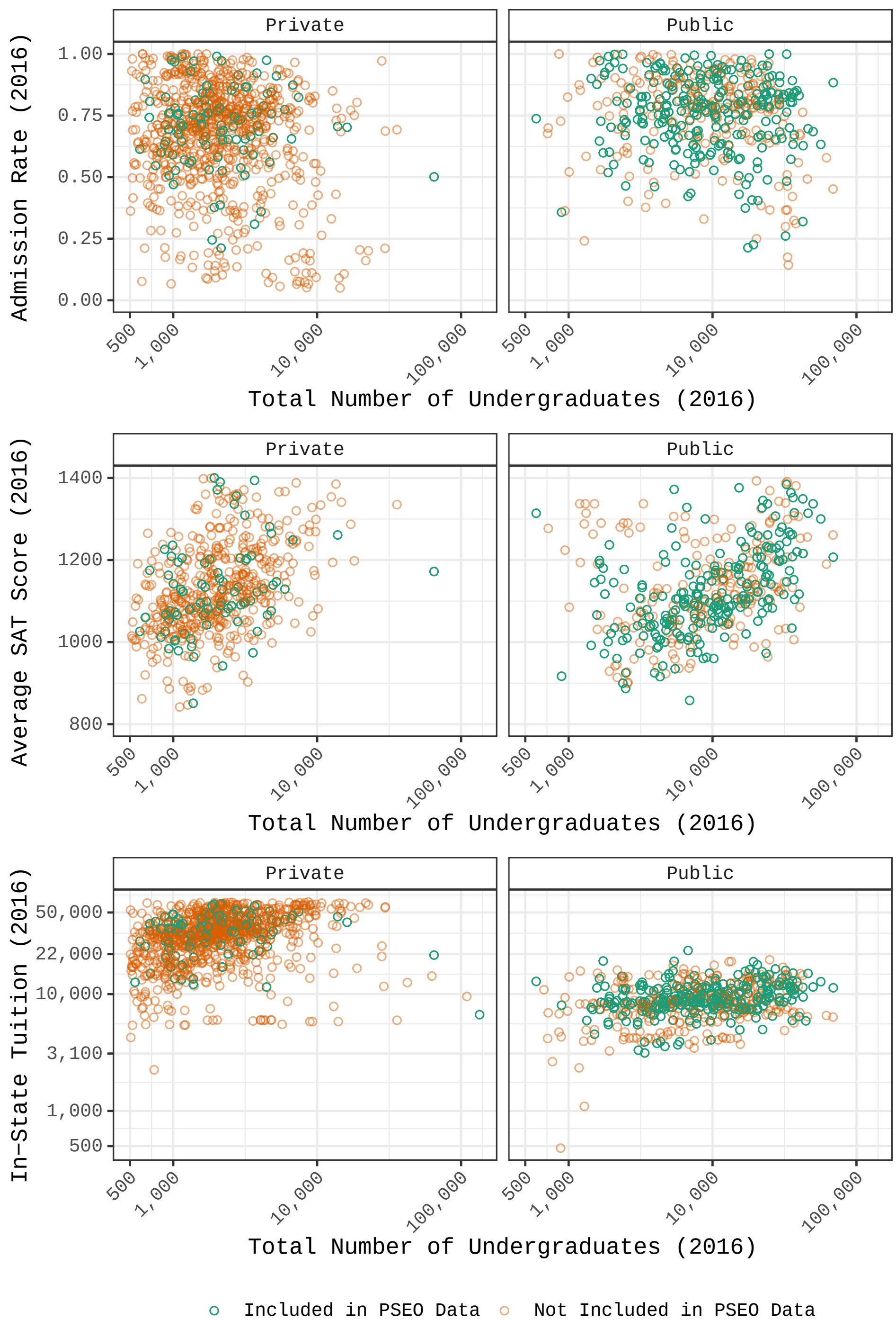

Figure 2: Scatter Plot of All Universities and Universities Included in PSEO Data, By Total Number of Undergraduate Students, In-State Tuition, Admission Rates, and Average SAT Scores

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes; The U.S. Department of Education's College Scorecard.

Notes: Only universities are shown that have at least 500 undergraduate students. Among all four-year degree-granting institutions in the College Scorecard data, undergraduate in-state tuition fees are missing for 49 institutions, average SAT scores are missing for 573 institutions, and admission rates are missing for 231 institutions.

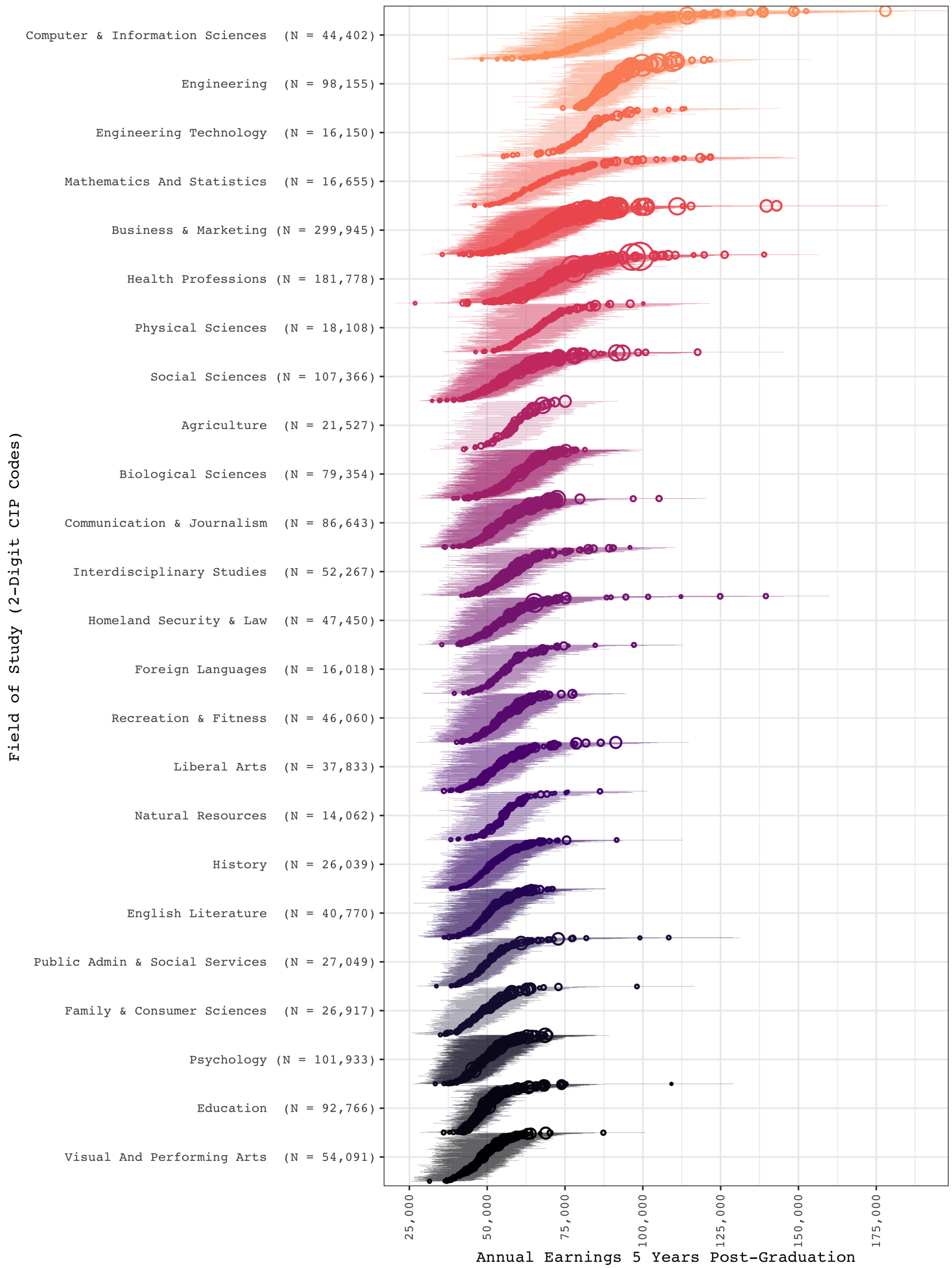

Figure 3: Distributions of Average Annual Earnings, Five Years Post-Graduation, for Specific Credentials (Fields of Study Within Specific Degree-Granting Institutions), By Aggregate Field of Study; Students Graduating 2013–2015

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes.
Notes: Groupings refer to CIP codes aggregated at the two-digit level, though each data point represents a credential (degree-granting institution and field of study combination) at the four-digit level. Colors are to help visually distinguish fields of study.

