Degrees of Inequality:
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' 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, fields of study, and specific credentials shapes earnings inequality among U.S. bachelor's degree, both from a static perspective and 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. Net of field of study and institution, credential- or departmental-level effects account for a small and largely stable share of earnings variation. For both fields of study and institution, the underlying structural variation behind their importance is shifting in nature. Field of study's growing importance is largely driven by baseline field of study linkages to industrial sectors that have seen rising average wages like finance, technology, and professional services. While variation between universities explains a smaller share of inequality, it is increasingly associated with observable institutional characteristics like test scores and enrollment. Despite dramatic growth in college enrollments over this period, 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 small number of 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; Sekhri 2020), by field of study[1] (Altonji, Kahn, and Speer 2016; Kim, Tamborini, and Sakamoto 2015; Kirkeboen, Leuven, and Mogstad 2016), and by their intersections, here termed "credentials" to refer to the unique combination of degree level, awarding institution, and specific field of study. These distinctions—what sociologists refer to as horizontal stratification[2]—shape early-career outcomes through distinct mechanisms. However, variation at the credential level for specific fields of study and university contexts is rarely observed, instead being proxied by survey data using coarsened binned categories. Further, most research has treated the different axes of horizontal stratification in isolation using static, cross-sectional frameworks (see reviews by Gerber and Cheung 2008; Reimer and Thomsen 2019), and so we have no knowledge of their relative importance or how these relationships may be changing over time. Figure 1 provides a stylized representation of these forms of horizontal stratification.

With the assistance of administrative data, shifting the unit of analysis away from the individual and shifting the data source away from survey-based data fills this knowledge gap, as it allows one to study precisely the extent to which institutions, fields of study, and credentials are differentiated in terms of pay and labor market outcomes. Whereas

[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 comparisons across levels of education. "Academic program" might be a suitable alternative, though no term is fully satisfactory.

[2] 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 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.

survey-level data elides important information on between-institution, between-field of study, and certainly between-credential differences, administrative does not suffer this fate. Knowledge on the distributional properties of credentials—namely, which fields of study are most commonly pursued at which institutions and how such distributions have changed over time—and the extent to which field of study and institutional earnings differences are separable phenomena are only knowable by using credential-level administrative data. The relevance of these phenomena is heightened amid expanding college enrollment and shifting labor market structures, as technological change, the rise of gig and precarious work, and declining unionization all challenge traditional models of how different kinds of education can generate inequality.

Theoretically, the forms of horizontal stratification discussed in this paper raise core sociological questions about how inequality is produced through organizational and categorical differences in higher education, as their various forms operate through largely analytically distinct mechanisms. Institutional effects often reflect processes of prestige signaling, cultural capital transmission, and social network formation, while field-specific effects are more tightly linked to occupational closure, skill specificity, and professional socialization, though both institutional and field-specific effects operate through all of the aforementioned channels to some extent. The fact that these mechanisms differ so substantially makes horizontal stratification a rich site for examining how different dimensions of education are embedded in broader systems of social reproduction. The theory of Effectively Maintained Inequality (Lucas 2001) provides a starting point for understanding these changes how horizontal stratification may play a role in perpetuating inequalities, though it does not elaborate how or why horizontal stratification operates or how such stratification squares with simultaneously-occurring industry-level and labor market change. Nevertheless, if horizontal differentiation now plays a dominant role in shaping outcomes among degree-holders, as suggested by this theory, then its growing importance should be measurable. This would also carry implications for the view of higher education as a "great equalizer," which has highlighted horizontal variation as central to its core findings (Torche 2011; Zhou 2019).

In what follows, I examine the dynamic 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 ("credentials," or 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. 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.

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 this research, I only focus on recipients of bachelor's degrees for tractability. However, I also 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 subsequent continued tertiary education and intervening job moves. I discuss the implications of this in detail below.

Finally, this paper examines how differences in credentials are mediated by school-to-work flows, tracing how graduates from different fields of study are sorted into specific industrial sectors. This perspective is essential, as changes in schooling are inseparable from shifts in the larger labor market. It builds on recent research on school-to-work linkages (DiPrete et al. 2017; Bol et al. 2019) and responds to a growing body of evidence that rising earnings inequality is driven less by individual traits than by structural changes at the firm and industry levels (Song et al. 2019; Wilmers and Aeppli 2021; Haltiwanger et al. 2024). Whereas prior studies have emphasized occupations or individual skills, I center industry as a key site for understanding horizontal stratification, given its growing role in shaping wage-setting, job quality, and mobility opportunities. Taking this schooling-to-industry perspective, enabled by the novel data I leverage, also highlights connections with changing occupational and demographic landscapes. By situating education within broader labor market transformation, this approach moves beyond frameworks such as Routine- or Skills-Biased Technological Change (RBTC) and STEM/non-STEM binaries, which often obscure how credentials are relationally linked to labor market outcomes. More broadly, it underscores that horizontal stratification reflects not only the skills students acquire but also the pathways that connect programs to economic sectors. Qualitative research documenting substantial earnings variation among graduates with the same credential (Streib 2023) further suggests that within-credential forces like industry flows may play a central and underexamined role in the production of inequality.

The remainder of the introduction proceeds in five steps. 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 then turn to the issue of selection, summarizing evidence on whether differences across institutions and fields reflect causal value added or sorting. Next, I discuss 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. I then consider how patterns of horizontal stratification have changed over time, situating them in the context of educational expansion and labor market transformation. Finally, I examine the underlying drivers of horizontal stratification, situating changes in institutions, fields, and credentials within broader transformations in higher education and the labor market.

*** Figure 1 About Here ***

Horizontal Stratification by Field of Study and Institution

Carnevale, Cheah, and Strohl (2013) find that differences in average annual earnings between degree-holders from different fields of study can exceed the overall college/high school earnings gap. In a human capital framework, fields of study differ greatly in the skills they confer to students, and these skills demand different earnings premiums on the labor market, differentiating the *general* human capital afforded by a vertically differentiated level of higher education from its horizontally-stratified *specific* forms (Kinsler and Pavan 2015; Kogan et al. 2021; Kambourov and Manovskii 2009; van de Werfhorst et al. 2001). Yet field effects are not 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.

Institutions 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 many of the aforementioned studies' findings reflect the causal effects of a degree from a prestigious institution or a certain field of study, field-specific and, in particular, institutional effects are partially inseparable in most data due to the unobserved differential distributions of fields of study across institutions. Otherwise put, a causal effect of an Ivy League 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.

This problem is compounded by how both axes of horizontal stratification are typically measured in survey-based data. Institutions are often proxied by observable characteristics 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. Both strategies obscure meaningful variation, either by masking differences across institutions or by flattening the closure-generating processes that distinguish specific fields. For instance, survey categories frequently 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, which encompass subfields with widely divergent outcomes but are too complex to be captured by most survey instruments. At the institutional level, treating all flagship public universities as equivalent ignores sharp cross-state differences in resources, selectivity, and outcomes, just as collapsing private institutions into a single category erases the wide gulf between elite research universities like Ivy League schools and tuition-dependent regional colleges. Even within Ivy League schools, there is dramatic variation in students' experiences and outcomes. As a result, much of the variation that matters most for understanding horizontal stratification has been invisible in prior research.

The value of fields of study and institutions is shaped not only by the human and social capitals they immediately impart upon graduation but also by the labor market destinations they make possible. Some credentials lead to high-paying occupations and industries immediately after graduation but have limited long-term growth (e.g., nursing). Others may have lower entry-level wages but steeper earning trajectories over time (e.g., medicine), while still others (e.g., technology or consulting) combine high starting pay with long-term mobility (Cheng and Song 2019). This life course variability is further complicated as credentials differ in their likelihood of leading to graduate education, stratifying outcomes and demanding an attention to specific credentials. However, these life course patterns of occupational and educational pathways are not just individualistic in nature, as they are also shaped by larger forces. Fields of study, institutions, and credentials are not static, as they evolve in response to changing labor markets. New fields emerge, old ones fade, and others adjust to shifts in occupations, industries, and new forms of work, and all of these processes occur differently across institutions. Many specific fields of study are also shaped by national academic policies and vocational training systems. Accordingly, a corpus of international comparative research has examined school-to-work linkages, showing that stronger linkages reduce unemployment and improve job outcomes, though they may limit flexibility and increase mismatch (DiPrete et al. 2017; Bol et al. 2019). This conceptual framework elucidates how educational credentials are embedded within institutional structures, even though most existing research emphasizes cross-national comparisons, in contrast to this study's focus on intra-national dynamics. This systems-level literature, alongside the present analysis, shifts attention away from individual selection and toward institutional and labor market factors that shape credential outcomes.

