From Major to Market: Causal Evidence on the Returns to Horizontal Job-Skill Match*

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Abstract

Job-skill mismatch is a pervasive feature of modern labor markets, with large shares of graduates working outside their fields of study and facing substantial wage penalties. While prior studies have documented the prevalence of job-skill mismatch, it's measurement is prone to error, and causal evidence on its impact and the contexts that shape it remains limited. We address these gaps by developing a continuous measure of horizontal alignment between graduates' majors and their industries of employment, based on program-to-occupation-to-industry crosswalks and observed employment distributions. To provide causal evidence on

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horizontal job-skill match on earnings, we estimate two-stage least squares models with individual fixed effects (FE-2SLS), using a Bartik-style shift-share instrument that exploits national industry shocks interacted with local employment structures. Our estimates show that job-skill alignment is strongly rewarded. A ten-percentage point increase in alignment raises annual earnings by nearly 9 percent, an effect magnitude comparable to the widely documented return of an additional year of schooling. Subsample analyses reveal that these effects are concentrated among STEM and manufacturing graduates, bachelor's and master's degree holders, women and non-binary workers, and those in tight labor markets.

Keywords: Job-skill mismatch, Horizontal mismatch, Labor market tightness, Bartik Instrument, Earnings inequality

JEL Codes: I26, J24, J31, J62, R23

1 Introduction

Almost three-quarters of jobs will require some form of postsecondary education or training by 2031 (Carnevale et al., 2023). While the returns to education vary by level and credential type (Jabbari et al., 2024), research shows that much of today's wage inequality occurs among college graduates themselves (Autor et al., 2020). Indeed, returns differ widely across majors (Altonji & Zimmerman, 2019), and in-demand skills strongly shape both worker pay and firm performance (Deming & Kahn, 2018). Evidence increasingly shows that it is not only how much education workers obtain but also their field of study and whether they can obtain employment in this field that determines their labor-market returns. As rapid technological advances continue to shape labor markets, job-skill mismatches are increasingly problematic, as recent survey data suggest that traditional education pathways do not always provide the skills students need to succeed in their field of employment. For example, Hansen (2021) found that more than half (53%) of recent college graduates did not apply to an entry-level job in their field because they felt unqualified, and nearly half (42%) cited a lack of skills required in job descriptions.

This points to the importance of job-skill match—the alignment between a graduate's field of study and their eventual occupation. Nevertheless, while much research has emphasized the varying economic returns of vertical attainment (e.g., differences across degree levels), less attention has been paid to horizontal alignment—in which workers are employed outside of their field of study. From the limited research that does exist on horizontal mismatch, we know that it is not only prevalent but also costly. Robst (2007a,b) found that more than 40 percent of U.S. college graduates work in jobs unrelated or only partly related to their degrees, with significant wage penalties. Cross-national studies confirm these patterns and further demonstrate variation across fields: generalist majors often face higher mismatch rates but smaller penalties, while spe-

cialized fields like engineering and health sciences exhibit the reverse (Nordin et al., 2010; Somers et al., 2019). Recent work shows that these mismatches also exacerbate structural inequities, with disadvantaged groups more likely to be misaligned and less able to reap the returns to alignment (Odle & Russell, 2024; Strohl et al., 2024). These studies are novel in their approaches and provide important insights into misalignment. At the same time, gaps remain that require further attention. Most notably, exogenous sources of variation are needed to establish causal evidence. Additionally, more nuanced measures of alignment are needed to reduce the potential for measurement error.

At the same time, evidence suggests that local labor-market conditions can shape both educational attainment and the payoff to alignment. A growing literature demonstrates that exogenous industry shocks influence enrollment and degree completions (Conzelmann et al., 2024; Grosz, 2022) and moderate the returns to educational attainment (Bartik, 2022; Kahn, 2010). Yet, traditional degree programs are often slow to adapt, creating time lags between shifting local demand and the supply of field-specific graduates. While local industries may expand or contract rapidly, students may complete programs that no longer align with labor-market needs, leaving them vulnerable to mismatch. Despite the centrality of these dynamics, little research has examined whether and how local labor-market shocks shape horizontal mismatch and its economic consequences. This represents a critical gap: if graduates are increasingly sorted into jobs outside their fields during downturns or periods of industrial restructuring, mismatch may depress the returns to education even when credential attainment is rising. In this paper, we address these gaps using linked longitudinal data from nine metropolitan areas across the United States between 2017 and 2023. We introduce a novel, continuous measure of horizontal job-skill alignment that captures the observed distribution of graduates across industries. To address endogeneity concerns, we ex-