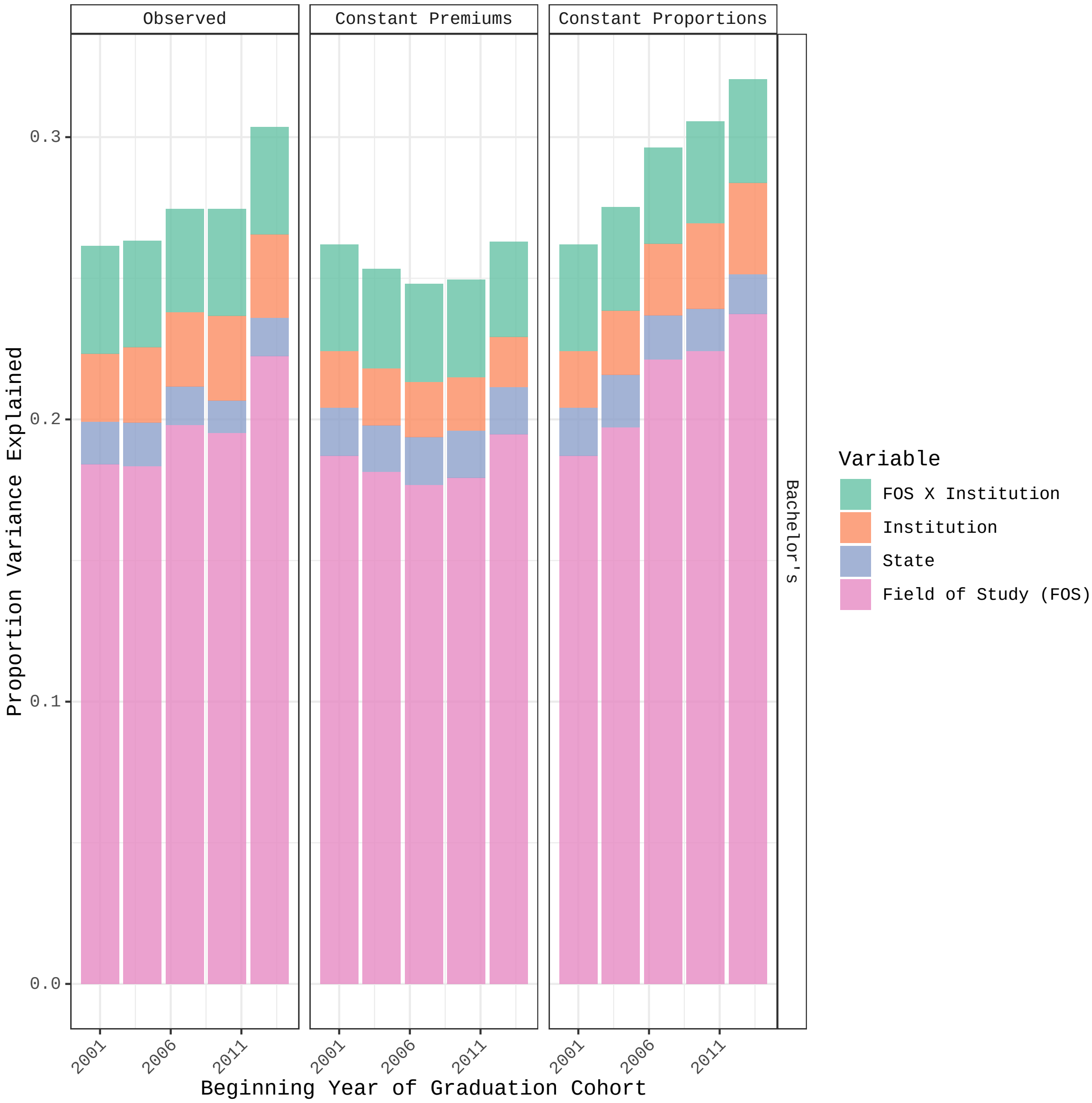

Figure 4: Variance Decomposition of annual earnings Five Years Post-Graduation by Field of Study (Major), Educational Institution, and Their Intersection Alongside Scenarios Assuming Constant Allocations Across Fields and Universities or Constant Average Annual Earnings Across Fields and Universities

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes.
Notes: "Constant Proportions" refers to the scenario in which all enrollments by field of study and degree-granting institutions are held constant at their 2001–2003 numbers, and "Constant Average Earnings" refers to the scenario in which enrollments are allowed to vary, but credential-specific average earnings are held constant.
Results reflect data reweighted to more closely represent all U.S. universities and colleges.