Finally, research on institutional effects in U.S. higher education often centers on elite universities, emphasizing distinctions between elites and non-elites. Yet such institutions represent an exceedingly small fraction of the broader system of higher education. Most degrees are conferred by colleges that differ along other institutional dimensions, such as enrollment patterns, the residential nature of the school, the percent of classes conducted online, and admissions and advising practices, rendering conventional metrics like SAT scores or selectivity insufficient for capturing this broader variation (Ciocca Eller 2023). Most college enrollees choose a college near home or are constrained by financial means, family obligations, and more, making variation in non-elite colleges an important object of study. For instance, in terms of intergenerational mobility, attending a more prestigious college does not uniformly yield higher returns, particularly across the broad range of less selective institutions. Administrative data show that many colleges with the highest intergenerational mobility rates are not highly selective (Chetty et al. 2017), underscoring the need to examine institutional outcomes individually across the broad range of institution types as apposed to in aggregate based on institution-level observables that differentiation between prestigious and non-prestigious colleges. Beyond observable traits related to selectivity and school quality, institutional contexts vary in ways that shape students' experiences and interact with class and family background (Armstrong and Hamilton 2013). Finally, as the previous section showed, variation in student outcomes is not only shaped by which institution one attends, but also by what one studies within that institution. Because institutions vary in their strengths across disciplines, and because students sort into programs in patterned ways, the institutional context cannot be understood apart from the fields it offers and supports. This makes it essential to analyze credentials as composite educational experiences, shaped jointly by institution- and field-specific environments, rather than treating either as isolated influences.

Selection Effects and Measuring the Value Added of Horizontally Stratified Degrees

Differences in outcomes across fields of study and institutions may reflect more than just curricular content, skills, prestige, human capital, and social capital, both real and perceived or signaled. Selection processes into fields of study and institutions are certainly at play, though it is unclear the extent to which these selection processes are related to earnings variation amongst graduates. After all, students may choose fields of study and institutions based on a mix of individual and family characteristics, academic preparation, career aspirations, and perceived labor market risk (Altonji, Blom, and Meghir 2012; Zhou 2019; Brewer, Eide, and Ehrenberg 1999; Loury and Garman 1995), but it is only if these characteristics interact with earnings characteristics net of credential characteristics that they are a source of worry for the analyses undertaken in the present research. Some studies do confirm the returns to selectivity amongst institutions (Borgen 2014; Bleemer 2021; Manski and Wise 1983), while others find little or no effect after adjusting for unobserved heterogeneity (Dale and Krueger 2002). Contrarily, while there are indubitably differences in who chooses to study certain subjects at specific institutions, there is little strong evidence that field of study earnings differences reflect strong selectivity bias with regards to who selects into fields of study (Bleemer and Quincy 2025; Dahl et al. 2023; Bleemer and Mehta 2022). Otherwise put: the observed earnings gaps across majors appear to stem less from who enters them than from what those majors confer (skills or otherwise) and how individuals are subsequently positioned in the labor market.

A recent comprehensive study of the college mobility pipeline by Bleemer and Quincy (2025) puts the question of selectivity into perspective. Their work documents the declining wage premium from college for low-income students and provides the most detailed evidence to date on whether horizontal stratification by field of study and institutional characteristics reflects causal wage premiums or simply selection into credentials. Drawing on more than a century of survey data, they show that college has become increasingly regressive since 1960, largely because of structural changes in the higher education system. These changes include declining institutional quality at the public universities most attended by low-income students, rising diversion into lower-value two-year and for-profit colleges, and growing stratification in major choice. Importantly, they demonstrate that selection into college and major accounts for only a small portion of this trend. Their estimates indicate that about 80% of earnings differences across institutions and nearly 100% of earnings differences across fields of study reflect the causal effect of those credentials themselves, rather than preexisting differences among students (Bleemer and Quincy 2025); the institutional estimate is consistent with results from Chetty, Deming, and Friedman (2023).

Although the present study does not attempt to model selection directly, these findings provide a useful benchmark for interpreting my results. They also highlight how horizontal stratification contributes to broader patterns of intergenerational inequality. Whereas Bleemer and colleagues focus primarily on mobility outcomes by parental income, this paper instead centers the structure and evolution of horizontal stratification itself: how the economic value of credentials has shifted over time and how these changes reflect broader transformations in higher education and the labor market. In contrast to their survey-based approach, I leverage a novel dataset that allows for much finer-grained analysis of credential-specific and relational dynamics.

Credential-Specific Horizontal Stratification and Simultaneously Accounting for Multiple Axes of Horizontal Stratification

While this paper has thus far examined field of study and degree-granting institution as separate axes of horizontal stratification, there is compelling evidence that their intersection—the institution-by-field combination, or "credential"—has effects that go beyond the additive influence of each dimension alone. Further, as I have discussed, measurement of one is not well-identified without the measurement of the other. Yet by analyzing each dimension in isolation, research often overlooks how these interactions play out in unpredictable ways. Two similarly ranked institutions can yield very different outcomes in fields that, on average, command similar premiums. For instance, one may have a stronger mathematics program while the other excels in economics. While continuous "interaction effects" may exist that systematically make some fields of study demand higher premiums at a certain kind of college, what's more likely is that specific relational and institutional forces are at play, as such departmental variation is seen even at colleges of similar rank and status.[3] Such relational forces will be discussed in detail below, but they are largely constituted by specific school-, field of study-, and credential-to-work linkages. Most studies rely on broad institutional groupings, which further obscures this important variation when attempting to examine the field-by-institution intersection. Only a small body of literature has examined both axes simultaneously, and most of it faces limitations due to small sample sizes or the aforementioned measurement constraints. For example, Thomas and Zhang (2005) use the Baccalaureate and Beyond Study to analyze both dimensions, while Kirkeboen et al. (2016) and Borgen and Mastekaasa (2018) leverage Norwegian administrative data. Only Borgen and Mastekaasa explicitly model institution-by-field intersections at the finest level, finding limited institutional variation beyond department-level effects. Related work by Eide, Hilmer,

[3]The language of "interaction effects" is a bit slippery when comparing the extant literature to this paper. Survey based research has examined interaction effects such as the benefit of a specific major at a more prestigious college. This is qualitatively different from an interaction effect between two categorical variables, like institution and field of study, which is what is used in the present study. This latter version of interaction effects captures credentials and is essentially a fixed effect specific to an individual university–field of study combination. It is not to be interpreted directly as a singular coefficient as most interaction effects are, and yet the underlying intuition is the same, as it is the additive effect on top of the singular field of study and institutional effects. Thus, it may simply be thought of as an extension of fixed effects models that adds credential-level complexity on top of field of study and institution effects in the case of my analysis.

and Showalter (2016) explores variation in selectivity across majors, revealing greater within-field inequality for some disciplines, though without institution-level resolution.

As the data landscape changes in the United States, there is a clear solution to the missing data on credential-specific outcomes—administrative data. In the American context, some aforementioned studies have engaged specific states in partnerships that allow researchers access to data on institutional contexts, specific fields of study, and individual characteristics (Bleemer 2021; Bleemer and Mehta 2022; Zimmerman 2014), though these are limited in scope and limited to public institutions. Administrative data solve several problems faced in previous research on horizontal inequality in higher education. First, measurement error is largely eliminated since institution names and precise fields of study are known. Second, having exhaustive data allows for even small fields of study to be described accurately and for fields of study effects to be differentiated from institutional effects. Finally, there are possibilities for novel linkages that come about as a result of administrative data, allowing individuals to be followed-up in a manner that might not be possible with survey data. Although a fully integrated administrative data infrastructure is still being developed in the U.S., the data used in this study represent a major step toward that goal, enabling credential-level analyses with a longitudinal perspective and coverage across the broader national labor market.

The Evolution of Trends in Horizontal Stratification Over Time

Prior sections have outlined the main axes of horizontal stratification—fields of study, institutions, and their intersections—as treated in existing research. Most of this literature is cross-sectional, offering a static snapshot of inequality within a given cohort or time period. Less attention has been paid to how the structure of horizontal stratification itself has evolved. This limitation is partly data-driven, but it has had broader implications for the theoretical foundations of work in social stratification. The majority of the extant empirical literature is built on survey data, which tend to focus on individual-level traits and outcomes, due to having insufficient sample sizes to make credible claims about larger institutions, groups, or organizations, let alone their changing dynamics over time. Survey data have revealed micro-level sorting mechanisms, such as how family background shapes choices, but they are poorly suited to identifying broader stratification patterns. These limitations stem from small sample sizes and narrow time frames, which make it difficult to disaggregate outcomes by credential or institution or to discern patterns over time. As a result, we have rich portraits of individual inequality-generating processes but lack a cohesive picture of macro-level change.