ploit exogenous variation in local mismatch generated by national industry demand shocks using a Bartik-style shift-share instrument. We then estimate the causal effects of horizontal mismatch on earnings using two-stage least squares models with individual fixed effects.

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Our study makes three contributions. First, we provide one of the first national, causal estimates of the returns to horizontal job-skill alignment, moving beyond descriptive or binary measures of mismatch. Second, we document heterogeneous effects across industries, majors, degrees, demographic groups, and labor-market conditions, highlighting the stratified nature of alignment. Third, by combining education, credit bureau, and labor-market data, we establish a scalable framework for monitoring alignment in real time and informing policies that strengthen education-to-employment pipelines.

2 Background

2.1 Job-Skill (Mis)match: Vertical and Horizontal Dimensions

Research on employment-education alignment (or job-skill match) often distinguishes between vertical mismatch and horizontal mismatch. Vertical mismatch refers to a discrepancy between the "level" of education attained by workers and the level required for their jobs. Workers who possess more education than required are categorized as overeducated, whereas those with less are categorized as undereducated (Duncan & Hoffman, 1981; Groot & Van Den Brink, 2000; Hartog, 2000; Verdugo & Verdugo, 1989). Extensive evidence shows that vertical mismatch is associated with lower economic returns, job dissatisfaction, and diminished productivity (McGuinness, 2006). Yet, some studies suggest that early-career overeducation may reflect a temporary stage in job search and career mobility rather than inefficiency (Hershbein et al., 2018; Sicherman, 1991).

By contrast, horizontal mismatch focuses on the "field" of education rather than its level. Workers are horizontally mismatched when they are employed in jobs unrelated to their degree field, even when their education level matches the job requirement (Robst, 2007a,b). From a human capital perspective, this represents a misallocation of field-specific skills, with potential private and social inefficiencies due to the underutilization of specialized human capital (Somers et al., 2019).

Measurement and Indicators of Horizontal Mismatch

A longstanding challenge in the study of horizontal mismatch concerns how best to define and operationalize the concept. Existing scholarship has developed two dominant approaches. The first relies on subjective measures, typically survey-based self-assessments in which graduates are

asked to evaluate the relatedness between their highest degree field and their current job. For instance, Robst (Robst, 2007a,b) employed data from the U.S. National Survey of College Graduates in which respondents indicated whether their work was "closely related," "somewhat related," or "not related" to their major. Subjective measures are advantageous in that they capture job content as workers experience it, allowing researchers to incorporate tacit knowledge about how education is applied in practice. However, these measures are also vulnerable to perceptual biases, varying interpretations of what constitutes "related" work, and differences in how workers frame their career trajectories over time.

In response to these limitations, scholars have advanced objective measures of mismatch, typically based on correspondence tables linking fields of study to occupational codes. In this approach, which has been widely applied in European studies, researchers classify a graduate as mismatched if the occupation they hold falls outside of the expected set of jobs associated with their degree program (Béduwé & Giret, 2011; Wolbers, 2003). The strength of objective measures lies in their consistency and replicability across datasets. Yet this standardization comes at a cost: by imposing rigid program-to-occupation linkages, objective measures may fail to recognize the portability of generalist skills across a wide range of job settings. As Somers et al. (2019) emphasized in their systematic review, reliance on either subjective or objective indicators alone produces widely varying estimates of mismatch prevalence, raising concerns about validity and comparability across studies. Other research has relied on indirect proxies. Bowlus (1995), for example, used job tenure and starting wages to infer match quality, under the assumption that "good matches endure" and that mismatch is capitalized into initial earnings. More recently, Fredriksson et al. (2018) operationalized match quality by comparing the skill bundles of new entrants to the revealed skill composition of incumbents in the same jobs, showing how mismatch

is reflected in separation risks and later wage growth. These studies illustrate a common theme: because match quality is inherently unobserved, it must be approximated through theoretically motivated and behaviorally grounded measures.