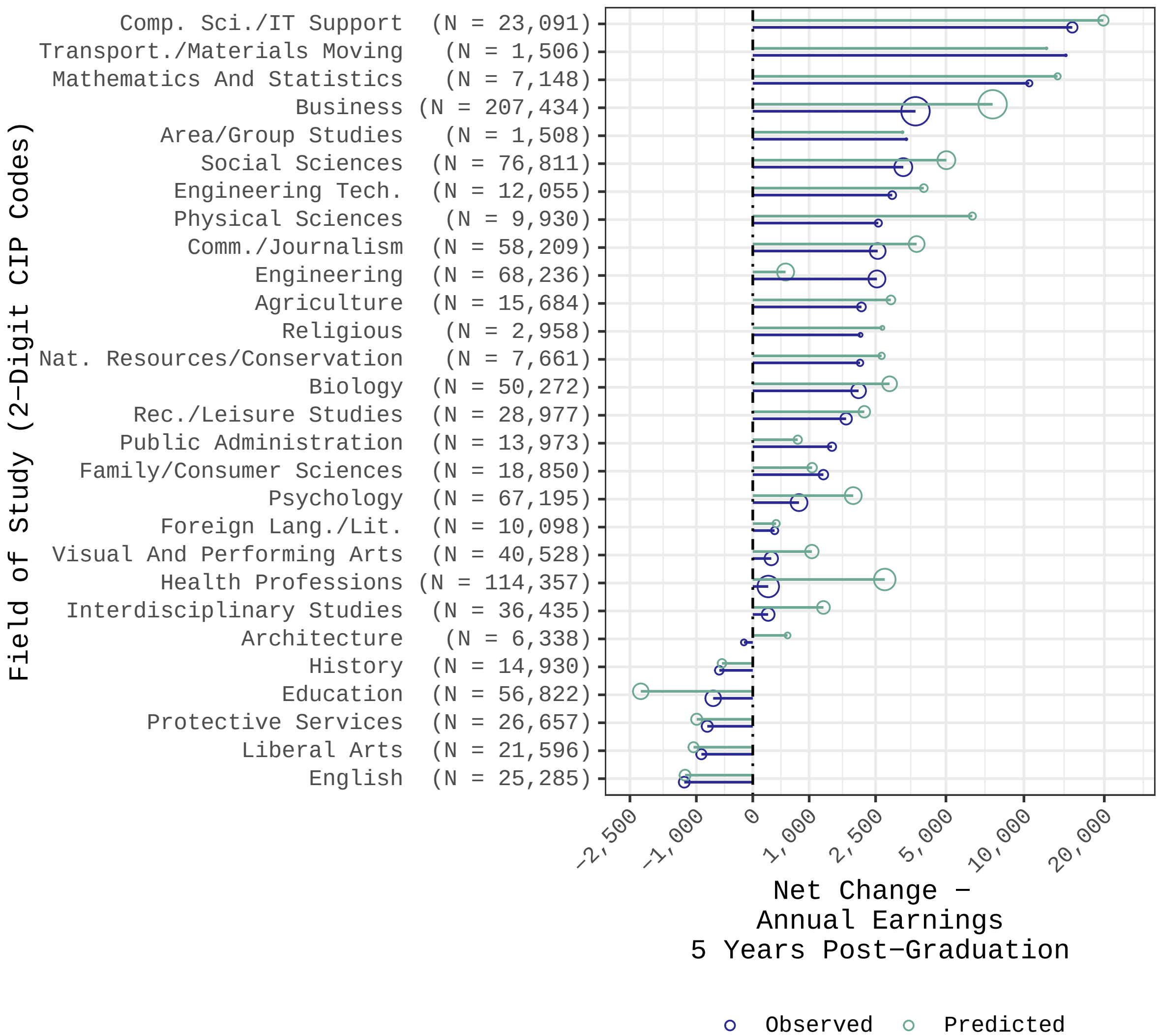

Figure 5: Change In Observed Average Field of Study (Two-Digit CIP Codes) Annual Earnings Five Years Post Graduation, Comparing Cohorts 2013–2015 to Cohorts 2001–2003

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes; The American Community Survey.
Notes: Only fields of study with at least 1,000 graduates per year (3,000 per cohort span) are shown. Size of circles is correlated with the number of students graduating in each cohort. 'N =" for each cohort refers to their absolute sizes for graduating cohorts 2013–2015.

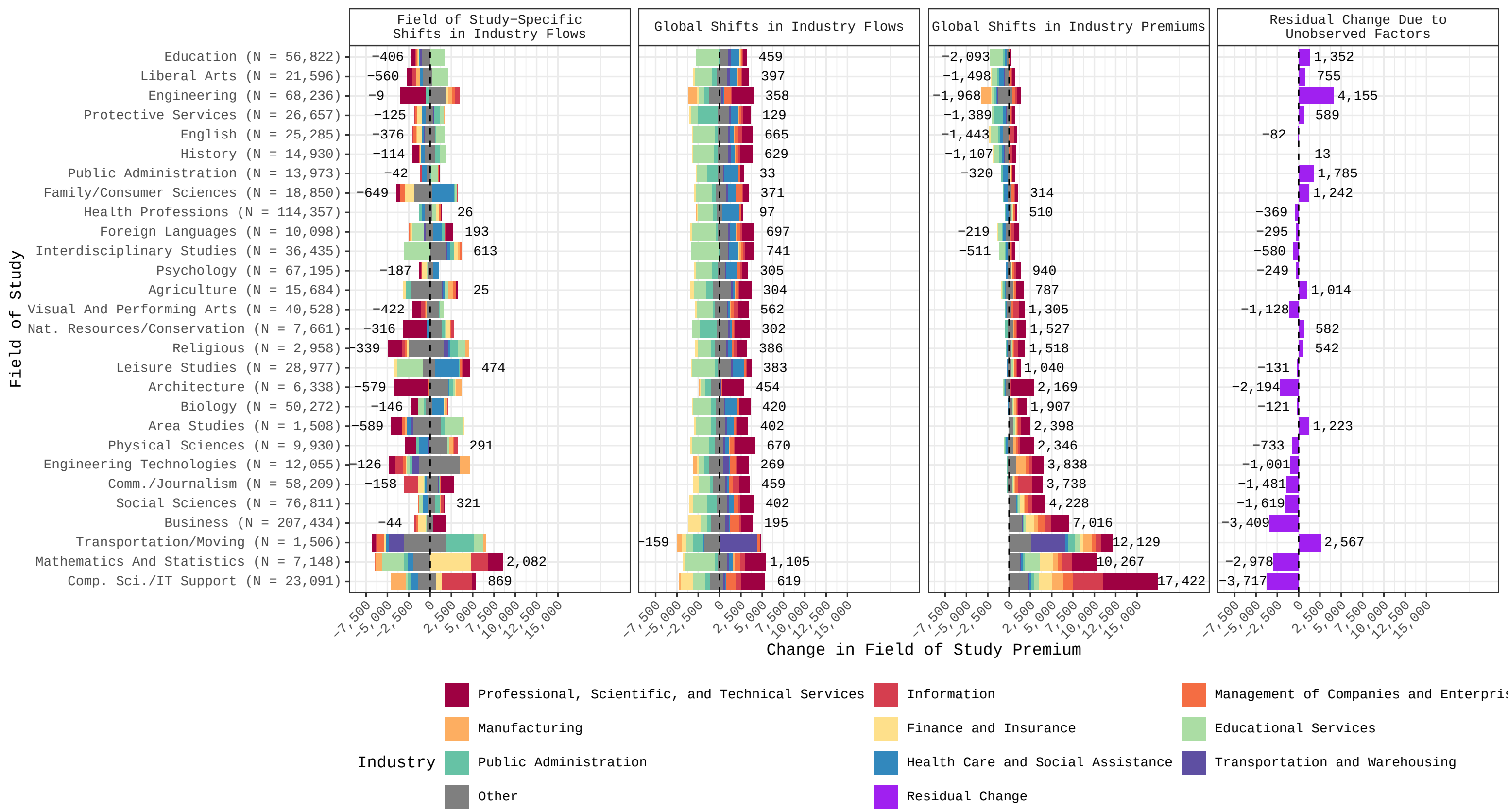

Figure 6: Kitagawa-Oaxaca-Blinder Decomposition of Observed Changes Between 2001–2003 and 2011–2013 Graduates in Field of Study average annual earnings at the Bachelor's Level, Using Observed Changes in FOS-Industry Flows Changes in Calculated Industry-Level Average Annual Earnings

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes, The American Community Survey.
Notes: Numbers next to each set of stacked bars represent the total change in average earnings for a given field of study, summed across all industry contributions of a given kind, be they positive or negative. The nine industries with the largest contributions are shown explicitly, while the others are labeled "Other."

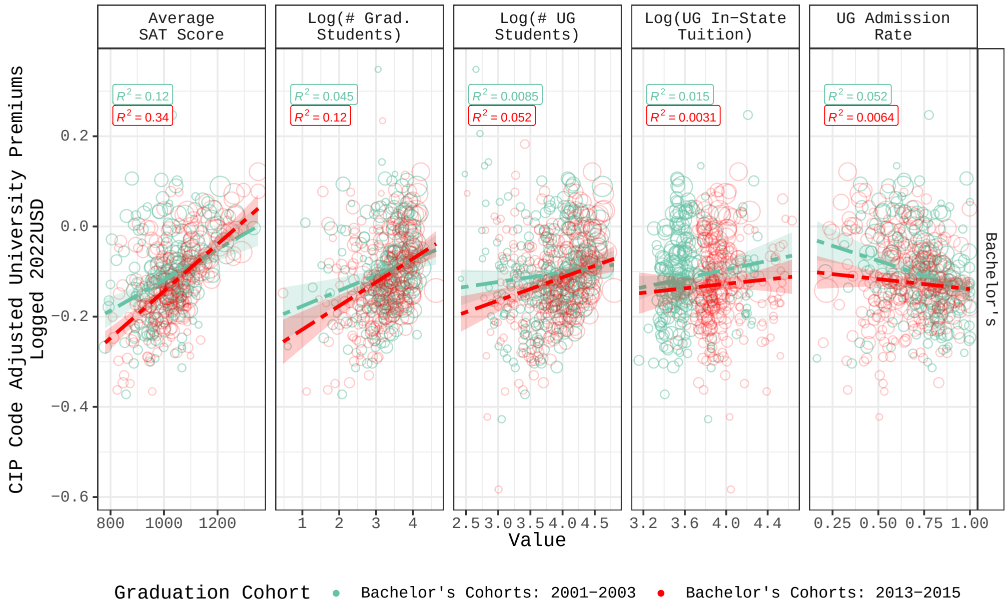

Figure 7: Degree-Granting Institution Average Premiums, After Adjusting for Distribution of Fields of Studies, Regressed on Institutional Characteristics for Two Cohorts

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes; The U.S. Department of Education's College Scorecard.