There are some exceptions to this phenomenon, though each is limited to addressing either one form of horizontal stratification at a time or vertical stratification. Brewer et al. (1999) use time-series data to estimate the growing earnings premium of elite college attendance, adjusting for selection. Araki (2020) shows that as education expands, the returns to higher credentials diminish, though without disaggregating by field or institution. Bloome, Dyer, and Zhou (2018) use NLSY79 and NLSY97 to examine why income persistence between vertically-stratified degree levels has remained stable despite educational shifts. These studies offer valuable insights into vertical or single-axis stratification but lack the granularity to trace how multiple forms of credential-based differentiation evolve and interact with labor market change.

A further exception is the RBTC literature, which traces shifts in labor demand induced by technological change and corresponding adaptations in education (see Katz and Autor 1999; Goldin and Katz 2008; Autor, Goldin, and Katz 2020). In this vein, Altonji, Kahn, and Speer (2014) provide a somewhat similar analysis to what I propose here by taking a longitudinal perspective in comparing the payoffs to certain college majors over time, though they do not attend to horizontal stratification by degree-granting institution, and they only attend to differentiation based on routine skills.

While valuable, this framing captures only part of the picture in a context of growing institutional and industrial complexity. RBTC emphasizes aggregate shifts and vertical stratification but overlooks how specific credentials are embedded in institutional and industrial structures. Moreover, technology and routine skill substitution are potentially no longer the only—or even the dominant—drivers of labor market change. In the next section, I discuss how recent transformations in firm organization, industry structure, and occupational sorting are reshaping how credentials translate into earnings, often in ways not well-captured by RBTC's original formulations.

Taken together, these developments underscore the need for a dynamic analytical framework that captures not only the role of horizontal stratification at a given moment, but also how its structure and consequences evolve in response to broader changes in higher education and the labor market. The Effectively Maintained Inequality (EMI) framework provides a key theoretical foundation, showing how advantaged groups respond to educational expansion by securing access to qualitatively superior opportunities, such as more selective institutions or higher-paying fields of study, in order to maintain their relative position (Lucas 2001). This framework has been especially powerful for explaining how horizontal forms of inequality emerge and persist under conditions of educational expansion. My approach builds on this insight but shifts the emphasis from individual strategies of differentiation to the evolving structural context in which educational credentials acquire value. Whereas EMI focuses on how families respond to expanding access, I examine how the institutional and industrial landscapes themselves are changing, reconfiguring the pathways through which different forms of horizontal stratification shape economic outcomes. The final section of this introduction develops the theoretical and empirical rationale for this approach, highlighting why the multiple forms of horizontal stratification must be understood in relation to their fundamental organizing forces: the changing structure of labor markets, the evolving linkages between education and work, and the shifting landscape of higher education.

Understanding the Underlying Drivers of Changing Patterns of Horizontal Stratification

In addition to assessing the relative importance of competing axes of horizontal stratification in shaping labor market outcomes over time, it is also necessary to examine how these axes are embedded in broader systems of social and economic change. Institution, fields of study, and credential-level differences reflect distinct underlying mechanisms of inequality, each structured by different organizing forces that themselves evolve over time. At the institutional level, characteristics such as size, selectivity, and location shape labor market returns, especially as the higher education landscape diversifies and college attendance grows. At the credential level, shifts in the distribution of fields across institutions may signal a growing alignment between institutional prestige and field-based advantage. Fields of study must be understood in relation to transformations in the labor market, particularly the restructuring of industries, occupations, and employment systems and changes in skill demand. This final form of stratification warrants special attention because of its dynamic nature and its direct responsiveness to labor market change. The remainder of this section motivates the paper's field of study-to-industry perspective by emphasizing the co-evolution of higher education and work, and the implications of that relationship for understanding how field-level differentiation emerges, persists, and transforms. As higher education has expanded, the organization of work has undergone profound change, shaped by technological innovation, shifting industrial composition, and evolving policy regimes. These changes have influenced not only which credentials students pursue, but also the sectors and roles those credentials make accessible. A dynamic account of field-based stratification must therefore attend to how the meaning and value of educational credentials shift in tandem with the broader structure of the labor market.

My approach differs from existing explanations of labor market change, which have often centered on technological drivers, particularly through the lens of RBTC. These accounts highlight how technological advances have reshaped labor demand by altering the substitutability of occupational tasks (Katz and Autor 1999; Goldin and Katz 2008; Autor et al. 2020). Relatedly, studies of STEM versus non-STEM pathways tend to adopt similar assumptions about the primacy of skill-biased change (Xie and Shauman 2003). While these perspectives have yielded important macro-level insights, they often focus on a single explanatory axis and risk overlooking how institutions, credentials, and labor markets interact in more complex and evolving ways.

Understanding how horizontal stratification evolves over time requires a perspective that extends beyond individual skills or occupational sorting. This study highlights the relationship between higher education and industry as a valuable, if underused, lens for analyzing field-level differentiation. While this emphasis is partly shaped by data structure (discussed below), it is also grounded in classic stratification theory and recent work in organizational sociology and labor economics. A growing literature shows that rising inequality is driven less by individual traits and more by structural changes in where and how people work, particularly increasing wage dispersion between firms (Wilmers and Aeppli 2021; Song et al. 2019). Because firms are embedded in industries—with shared regulatory, geographic, and market characteristics—industries have become increasingly consequential in shaping life outcomes (Haltiwanger et al. 2024). High-wage sectors like tech and finance have absorbed much of recent productivity growth, while low-wage industries such as food service and retail have expanded with little improvement in earnings. In this context, industry offers a tractable and theoretically grounded unit of analysis for understanding how credentials are rewarded, complementing—but not displacing—occupation- and skill-based perspectives.

While occupations have long anchored stratification research in sociology (Blau and Duncan 1967; Grusky and Weeden 2002; Erikson and Goldthorpe 1992), industry offers a complementary lens that highlights the institutional and structural contexts in which occupations are situated. Industries shape wage-setting regimes, hiring practices, and regulatory environments, all of which affect how educational credentials are converted into labor market outcomes. As occupational boundaries grow more fluid and firm-level data remain difficult to access, industry provides a convenient and theoretically grounded perspective for analyzing horizontal stratification. This approach builds on dual labor market theory (Kalleberg and Lincoln 1988; Sakamoto and Powers 1995) and more recent organizational and relational accounts of inequality (Wright 1998; Avent-Holt and Tomaskovic-Devey 2014), and aligns with empirical work showing how firm and industry characteristics contribute to inequality (Tomaskovic-Devey et al. 2020; Avent-Holt et al. 2020; Godechot et al. 2024). For example, Godechot et al. (2024) documents how sectoral shifts such as deindustrialization, financial expansion, and geographic clustering have reshaped the structure of inequality. Without denying the relevance of occupations, this perspective offers a justified alternative, well suited to a moment of particularly momentous industry-level transformations. I therefore treat industry as the key site for tracing how fields of study link to labor market destinations. This allows for a dynamic account of horizontal stratification that links educational credentials to evolving institutional and economic structures, contributing to broader sociological understandings of how higher education generates inequality.

Methods

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 largely different mechanisms: fields of study shape earnings through occupational and industrial linkages; institutions structure outcomes via prestige, resources, and social capital; and credentials reflect the interactive effects of both and specific relational links between industries, firms, and credentialing departments. Together, these axes form the core of how horizontal stratification shapes labor market outcomes among bachelor's degree holders.

The empirical analysis unfolds in several steps. First, I generate simulated individual-level earnings data from the aggregated credential-level statistics provided in the PSEO. This enables estimation of the full distribution of earnings within and across credentials, allowing for the application of variance decomposition techniques that incorporate within- and between-group variation. I then decompose total earnings inequality across cohorts to estimate the share attributable to each axis of horizontal stratification, including the degree to which it is driven by changing average earnings within credentials and distributional changes of credentials themselves.

Building on this foundation, the next set of analyses examines each domain in turn, using methods suited to its underlying mechanisms. For fields of study, I analyze changes in average earnings through the lens of field-to-industry flows and industry wage structures, using decomposition techniques to isolate whether observed trends are driven by changes in industry placement, changing industry wages, or both. I also compare changes in field of study earnings due to industrial change to what might be expected due to demographic change for comparison's sake. For institutions, I assess whether observable characteristics such as selectivity, size, tuition, and enrollment explain variation in earnings net of field composition, and how those relationships have evolved over time. For credentials, I evaluate whether field–institution pairings have become more stratified, testing whether high-earning fields are increasingly concentrated in high-earning institutions, consistent with a deeper consolidation of educational advantage.