Building on these traditions, Odle & Russell (2024) argued that the field requires new approaches to measuring horizontal mismatch that reflect how employers actually use educational skills in practice. They critique both subjective and objective measures for either overstating or understating mismatch depending on how occupations and fields of study are classified, and they propose indicators that are more sensitive to labor-market demand and employer utilization of field-specific skills. Their framework is not only diagnostic but also policy-oriented, emphasizing that mismatch indicators should capture real-world connections between educational programs and employment outcomes.

In this regard, we extend this line of reasoning by introducing what we term a behavioral measure of horizontal mismatch. Rather than relying on graduates' self-perceptions, predetermined correspondence tables, or ex post wage and tenure outcomes, our approach is grounded in the observed distribution of graduates across industries. Specifically, we calculate the share of graduates from a given major employed in particular industries, which provides a direct lens into how educational specializations are absorbed into the labor market. This probabilistic measure captures the degree of alignment for every graduate on a continuous scale, allowing us to study "general mismatch" systematically rather than relying on binary stopgap distinctions.

Our approach aligns with Odle & Russell (2024)'s call for demand-sensitive indicators while offering a concrete and scalable operationalization that can be consistently applied across time, space, and fields of study. At the same time, it builds on the behavioral logic of Bowlus (1995) and Fredriksson et al. (2018), who measured mismatch through revealed job outcomes rather than

ex ante correspondence tables. By anchoring measurement in realized allocation patterns, our empirical measure provides a more nuanced and policy-relevant account of horizontal mismatch and bridges theoretical and empirical traditions with a demand-sensitive, scalable framework.

Empirical Evidence on Horizontal Mismatch and Its Consequences

Studies consistently find that horizontal mismatch is both widespread and economically consequential. Using U.S. data from the National Survey of College Graduates, Robst (2007a) reported that roughly 20% of graduates worked in jobs unrelated to their field of study, while an additional 25% reported partial relatedness. He further demonstrated that mismatched workers earn significantly less than their well-matched peers. Extending these insights, Odle & Russell (2024) demonstrated that horizontal mismatch remains a salient determinant of labor-market outcomes in the United States. They find that graduates employed in industries aligned with their degree earn 7-17 percent more than their mismatched peers, with penalties for mismatch are especially large for specialized fields such as STEM and health care.

Cross-national evidence corroborates these patterns. Nordin et al. (2010), examining Swedish register data, found that horizontally mismatched workers earned substantially lower wages. Somers et al. (2019), in a systematic review of 24 empirical studies, concluded that horizontal mismatch consistently reduces wages, lowers job satisfaction, and increases study-program regret. These findings underscore that horizontal mismatch continues to shape labor-market inequalities, while also highlighting the importance of developing demand-sensitive measures of alignment.

Heterogeneities on Horizontal Mismatch and Its Consequences

A growing body of research emphasizes that horizontal mismatch is not evenly distributed across the workforce. Disadvantaged groups are more likely to be misaligned and to face steeper penalties when the mismatch occurs. Starting with demographic characteristics, Strohl et al. (2024) document that misalignment is especially acute for rural graduates and for certain racial and ethnic groups, exacerbating structural inequalities in access to high-return credentials. Odle & Russell (2024) likewise find systematic variation in alignment patterns across industries and by gender, with women and non-binary graduates exhibiting somewhat higher alignment rates than men, though often in lower-paying sectors. Together, these findings highlight that mismatch operates as a stratifying mechanism, reinforcing demographic inequalities in educational payoffs and labor-market outcomes.