Table 1: Table displaying exemplars of existing literature on horizontal and vertical stratification in income based on education, separated into point-in-time and change-over-time accounts.

		Within Cohorts (point-in-time)	Across Cohorts (change-over-time)
Vertical Stratification (between degree-level)		• Heterogeneous returns to college (Brand and Xie 2010) • College as equalizer (Torche 2011; Zhou 2019)	• Education–technology race framework (Goldin and Katz 2008) • Task polarization and wage trends (Autor 2014) • College premium plateau (Autor et al. 2020)
Horizontal Stratification (within degree-level)	**Field of study**	• Causal field-of-study effects, Norway (Kirkeboen et al. 2016) • Field-of-study channeling and stratification (van de Werfhorst 2002) • Earnings by major (Carnevale et al. 2013) • ∗*See bottom-right cell.*∗	• Changes in College Skills and the Rise in the College Wage Premium (Grogger and Eide 1995) • ∗*See bottom-right cell.*∗
	Institution	• Effects of elite college attendance (Brewer et al. 1999) • Estimating the returns to elite colleges (Dale and Krueger 2002) • Effects of college prestige (Brand 2006) • ∗*See bottom-right cell.*∗	• Changes in college match in NLSY (Dillon and Smith 2020) • ∗*See bottom-right cell.*∗
	Field & institution	• Horizontal Stratification in Norway (Borgen and Mastekaasa 2018) • ∗*See bottom-right cell.*∗	• Changing Regressivity of College Degree (Bleemer and Quincy 2025) • Changing Horizontal Stratification (*The present study*)

Notes: ∗ Change-over-times accounts necessarily always overlap with point-in-time accounts. Likewise, accounts of horizontal stratification by field of study and institution always overlap with accounts separately by field of study or institution. Studies that do so are only included in their most specific cell in the above table to avoid needless repetition.

Table 2: Characteristics of PSEO Sample, All U.S. 4-Year Colleges, and the Reweighted PSEO Sample, By Instituion

	Admission Rate	Average SAT	In-State Tuition	Graduates	Undergraduates	% Private
Target	71.3 %	1,169	16,612	1,231	7,643	38.9 %
Sample	74.3 %	1,127	12,939	3,276	11,894	14.7 %
Reweighted	70.6 %	1,161	13,197	1,279	8,176	34.0 %

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes.

Notes: Methods for weighting data are detailed in the supplementary appendix.

Table 3: Summary Characteristics of Workers Five Years After Graduation Included In Data

Graduation Cohort	Individuals	Schools	FOS (4 Digit)	FOS (2 Digit)	FOS-School (4 Digit)	FOS-School (2 Digit)	Average Salary (2022USD)
Full Data							
2001-2003	586,872	275	227	34	4,890	2,849	58,427
2004-2006	902,432	338	251	36	6,310	3,620	57,494
2007-2009	932,181	376	256	36	7,379	4,156	55,410
2010-2012	1,134,101	434	273	36	8,888	4,941	58,497
2013-2015	1,309,057	460	274	36	9,808	5,387	61,311
Restricted Set							
2001-2003	579,723	270	227	34	4,842	2,818	58,354
2004-2006	801,515	270	247	36	5,523	3,134	57,342
2007-2009	746,814	270	247	35	5,703	3,197	55,310
2010-2012	818,058	270	258	35	6,161	3,378	57,967
2013-2015	900,124	270	261	36	6,635	3,555	60,646

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes.

Notes: The restricted data set only contains those schools which are present in all five cohorts.

Table 4: Top and Bottom Ten University-Fields of Study Combinations by Median Earnings Five Years Post-Graduation

University	Field of Study	Earnings Rank	Median Annual Pay (2022USD)	25th and 75th Annual Pay Percentiles (2022USD)	Number Graduates	% of Grads in Major Ind.
Top and Bottom 10 Credentials - Bachelor's - Graduates 2001-2003						
TX Tech Univ.	Engineering	1	192,914	[150,091, 250,007]	32	0.32
TX A&M Univ.	Engineering	2	166,293	[128,850, 220,166]	99	0.30
Univ. of TX - Austin	Engineering	3	164,801	[126,484, 220,373]	66	0.32
Colorado School of Mines	Engineering	4	156,629	[125,880, 213,300]	53	0.40
Montana Technological Univ.	Engineering	5	153,211	[108,199, 197,490]	52	0.27
OR State Univ.	Pharmacy	6	150,091	[135,781, 166,639]	54	0.33
Purdue Univ.	Pharmacy	7	142,605	[117,974, 163,485]	114	0.53
LA State Univ. & A&M Colg.	Engineering	8	140,944	[113,341, 171,849]	35	0.31
Univ. of LA at Monroe	Pharmacy	9	137,486	[119,561, 160,715]	33	0.85
Univ. of Montana (The)	Pharmacy	10	132,068	[112,895, 152,543]	145	0.48
Fort Lewis Colg.	Anthropology	4,881	32,304	[24,601, 43,164]	31	0.16
North Greenville Univ.	Religious	4,882	32,304	[25,573, 41,247]	58	0.19
Kent State Univ.	Drama/Theatre	4,883	32,219	[25,944, 44,441]	49	0.16
Univ. of OR	Ethnic, Cultural Minority, Gender, And Group Studies	4,884	32,004	[25,476, 45,923]	53	0.29
McNeese State Univ.	Fine And Studio Arts	4,885	31,462	[25,726, 46,077]	30	0.31
LA State Univ. & A&M Colg.	Drama/Theatre	4,886	30,499	[22,705, 47,315]	38	0.18
Univ. of Northern Colorado	Music	4,887	30,132	[21,188, 49,171]	59	0.25
Shenandoah Univ.	Drama/Theatre	4,888	29,535	[18,267, 43,942]	63	0.31
Univ. of WI - Madison	Music	4,889	29,471	[19,726, 52,390]	42	0.18
Univ. of Colorado Boulder	Religious	4,890	27,929	[20,809, 41,247]	31	0.23
Top and Bottom 10 Credentials - Bachelor's - Graduates 2013-2015						
Univ. of IL Urbana-Champaign	Computer Science	1	166,721	[112,653, 254,204]	602	0.40
Univ. of IL Urbana-Champaign	Math and Comp. Science	2	159,898	[115,503, 215,797]	48	0.27
CUNY York Colg.	Health Professions	3	155,421	[123,532, 180,099]	66	0.63
Univ. of MI	Engineering	4	152,543	[105,327, 217,603]	185	0.32
TX A&M Univ.	Engineering	5	152,452	[100,629, 196,714]	434	0.29
Univ. of MI	Comp. Sci./IT Support	6	149,209	[100,201, 219,616]	937	0.33
Univ. of IL Urbana-Champaign	Engineering	7	139,026	[102,524, 193,422]	354	0.31
Univ. of TX - Austin	Engineering	8	138,198	[93,492, 176,053]	310	0.31
Univ. of HI at Hilo	Pharmacy	9	136,317	[115,039, 158,518]	173	0.48
Univ. of VA	Comp. Sci./IT Support	10	133,589	[104,328, 194,440]	239	0.44
VA Commonwealth Univ.	Dance	9,799	29,535	[23,235, 47,728]	33	0.17
Southeast MO State Univ.	Visual/Performing Arts	9,800	29,357	[22,629, 41,247]	46	0.27
Univ. of WI - Superior	Fine And Studio Arts	9,801	29,214	[23,506, 37,919]	41	0.21
S. OR Univ.	Fine And Studio Arts	9,802	29,097	[21,314, 40,050]	48	0.22
Univ. of Montana (The)	Drama/Theatre	9,803	28,630	[21,459, 42,445]	64	0.19
GA S. Univ.	Drama/Theatre	9,804	28,357	[20,809, 34,799]	35	0.18
Kennesaw State Univ.	Drama/Theatre	9,805	28,143	[21,871, 42,845]	49	0.14
Shenandoah Univ.	Drama/Theatre	9,806	28,126	[20,947, 37,683]	60	0.20
Central CT State Univ.	Drama/Theatre	9,807	26,002	[18,608, 37,919]	33	0.13
Morris Colg.	Health Professions	9,808	24,449	[18,677, 33,810]	37	0.25

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes.