Data

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. I focus on five-year post-graduation outcomes, which reflect mid-career earnings 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. Otherwise put, the effects shown here represent the *reduced form* of a bachelor's degree or the total effect of a bachelor's degree, even if it is mediated by continued education. 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 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, the breadth of institutions allows for rich analyses of variation in credential outcomes. I adjust for imbalances in institutional representation 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 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.

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

While the relative importance of field of study, institution, and credential-level effects can be estimated using aggregated data alone, I simulate individual-level income data from credential-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 must simulate individual-level income data from the aggregate statistics provided in the PSEO dataset.[4] In the earnings dataset, for each 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. [5] 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 (credential–graduation cohort combination), incomes are distributed log-normally. For each cell,

[4]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.

[5]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.

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 all 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.

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 credentials that may be driving changes in stratification or if it is simply different average earnings attached to each that are driving the effects.

Decomposing Earnings Inequality Along Axes of Horizontal Stratification

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:

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

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).

The methods described up to this point will 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.

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).

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

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

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

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

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:

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

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, 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:[6]

[6] 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.

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

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 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 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.

*** Figure 2 About Here ***

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 1 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 1. 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 little discussion is devoted to it throughout. 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 3) Much meaningful variation between schools likely transcends the public/private and elite/non-elite dichotomies and comes down to more nuanced variation based on instruction type, resources, school environment, and advising structures.

*** Table 2 About Here ***

Table 2 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.[7] 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 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., caregiving, further schooling, informal work), 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 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 A3 and are discussed where appropriate below.

In Table 2, 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

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

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 3 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 3 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 holds at the aggregate level and does not imply that field of study always outweighs institution for individuals. 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 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 A3 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, and upweighting 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 4 About Here ***

A natural follow-up to the previous results is whether observed changes are driven by allocation 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 allocation. In fact, 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 4 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. 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 A3), though its power is slightly attenuated.

*** Figure 5 About Here ***

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, whereas industry-based measures consistently explain the bulk 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 A4. 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 of prestige, like tuition fees for in-state students and the admission rate, do not show the same patterns.

The strongest and most dynamic relationship is that of average SAT Score and institution-level average annual earnings, with the R^2 increasing from 0.11 to 0.35 between the two cohort spans. Likewise, the variance explained by the logged number of graduate students increased from 0.06 to 0.17 and the logged number of undergraduates increased from 0.01 to 0.09. 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. 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.

*** Table 5 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 5 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 credentials or 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. 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. 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 consolidation, 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 credentials. 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 (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.

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. 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.

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 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). While the evidence in support of these figures 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 selection 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 that flow through 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. Further, although some institutional characteristics, such as selectivity and graduate enrollment, are increasingly associated with graduate 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. As such, the paper does not attempt to identify micro-level selection mechanisms or causal pathways related to individual characteristics. Nonetheless, sensitivity checks (Appendix Figure A3) 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. The finding that field-of-study inequality closely tracks changes in industry structure further reduces the likelihood that compositional selection alone accounts for the observed trends.

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.

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.

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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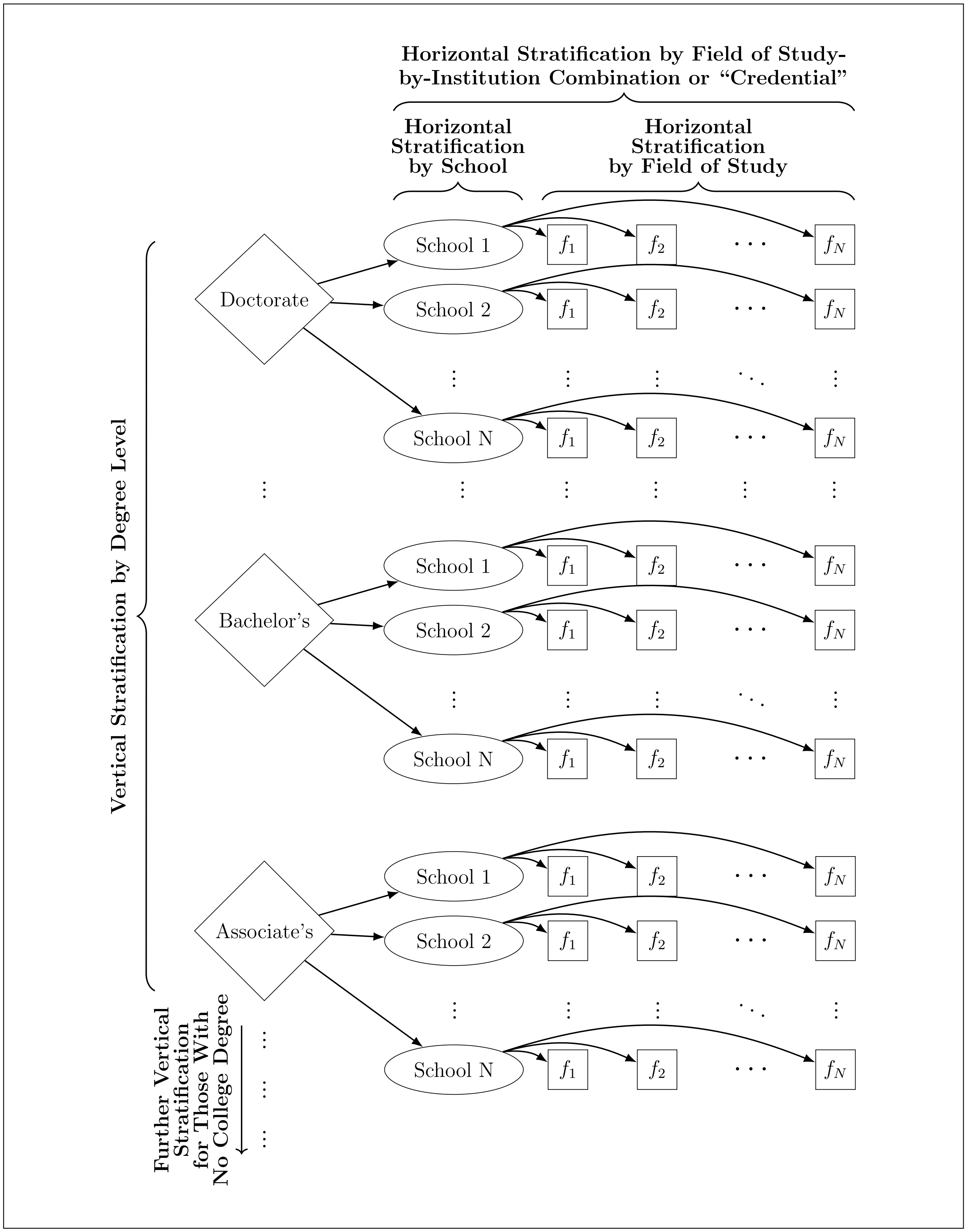

Figure 1: Schematic Showing Vertical Stratification and Horizontal Stratification by Both School and Field of Study

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.