Moving onto structural characteristics, Strohl et al. (2024) demonstrated that nearly 30% of U.S. middle-skills credentials (certificates and associate's degrees) are awarded in programs with no direct occupational match, creating widespread inefficiencies in labor markets, as well as economic inequalities. Additionally, Robst (Robst, 2007a,b) found that the wage penalty for misalignment was especially pronounced for graduates from occupation-specific majors such as engineering and health sciences. Somers et al. (2019) also highlighted heterogeneity across fields: generalist degrees such as arts and social sciences exhibit higher mismatch incidence but smaller wage penalties, while specialized fields like medicine and engineering have lower mismatch rates but steeper penalties when the mismatch occurs. Cross-national research echoes these disparities: Nordin et al. (2010) showed that mismatch penalties vary depending on whether majors confer generalist versus specialist skills, a pattern that may differentially affect students from underrepresented backgrounds who cluster in certain fields of study.

This evidence underscores that horizontal mismatch is both widespread and unequal. Yet mismatch is not shaped by demographic characteristics alone. It also reflects the structure and dynamics of local labor markets, which influence whether graduates can translate their educational training into related employment opportunities. To fully understand mismatch, therefore, it is necessary to consider heterogeneity not only across educational fields and demographic groups, but also across regional labor-market conditions.

2.2 Labor Market Shocks and Demands

A longstanding theme in human capital theory is that individuals adjust their educational choices in response to labor-market conditions, weighing the opportunity costs of schooling against its expected returns (Becker, 1964; Mincer, 1958). When the demand for low-skilled labor rises, prospective students may be drawn into the workforce immediately after high school, whereas increases in high-skilled labor demand encourage further schooling to capture future earnings premia (von Simson, 2015). Empirical studies confirm that educational attainment is sensitive to local labor-market shocks. For example, Hillman & Orians (2013) showed that a 1 percentage-point increase in unemployment raised full-time community college enrollment by 3.3 percent, consistent with the counter-cyclical nature of enrollment. Similarly, von Simson (2015) found that higher youth employment rates in Norway increased secondary-school dropout probabilities, while Black et al. (2005) documented that rising wages for coal miners depressed high-school enrollments in the United States. These findings underscore the dual channels through which local labor demand—by altering both opportunity costs and wage returns—shapes educational trajectories.

More recent work has leveraged shift-share designs to capture the causal effects of labor-

market shocks on educational attainment. Grosz (2022) employed a Bartik-style instrument to show that a 1 percent increase in national industry demand led to a 0.53 percent increase in community college completions in California, largely driven by shifts in student demand. Likewise, Conzelmann et al. (2024) found that bachelor's degree completions respond elastically to major-specific shifts in national demand, with an estimated elasticity of 1.3. These studies demonstrate that exogenous changes in industry demand, as captured by shift-share instruments, provide a credible strategy for identifying how local labor markets shape educational outcomes.

Importantly, local demand conditions not only influence enrollment and completion of education but also moderate the returns to credentials once workers enter the labor market. Kahn (2010) showed that college graduates entering the labor market during recessions suffered "large, negative, and persistent" wage penalties, while Adrian & Lydon (2019) found that tighter labor markets in Ireland yielded higher earnings. In the U.S., Bartik (2022) demonstrated that local labor demand increased earnings for workers without a bachelor's degree, suggesting that non-degree or sub-baccalaureate credentials may benefit from demand shocks. At the same time, Hershbein et al. (2018) revealed that labor-market concentration heightened skill requirements but suppressed wages, pointing to the complex ways in which local conditions shape educational returns.

Yet, while this literature convincingly links labor-market shocks to overall educational attainment, there has been far less empirical attention to how such shocks shape horizontal mismatch. This represents a critical gap, since the consequences of the mismatch hinge not only on how many graduates complete degrees but also on whether local labor markets can absorb them into field-related work.

2.3 Theoretical Expectations

Building on the existing literature on job-skill alignment, we pose the following hypotheses:

Hypothesis 1 (Main effect)**.** *Horizontal job-skill alignment will increase earnings.*

Hypothesis 2 (Heterogeneous effect)**.** *The impact of job-skill alignment will vary systematically across demographic groups, levels of educational attainment, fields of study, industries, and local labor-market conditions.*