Notes: Numbers of graduates are cumulative over three graduating cohorts for bachelor's degrees. "% of Grads in Major Ind." refers to the proportion of grads in a given credential who work in the most common industry. Because of data limitations, these refer to the parent 2-digit CIP code of the credential in question. All other statistics are calculated at the 4-digit CIP code level.

Table 5: Top 10 Fields of Study for Cohorts 2001-2003 and 2013-2015, By CIP Code Aggregation Level

CIP Code	CIP Description	Percent Share	Rank	CIP Code	CIP Description	Percent Share
2 Digit CIP Codes						
52	Business & Related Services	29.9 %	1	52	Business & Related Services	24.5 %
13	Education	8.2 %	2	51	Health Professions	9.1 %
45	Social Sciences	6.9 %	3	42	Psychology	6.5 %
51	Health Professions	5.9 %	4	13	Education	6.5 %
42	Psychology	5.7 %	5	45	Social Sciences	6.4 %
11	Comp. Sci. & Info. Support.	5.5 %	6	9	Comm, Journalism & Related	4.9 %
9	Comm, Journalism & Related	4.7 %	7	26	Biological & Biomedical Sci.	4.5 %
30	Multi/Interdisc. Studies	3.5 %	8	14	Engineering	3.9 %
14	Engineering	3.5 %	9	11	Comp. Sci. & Info. Support.	3.9 %
26	Biological & Biomedical Sci.	3.4 %	10	50	Visual & Performing Arts	3.8 %
4 Digit CIP Codes						
52.02	Business Admin, Mgmt & Ops	9.1 %	1	52.02	Business Admin, Mgmt & Ops	8.0 %
13.12	K-12 Education	5.4 %	2	42.01	Psychology (General)	5.6 %
42.01	Psychology (General)	5.0 %	3	51.38	Nursing	5.3 %
52.13	Mgmt. Sciences & Quant. Methods	4.1 %	4	13.12	K-12 Education	4.2 %
52.03	Accounting & Related Services	3.9 %	5	26.01	Biology (General)	3.6 %
30.99	Multi/Interdisc., Other	3.2 %	6	52.03	Accounting & Related Services	3.6 %
52.08	Finance & Financial Mgmt	3.1 %	7	24.01	Liberal Arts & (General) Studies	3.0 %
51.38	Nursing	2.7 %	8	52.08	Finance & Financial Mgmt	2.4 %
26.01	Biology (General)	2.7 %	9	23.01	English Lang. & Lit. (General)	2.3 %
45.11	Sociology	2.7 %	10	43.01	Criminal Justice	2.3 %

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes.

Notes: Percent shares are based on weighted sample.

Table 6: Variance, Covariance, and Correlations of Institution and Field of Study Fixed Effects Across Graduating Cohorts

Graduation Cohort	Covariance Institution-FOS	Correlation Institution-FOS	Variance Institution	Variance FOS	Total Variance
2001–2003	0.0010	0.0629	0.0083	0.0322	0.1904
2004–2006	0.0009	0.0514	0.0089	0.0322	0.1902
2007–2009	0.0010	0.0553	0.0092	0.0376	0.2052
2010–2012	0.0009	0.0483	0.0096	0.0372	0.2052
2013–2015	0.0012	0.0624	0.0098	0.0405	0.1990

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes.
Notes: All metrics are with respect to inflation-adjusted logged average earnings.

Supplemental Appendix

Degrees Apart:

Changing Horizontal Stratification in Bachelor's Degrees by Institution and Field in the 21st Century

Contents

Supplementary Methods

Comparing the Representativeness of PSEO Data to All United States Institutions of Higher Education

The PSEO data are based on state-, agency-, and institution-level agreements with the U.S. Census Bureau, the IRS, and the LEHD. As such, the data are not representative of all institutions of higher education that offer bachelor's degrees. To quantify this discrepancy and adjust for it, I use an entropy balancing procedure that reweights the observed PSEO sample so that it matches the broader population of universities and colleges on a set of observable characteristics.

Using the Department of Education's College Scorecard (also used in the main analysis), institutional attributes such as mean SAT scores, whether it is public or private, undergraduate tuition, undergraduate enrollment, graduate enrollment, and selectivity can be gleaned for the near-universe of U.S. institutions of higher education.

Formally, let the "target" group be institutions not included in the PSEO for the entire temporal span of the dataset and the "sample" group be institutions included throughout. Entropy balancing chooses nonnegative weights w_u for the included (sample) institutions to minimize the Kullback–Leibler divergence from uniform weights subject to first moment-matching constraints on observed covariates. Denoted by $\mathbf{X}_u$ in equation 1 is the vector of institution-level characteristics:

$$\mathbf{X}_u = \left[\text{Private}_u,\ N_u^{\text{gr}},\ \log N_u^{\text{gr}},\ N_u^{\text{ug}},\ \log N_u^{\text{ug}},\ \log(\text{Tuition}_u),\ \text{SAT}_u,\ \text{AdmRate}_u\right]^\top \quad (1)$$

Equation 2 shows the optimization problem.

$$\min_{\{w_u \geq 0\}} \sum_{u \in \text{Sample}} w_u \log w_u \quad \text{s.t.} \quad \sum_{u \in \text{Sample}} w_u \, \mathbf{X}_u = \frac{1}{N_{\text{Target}}} \sum_{u' \in \text{Target}} \mathbf{X}_{u'}, \sum_{u \in \text{Sample}} w_u = 1 \quad (2)$$

Intuitively, this assigns more weight to included institutions whose characteristics are underrepresented relative to the target and less weight to those that are overrepresented, while preserving as much of the original distribution as possible.

I limit extreme weights to their values at the 2.5th and 97.5th percentiles to mitigate the influence of outliers. The resulting weights are applied to the included institutions in all reweighted summaries and figures. The effectiveness of the reweighting (i.e., balance on the covariates listed above before and after weighting) is displayed in the main text in Table 2.

Calculating Industry-Level Average Earnings from ACS Data

Since graduation year is not observed in the ACS, I assume that all graduates were on average 23-years-old upon graduation, and I used the annual earnings of all workers working full time who are aged 27-29 at the time of the survey. While not a perfect solution, the methods described below will show that it only matters for calculating annual earnings relative to each other since the primary datasource remains the PSEO-based distributions of annual earnings by field of study.

Calculating Average Annual Earnings by Field of Study Adjusting for Industry Shares

These average annual earnings by field of study and industry net of each other $\alpha_{f,y}$ and $\beta_{ind,y}$, respectively, in a given year (y) can be computed based on share of flows from field of study to industry as a proportion of total graduating students $S_{f,ind,y}$. We may assume the following additive decomposition model (equations 3 and 4):

$$\omega_{f,y} = \alpha_{f,y} + \sum_{ind} S_{f,ind,y} \cdot \beta_{ind,y} \tag{3}$$

$$\omega_{ind,y} = \beta_{ind,y} + \sum_{f} S_{f,ind,y} \cdot \alpha_{f,y} \tag{4}$$

Where $\omega_{f,y}$ is the observed average annual earnings for a field of study in a given year, known from the LEHD/PSEO data, and $\omega_{ind,y}$ is the average annual earnings in an industry in a given year for all college graduates, known from the ACS data. To solve the above system of equations, I must simply add a constraint that the mean industry effects are mean zero:

$$\sum_{ind,y} \beta_{ind,y} = 0 \tag{5}$$

This system of three equations (equations 3-5) may then be solved using least squares, performed separately for each year. With the final estimates of $\hat{\alpha}_{f,y}$ and $\hat{\beta}_{ind,y}$, which correspond to the industry-adjusted field of study-specific average wages and the field of study-adjusted industry-specific average wages respectively, it is possible to calculate average expected annual earnings by field of study and industry combination.