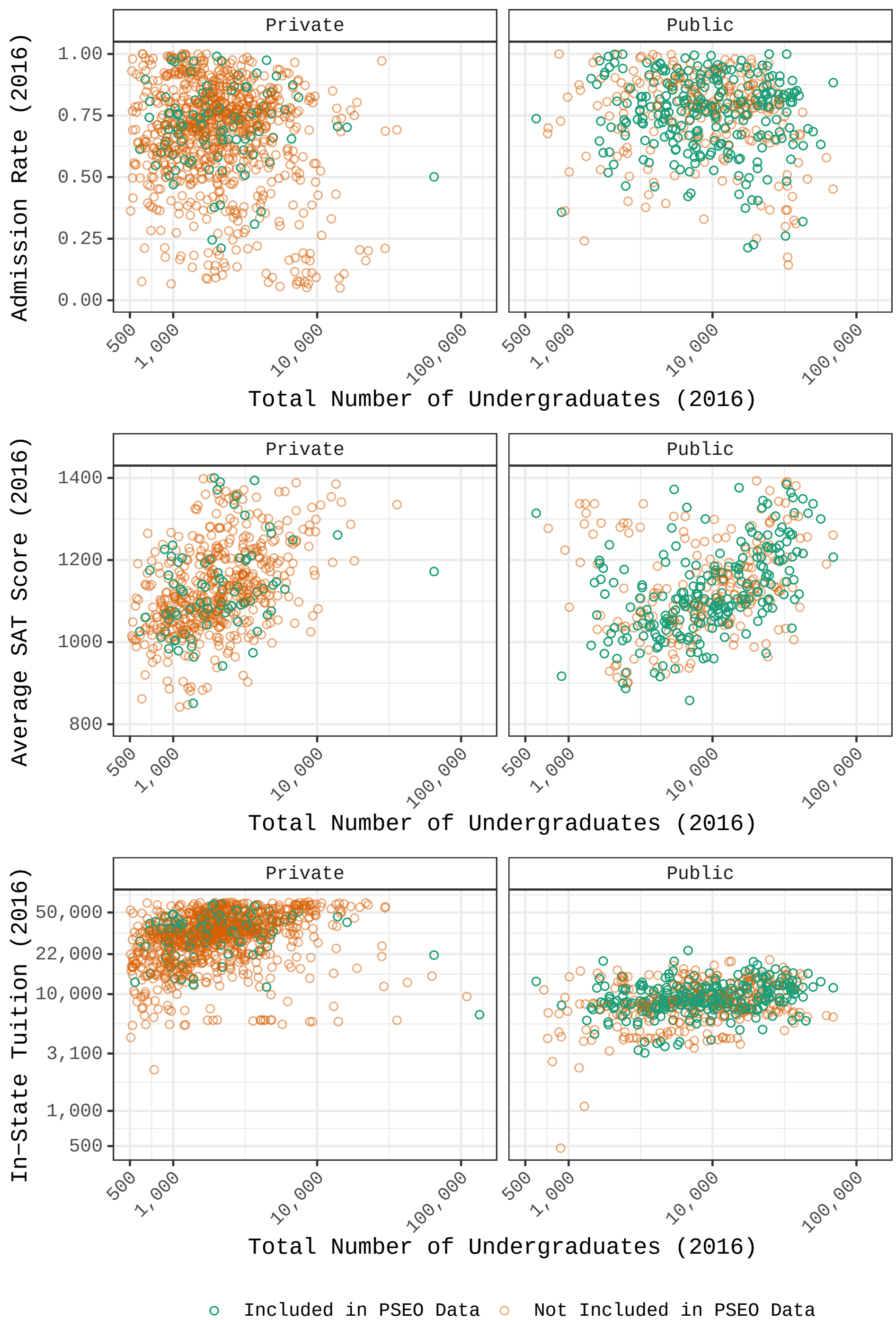

Figure 2: Scatter Plot of All Universities and Universities Included in PSEO Data, By Total Number of Undergraduate Students, In-State Tuition, Admission Rates, and Average SAT Scores

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.

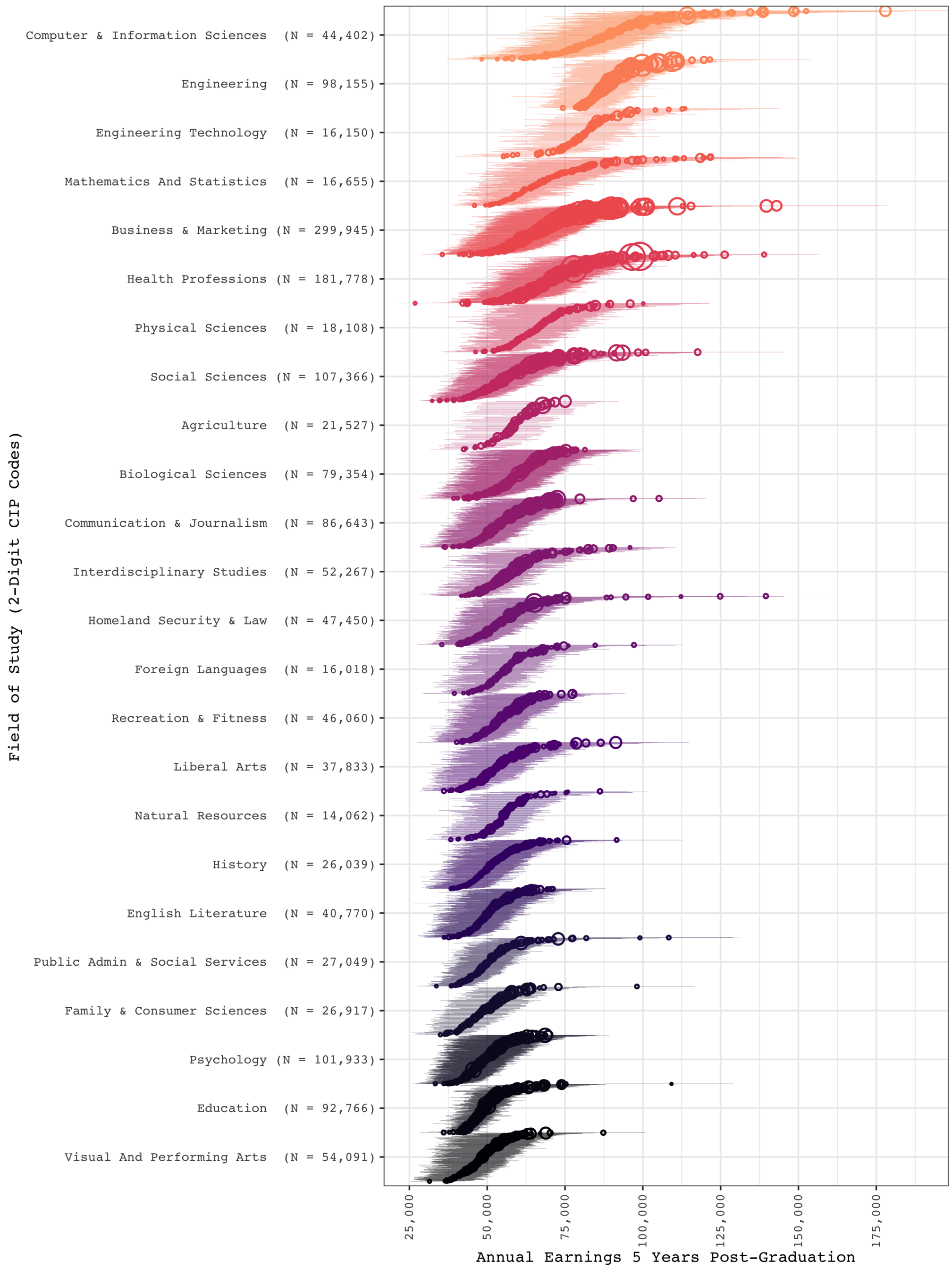

Figure 3: Distributions of Average Annual Earnings, Five Years Post-Graduation, for Specific Credentials (Fields of Study Within Specific Degree-Granting Institutions), By Aggregate Field of Study; Students Graduating 2013–2015

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.

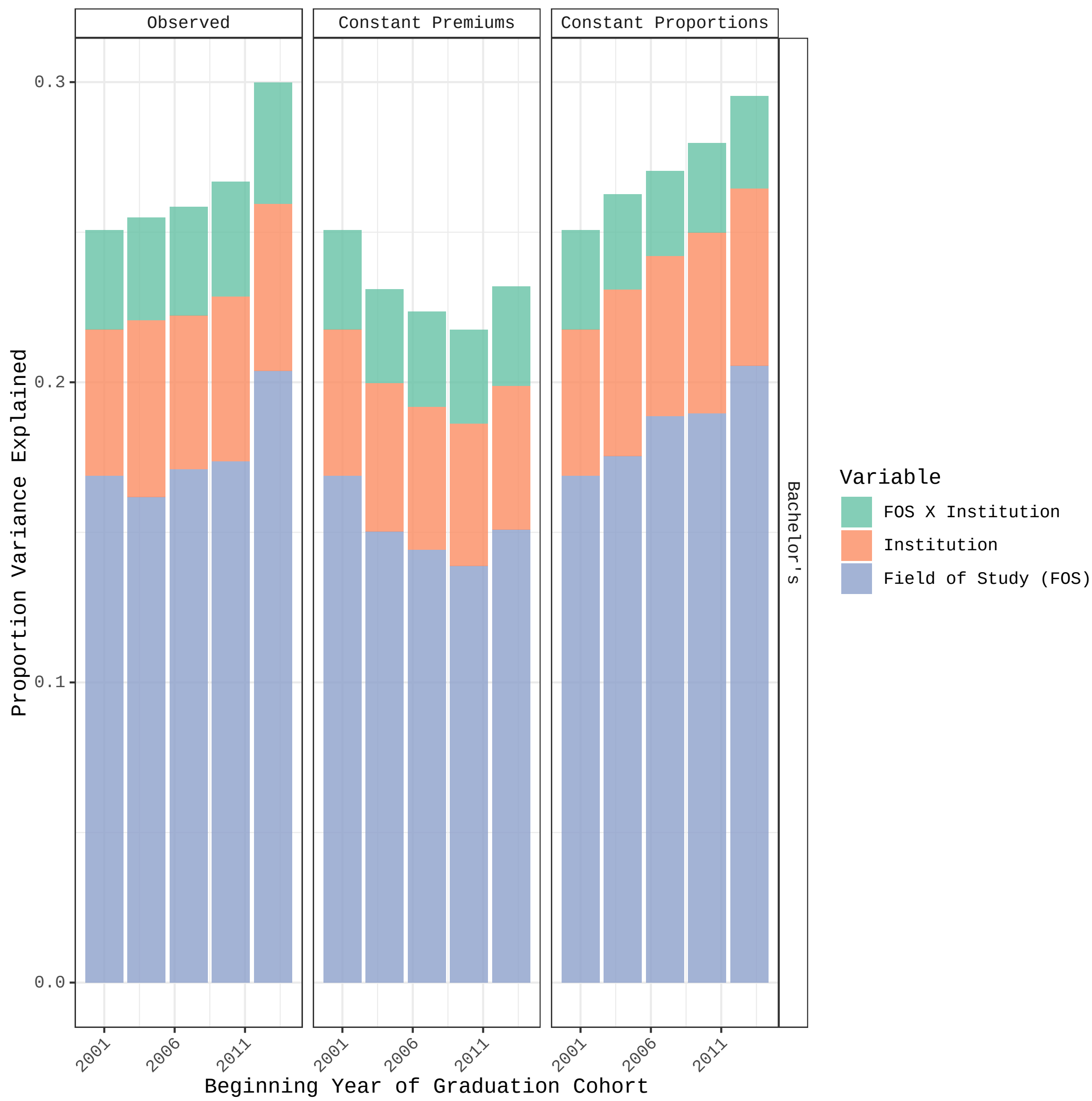

Figure 4: Variance Decomposition of annual earnings Five Years Post-Graduation by Field of Study (Major), Educational Institution, and Their Intersection Alongside Scenarios Assuming Constant Allocations Across Fields and Universities or Constant Average Annual Earnings Across Fields and Universities

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.

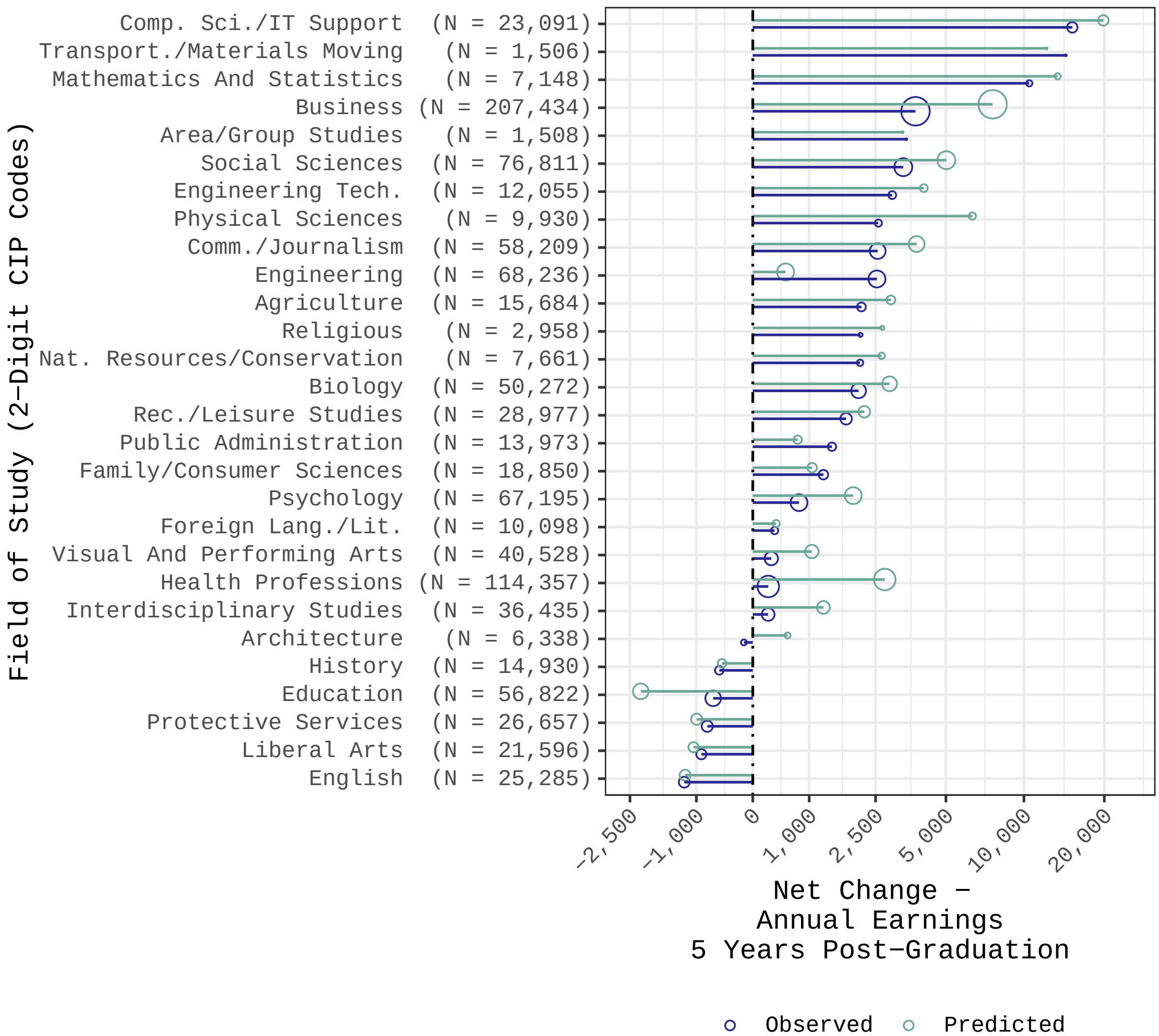

Figure 5: Change In Observed Average Field of Study (Two-Digit CIP Codes) Annual Earnings Five Years Post Graduation, Comparing Cohorts 2013–2015 to Cohorts 2001–2003

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.