Using the estimates of $\hat{\alpha}_{f,y}$ and $\hat{\beta}_{ind,y}$ from above combined with flows data, the predicted aggregate average annual earnings for a given field of study in a particular year ($\omega'_{f,y}$) can be compared to their observed values ($\overline{\omega}_{f,y}$), giving a sense of the extent to which observed shifts in annual earnings are due to changing flows to industry and industry-level expansion and contraction. It is worth noting at this moment that this analysis relies on the additivity of industry effects and field of study effects and that there be no interactive effects between the two. Otherwise put, a student with a computer science degree and a liberal arts degree, both working in the same industry of "Information" would earn salaries commensurate with the additive effects of their fields of study and industries. This would not allow for any synergistic effects for computer science majors, given they are working in a industry that is especially proximate to their field of study. While this is a strong assumption, it once again makes my estimates an underestimate of the total effect of industry in the following analysis since interactive effects are disregarded. Further, in the following analysis, I explicitly quantify this residual effect for comparison and interpretation.

Assessing Changes in Field of Study Premiums Alongside Underlying Demographic Changes and Changes to Industry Flows

It is not mutually incompatible that changing field of study average wages may reflect changing industry destinations and industry-level average wages and that fields of study may be changing demographically, which in turn changes the prestige or desirability of a given field of study. Indeed, these two processes may be happening simultaneously and/or because of each other without being necessarily competing explanations. Nevertheless, comparing how parsimonious each is in explaining changing field of study-level premiums is a natural first step in understanding which question is more first-order.

In order to compare how well each source of variation predicts changes in average wages in the time period examined, I pursue a fixed effects model that fully accounts for between-unit heterogeneity and adds within-unit continuous regressors. I then examine the within-unit R^2 in order to understand how well each does. As with most primary analyses, this is performed on wages for recipients of bachelor's degrees, five years after they graduated. For each field of study-specific average wage $\overline{\omega}_f$, observed separately for each graduation year y, X years after graduation, I regress it on field of study-specific fixed effects F_f. To test the predictive power of demographic change, I add a vector of field of study-specific demographic variables $\xi_{f,y}$, which includes the percentage in each field of study that is male or female and either white, black, asian, and hispanic (the intersection thereof). This is eight continuous variables in total. To test the predictive power of industry flows, I simply add the expected average income based on the industry-weighted average of industry-specific average wages, as explained in the main text. This is a singular variable.

As this is a fixed effects model, the static characteristics of each field of study will be captured by the field of study fixed effect. Baseline values of either expected wages based on industy composition or demographic characteristics will be "netted out," so the only source of variation will be within-unit changes in these continuous indicators. Thus, I will use the within-unit R^2 to understand the predictive power of $\xi_{f,y}$ and $ln(\overline{\omega}^*_{f,Y})$, alternatively. A value of 1 would indicate 100% explanatory power of either to explain wage changes over the period observed, as compared to 0, which would indicate no predictive power. Using these methods, I can also create an alternative version of the main text's Figure 5, which shows predicted changes in field of study average wages based on demographic changes.

$$ln(\overline{\omega}_f|Y = y + X) = F_f + \xi_{f,y} + \epsilon_{f,y} \tag{6}$$

$$ln(\overline{\omega}_f|Y = y + X) = F_f + ln(\overline{\omega}^*_{f,Y}) + \epsilon_{f,Y} \tag{7}$$

Regression estimates are shown in in Appendix Table A1, and an alternative version of Figure 5 is shown in Appendix Figure A5, below.

Robustness Checks Specifications

Appendix Figure A4 displays eight robustness checks. Below, each is detailed in the order that it appears in the figure.

- **2 Digit CIP Codes + Log-Normal Distribution** – I replace 4 digit CIP Codes (N = 267) with parent 2 digit CIP Codes (N = 36). As in the primary analysis, the outcome (earnings) is logged.
- **2 Digit CIP Codes Without Logged Outcomes** – I replace 4 digit CIP Codes (N = 267) with parent 2 digit CIP Codes (N = 36). The outcome (earnings) is untransformed.
- **2 Digit CIP Codes WIthout Logged Outcomes** – I replace 4 digit CIP Codes (N = 267) with parent 2 digit CIP Codes (N = 36). The outcome (earnings) is untransformed. I include non-workers as earners with an income of \$0. The number of workers not employed is available at the credential-cohort level for 2 digit CIP Codes, though it is not available at the 4 digit Level.
- **4 Digit CIP Codes + Log-Normal Distribution** – This is the primary analysis, where the outcome is log-normalized, and 4 digit CIP Codes are used.
- **4 Digit CIP Codes + Pareto Distribution** – I replace the assumed log-normal distribution within each credential with a piecewise log-normal/Pareto distribution. This distribution is identical for all workers below the 98th percentile. For those above the 98th percentile, I replace the assumed log-normal distribution within each credential with draws from a Pareto distribution with an α value of 2.
- **4 Digit CIP Codes + Reordered Fixed Effects** – This specification is identical to the primary analysis but reverses the order of inclusion of fixed effects, with institutional fixed effects added before those for field of study. In practice, this approach necessarily attributes a larger share of earnings variation to institutions, since differences by field are only measured after controlling for where students

studied. In this scenario, the institutional effects also capture differences that may in fact be attributable to variation in fields of study.

- **4 Digit CIP Codes + Unweighted** – This analysis uses the same specification as the primary model but does not weight use the weights calculated to make the sample more closely match the target population of all U.S. schools offering 4-year degrees.

- **Semi-Aggregated (N = 64) 4-Digit CIP Codes + Log-Normal Distribution** – This analysis uses the same specification as the primary model but replaces the 267 CIP codes with a more aggregated set of 64 CIP codes. As opposed to using 2 digit CIP codes, this uses the 30 largest 4 digit CIP codes alongside "remainders." For instance, CIP code 13.12 or "K-12 Education" is used, and a new "remainder" CIP code is created for all CIP codes that begin with 13 but are not 13.12. For 2 digit parent CIP codes with multiple children 4 digit CIP codes that are in the top 30 CIP codes, all get separate entries before calculating the remainder. 2 digit CIP codes with no children 4 digit CIP codes constituting the top 30 are still included. This condition is created to show that it is not merely mechanistic that fields of study capture so much variation compared to institutions, as much of the result can be replicated with a restricted set of CIP codes.