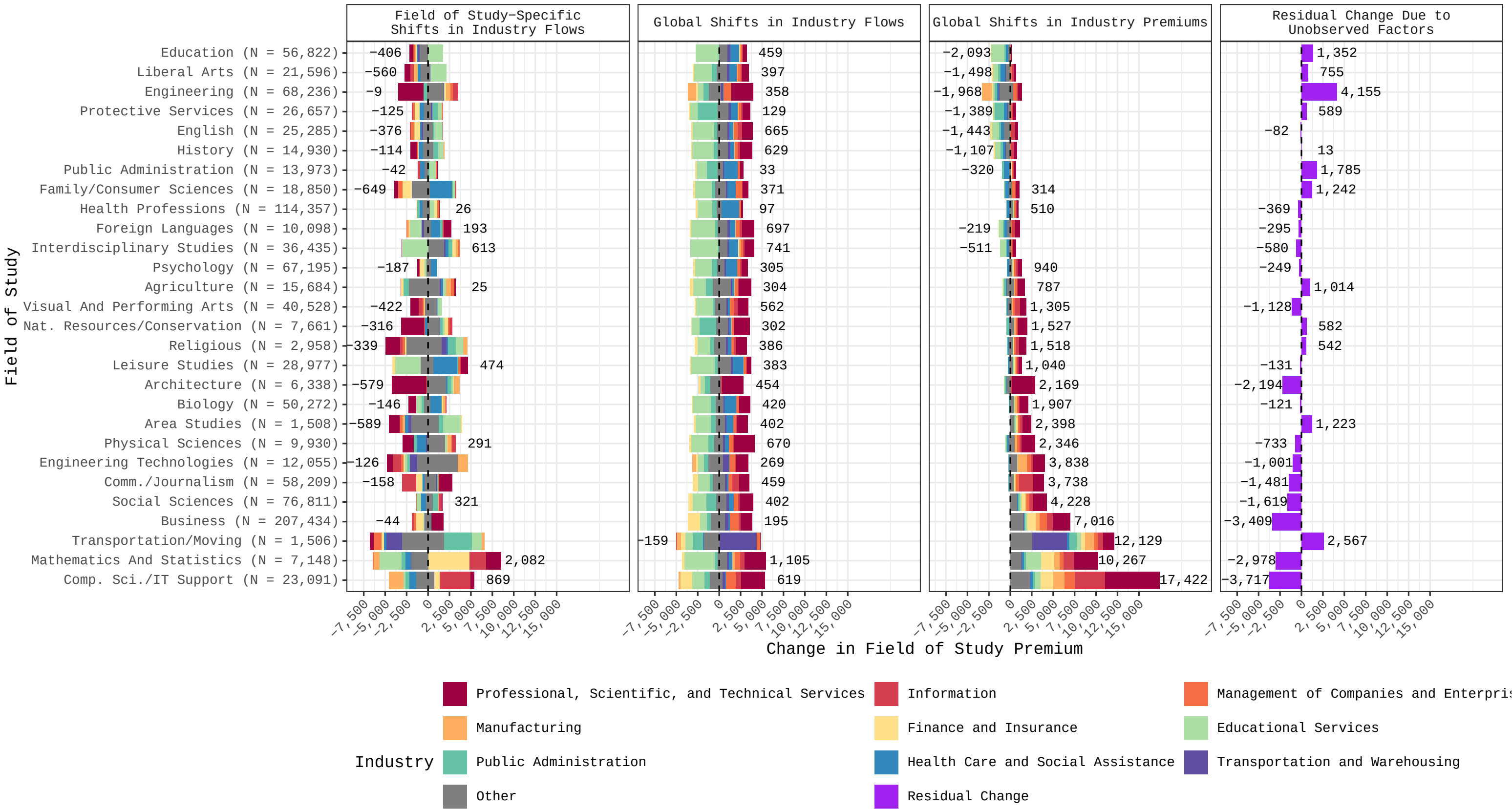

Figure 6: Kitagawa-Oaxaca-Blinder Decomposition of Observed Changes Between 2001–2003 and 2011–2013 Graduates in Field of Study average annual earnings at the Bachelor's Level, Using Observed Changes in FOS-Industry Flows Changes in Calculated Industry-Level Average Annual Earnings

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."

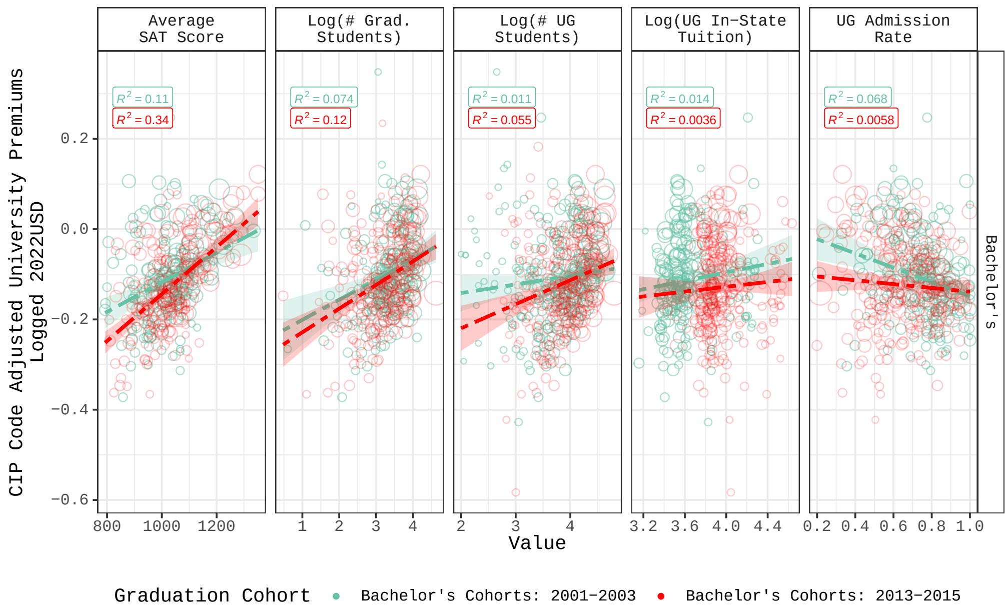

Figure 7: Degree-Granting Institution Average Premiums, After Adjusting for Distribution of Fields of Studies, Regressed on Institutional Characteristics for Two Cohorts

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

Table 1: 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 2: 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 3: 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 4: 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 5: 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 of Inequality:

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 1.

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 A4, below.

Robustness Checks Specifications

Appendix Figure A3 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

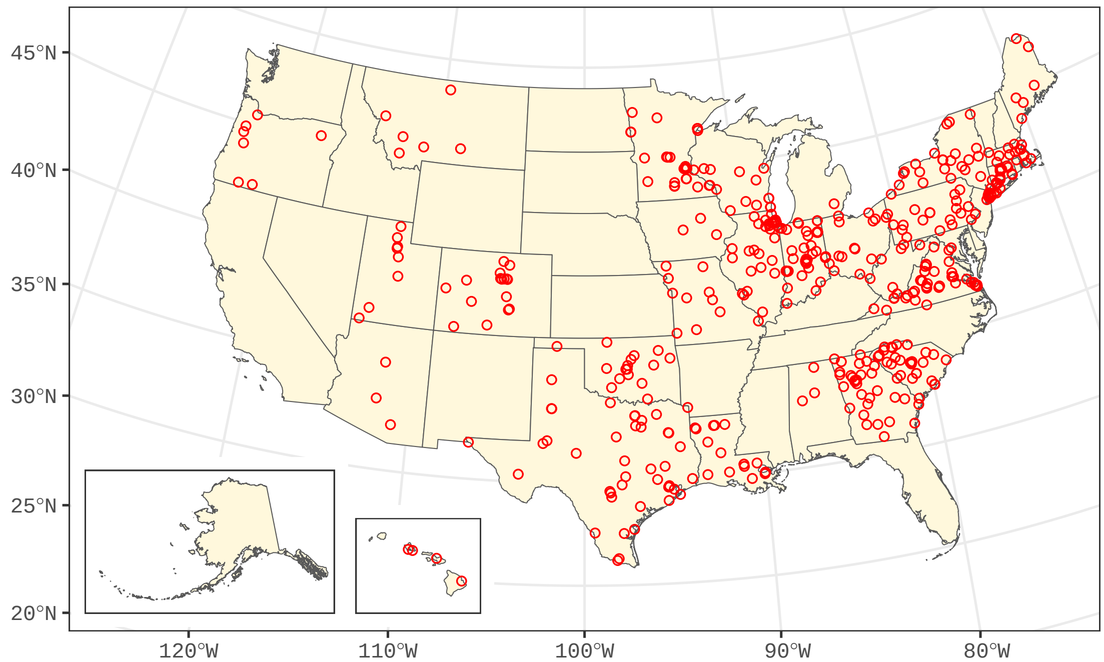

Figure A1. Map of Included Degree-Granting Institutions Showing Unequal Coverage by State

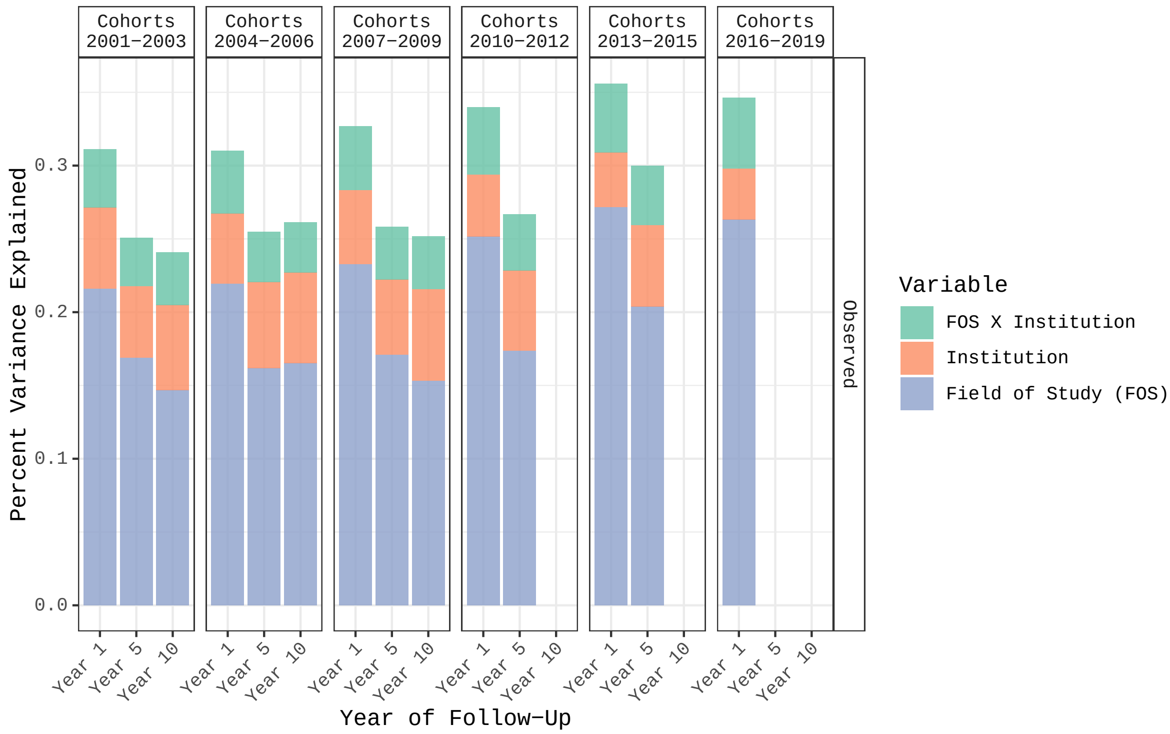

Figure A2. Replication of Primary Analysis, Visualized by Cohort and Year of Follow-Up

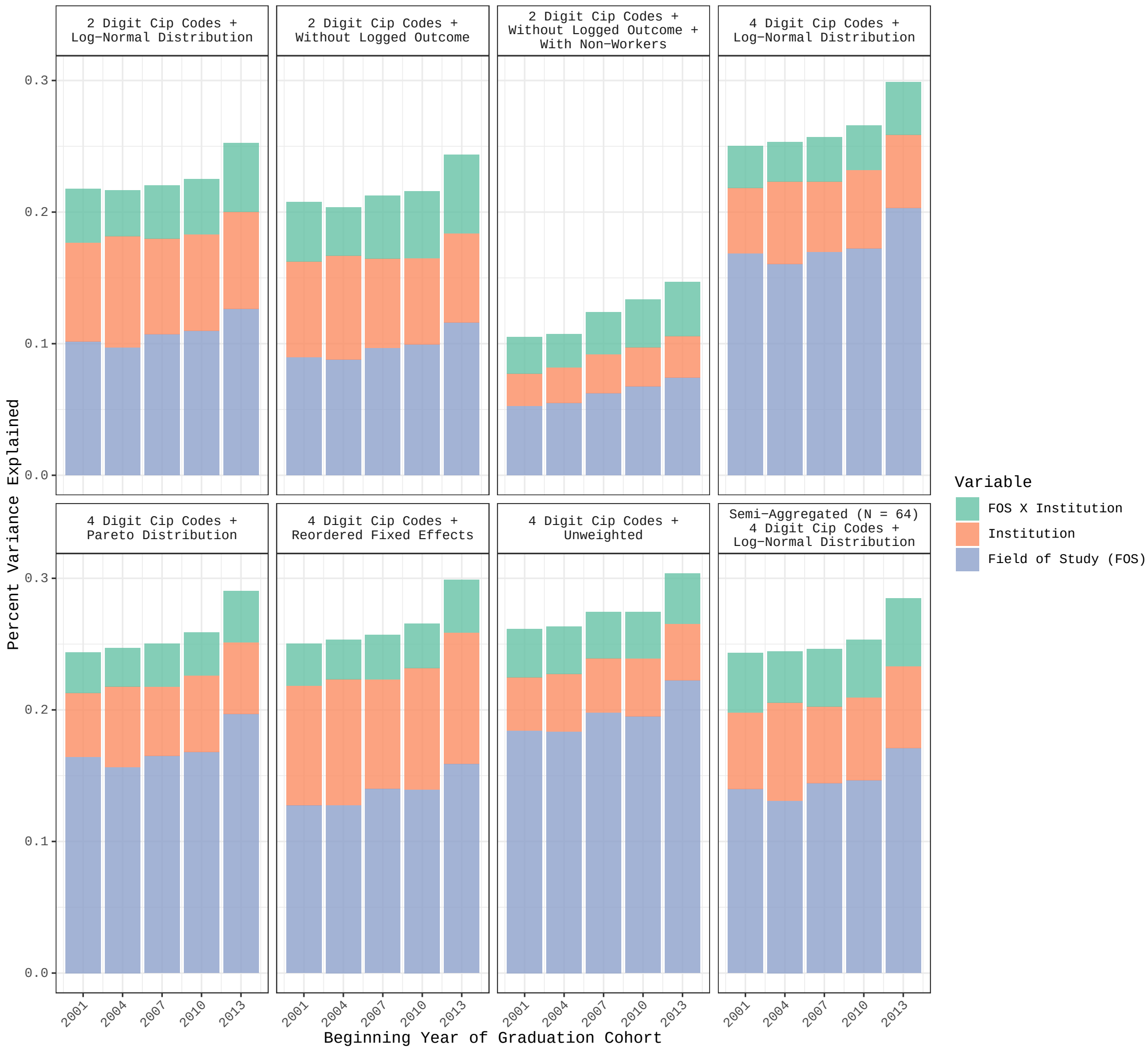

Figure A3. Various Robustness Checks of the Primary Decomposition Analysis, Variably Alternating the Level of CIP Code Aggregation, Logged and Unlogged Outcomes, the Distribution Functional Form, Weights for Missingness, and the Presence of Non-Workers

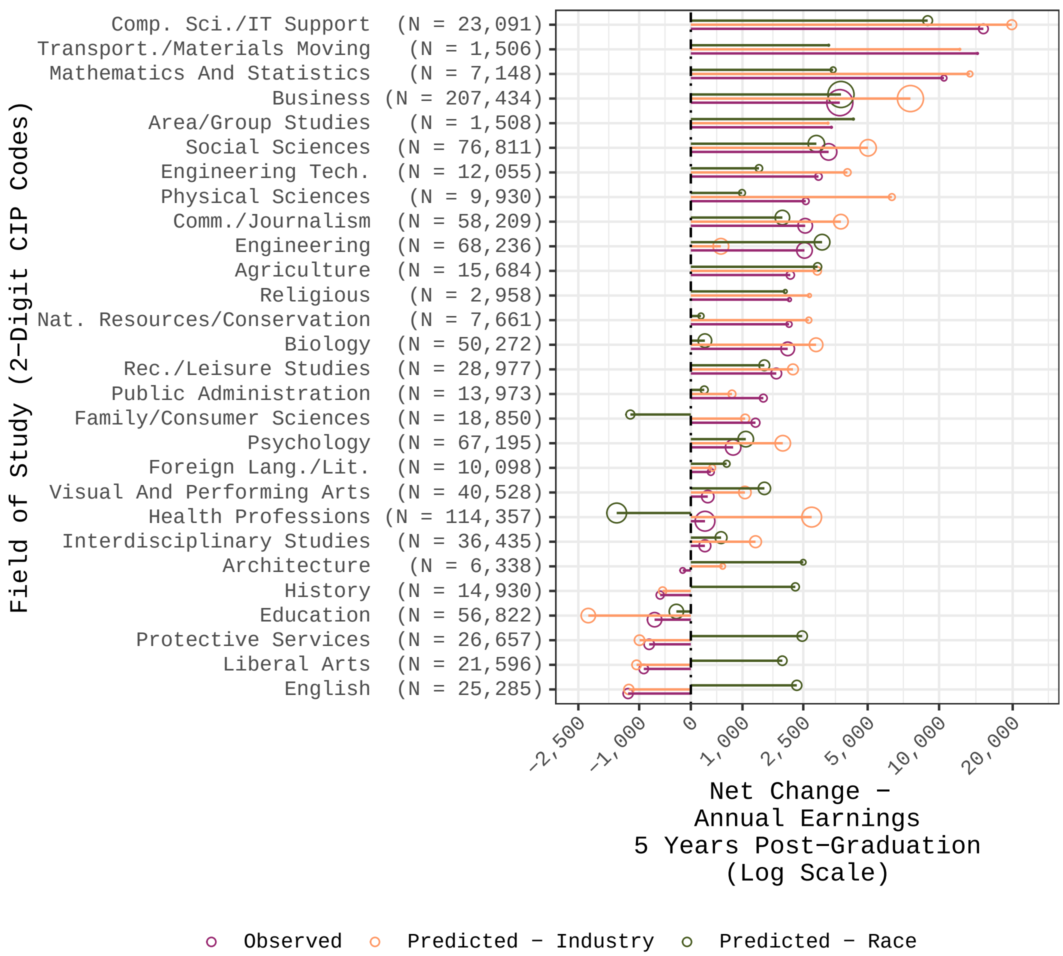

Figure A4. Figure 5 With Added Comparison for Expected Changes in Earnings Based on Demographic Recomposition by Field of Study.

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.