Supplemental Figures

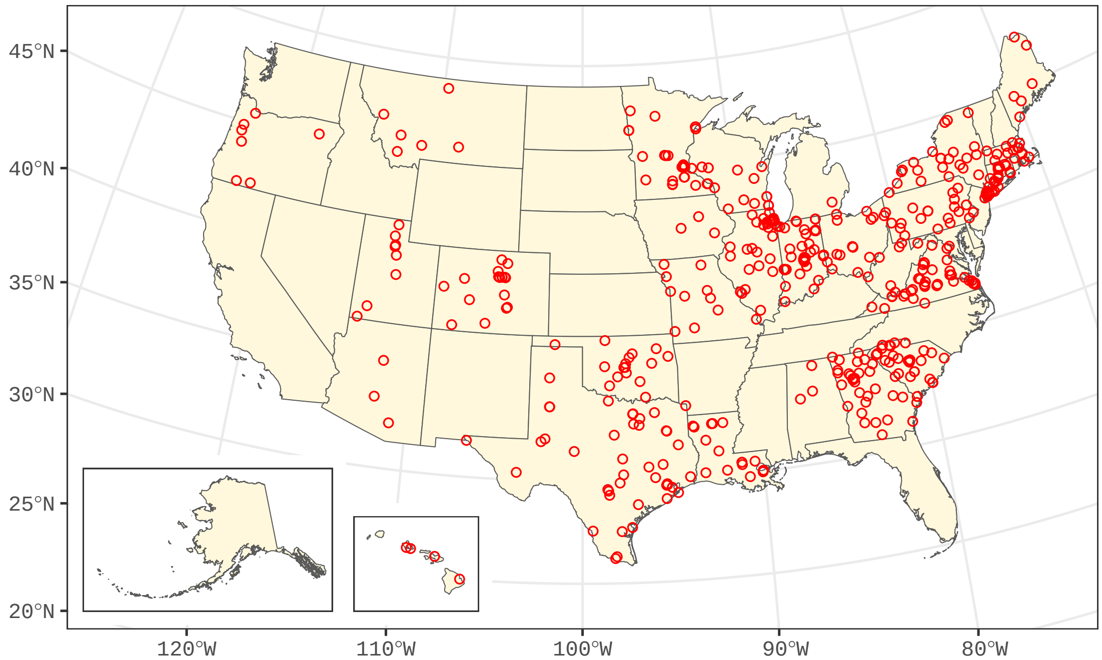

Figure A1. Map of Included Degree-Granting Institutions Showing Unequal Coverage by State

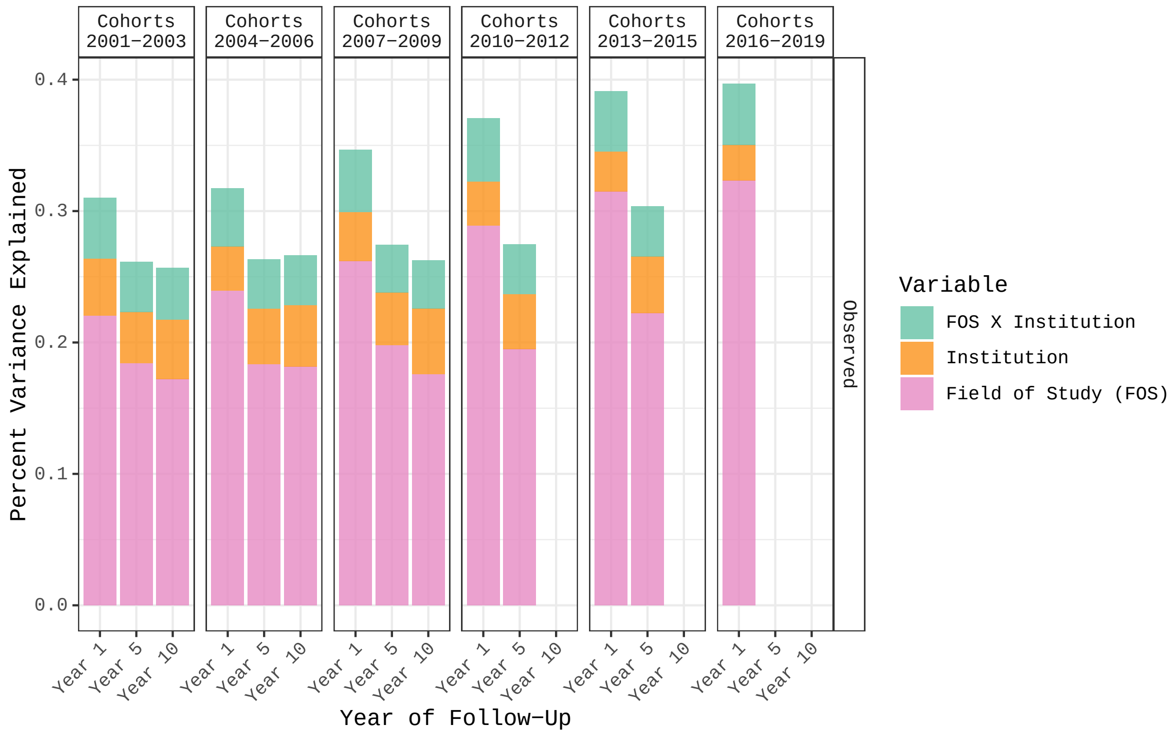

Figure A2. Replication of Primary Analysis, Visualized by Cohort and Year of Follow-Up

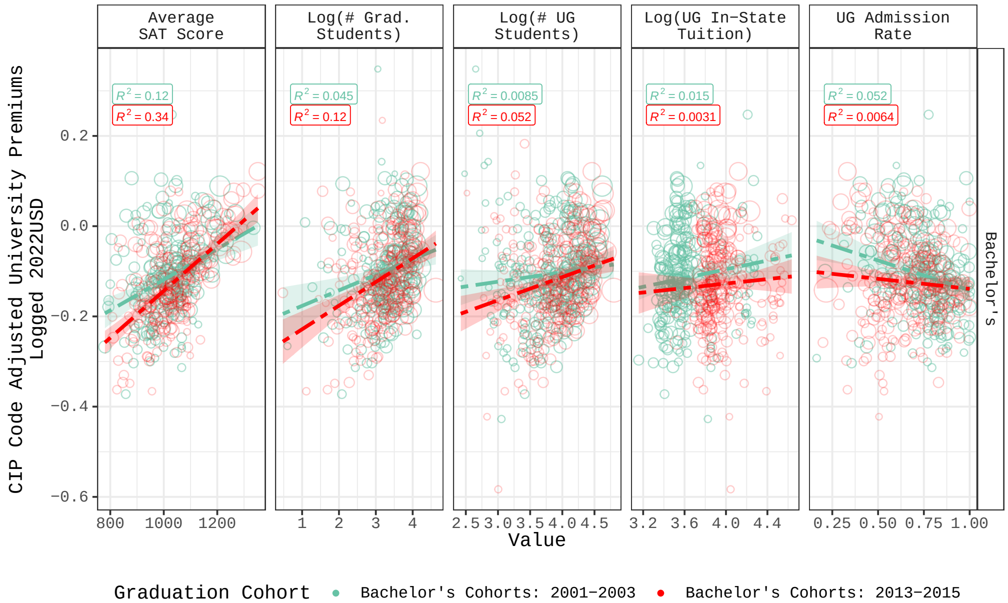

Figure A3. Reanalysis of Main Text Figure 7: Institution Average Premiums, After Adjusting for Distribution of Fields of Studies, Regressed on Constant Institutional Characteristics (Average Institutional Characteristics Across All Cohorts) for Two Cohorts

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes; The U.S. Department of Education's College Scorecard.

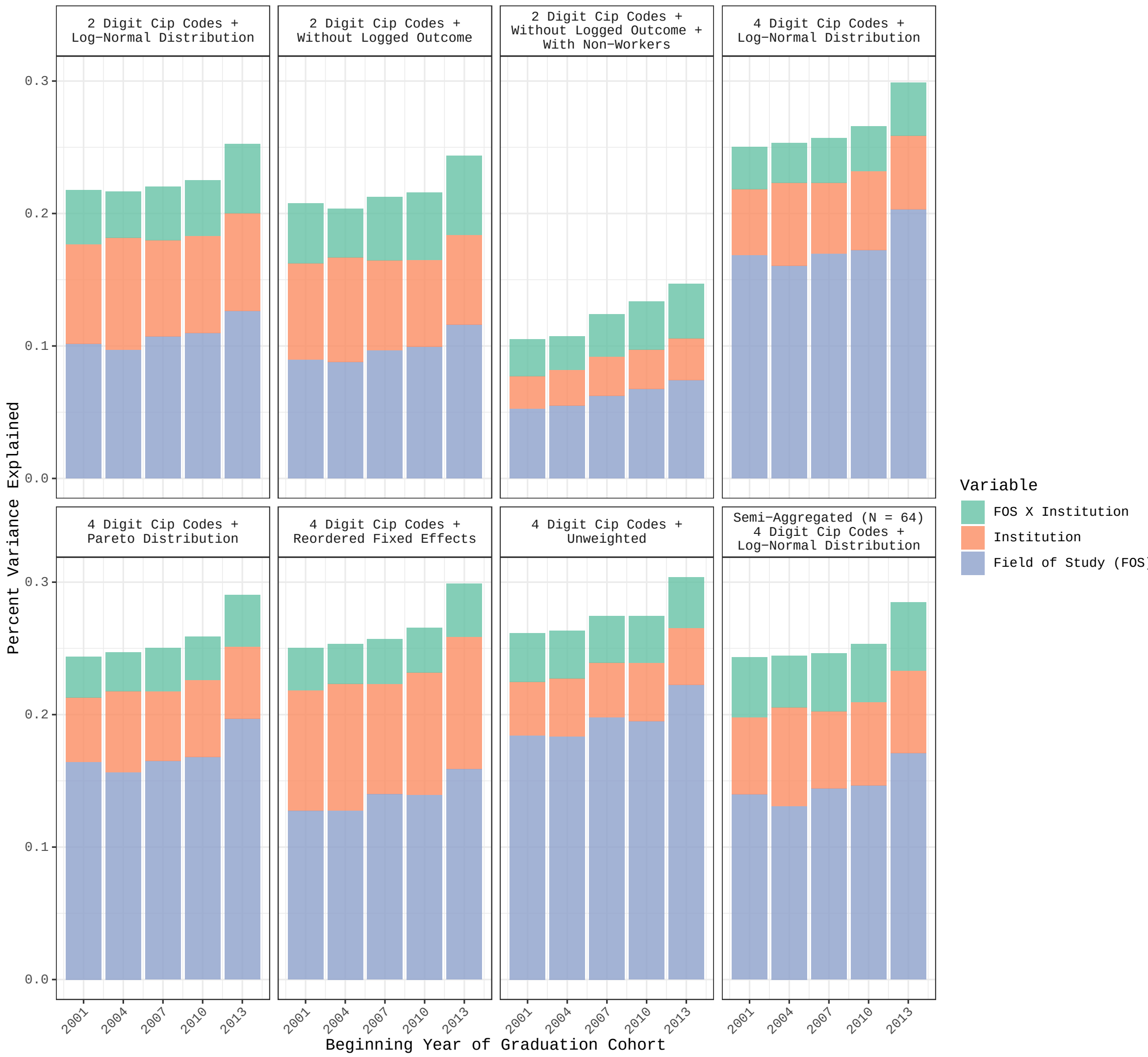

Figure A4. Various Robustness Checks of the Primary Decomposition Analysis, Variably Alternating the Level of CIP Code Aggregation, Logged and Unlogged Outcomes, the Distribution Functional Form, Weights for Missingness, and the Presence of Non-Workers

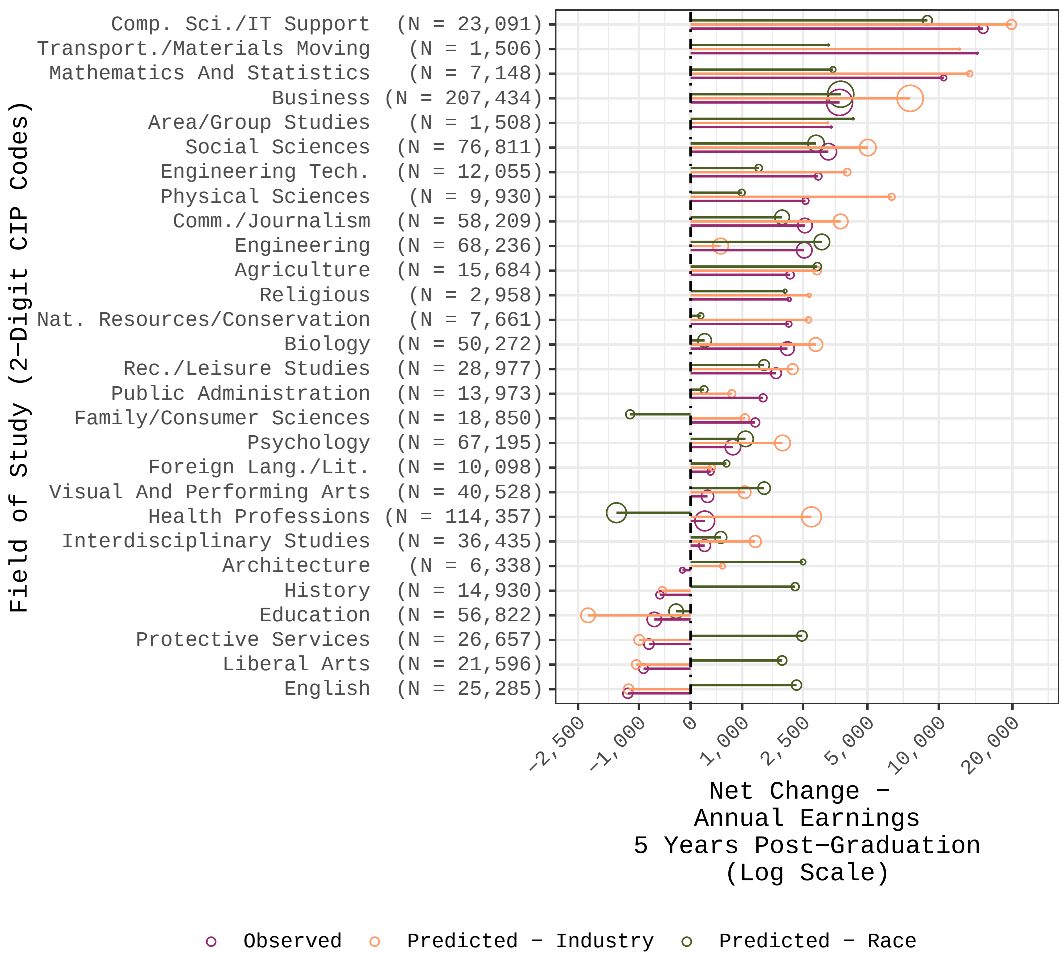

Figure A5. Figure 5 With Added Comparison for Expected Changes in Earnings Based on Demographic Recomposition by Field of Study.

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes, American Community Survey, National Center for Education Statistics, The College Scorecard.

Notes: Only fields of study with at least 1,000 graduates per year (3,000 per cohort span) are shown. Size of circles is correlated with the number of students graduating in each cohort. "N = " for each cohort refers to their absolute sizes for graduating cohorts 2013–2015.

Supplemental Tables

Table A1. Fixed Effects Models Comparison - Field of Study Average Earnings Predicted By Demographics or Industry

	Log(Average Earnings)	
Model:	(1)	(2)
Variables		
Pred. Earnings Based on Industry (Logged)	0.7980***	
	(0.0552)	
White Men		-0.2922
		(0.3656)
White Women		0.0472
		(0.2120)
Black Non-Hispanic Women		-0.9098
		(0.9289)
Black Non-Hispanic Men		-0.0610
		(1.4813)
Asian Men		1.7255*
		(0.8260)
Asian Women		-2.9202**
		(1.0579)
Hispanic Women		-0.1739
		(0.5425)
Hispanic Men		0.6782**
		(0.2433)
Fixed-effects		
2-Digit CIP Code (32)	Yes	Yes
Graduation Cohort (5)	Yes	Yes
Fit statistics		
Observations	160	160
R^2	0.99623	0.98104
Within R^2	0.85615	0.27669

Clustered (2-Digit CIP Code) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

Data source: Longitudinal Employer-Household Dynamics Post-Secondary Education Outcomes, American Community Survey, National Center for Education Statistics, The College Scorecard.
Notes: Demographics are the percent of each field of study that belong to each category. They do not sum to one, as there is a remainder that belong to one or more races and American Indian and Alaska Natives.