> **Hypotheses 2A and 2B** (Gender and race/ethnicity)**.** *The effects of alignment will differ by demographic group. Males and racial/ethnic minority graduates will experience lower relative wage gains from alignment.*
>
> **Hypothesis 2C** (Educational attainment)**.** *The returns to alignment will vary by credential level. Bachelor's and graduate degree holders will experience higher relative wage gains from alignment.*
>
> **Hypotheses 2D and 2E** (Fields of study and industries)**.** *The returns to alignment will vary by the specificity of training. Those with more specialized majors (e.g., STEM, healthcare, education) will experience higher relative wage gains from alignment than those with more generalist majors (e.g., manufacturing, arts, social sciences).*
>
> **Hypothesis 2F** (Local labor-market conditions)**.** *The returns to alignment will vary by labor-market dynamics. Those in tighter labor markets will experience higher relative wage gains from alignment.*

3 Methods

3.1 Empirical Model Design

We are interested in estimating the causal effect of job mismatch on earnings. Let i index individuals, c denote their earned program classification (CIP), m represent the Metropolitan Statistical Area (MSA) of work locations, and t indicate the time period (year). Our baseline specification is:

$$log(w_{icmt}) = \alpha + \beta \text{Mismatch}_{icmt} + \gamma' \mathbf{X_{icmt}} + \mu_m + \tau_t + \epsilon_{icmt} \tag{1}$$

where $log(w_{icmft})$ denotes the log of annualized gross income; Mismatch_{icmt} is a continuous variable that ranges from 0 to 1 for whether individual i with program classification (CIP) c and work in MSA region m at calendar year t; $\mathbf{X_{imct}}$ is a vector of controls (age, gender, and degree); μ_m and τ_t are MSA and time fixed effects.

In addition to controlling for region and time fixed effects (pooled), we estimate two alternative specifications: one incorporating individual random effects (RE) and another using individual fixed effects (FE). The RE specification assumes that observable individual characteristics are uncorrelated with unobserved individual-specific effects. This approach is particularly useful for estimating the impact of time-invariant characteristics such as gender, race, or major. In contrast, the individual FE specification accounts for all unobserved, time-invariant individual traits, making it a more stringent and conservative approach.

Bartik Instrument

Estimating β, our coefficient of interest, using conventional regression models (regardless of pooled, RE, or even FE), however, may suffer from endogeneity, as unobserved individual ability

could allow more capable workers to select programs or industries that typically exhibit better match quality and higher earnings. Moreover, measurement error is a potential concern, since our proposed measure of matching quality may be noisy, potentially attenuating the true relationship between job matching quality and earnings. To address these issues, we exploit quasi-random variation in local mismatch rates driven by national industry demand shocks, using a *Shift-Share* Bartik instrument approach (Bartik, 1991). The intuition is that regions with different initial industry structures experience differential exposure to national labor demand changes, leading to plausibly exogenous changes in mismatch.

Using the shift-share Bartik Instrument as our instrument, we estimate the causal impact of job mismatch on earnings using a two-stage least squares (2SLS) approach. Let i index individuals, c denote CIP, m represent MSAs, f indicate job industries, and t denote time periods. The corresponding IV framework is specified as,

$$\begin{aligned} &\text{Stage 1:} \quad \text{Mismatch}_{icmt} = \alpha + \delta\, \text{Bartik}_{mft} + \gamma' \mathbf{X_{icmt}} + \mu_m + \tau_t + \epsilon_{icmt} \\ &\text{Stage 2:} \quad log(w_{icmft}) = \beta\, \widehat{\text{Mismatch}}_{icmt} + \theta' \mathbf{X_{icmt}} + \mu_m + \tau_t + v_{icmt} \end{aligned} \tag{2}$$

The identification relies on several key assumptions. First, the instrument must be relevant. Specifically, the Bartik instrument, constructed as the interaction of national industry growth with baseline regional shares, must be strongly correlated with local mismatch rates. Second, the exclusion restriction requires that the Bartik instrument affects individual earnings only through its impact on mismatch, not through other direct channels. In our preferred specification, we include region and time fixed effects to absorb common shocks affecting wages in all industries.

Most importantly, in order for the shift-share instrument to be valid and satisfy the exogeneity requirement, the identification must come from either many exogenous shifts in national job

openings or exogenous local shares during the baseline period (Borusyak et al., 2025). In our context, we consider the former (i.e., exogenous national shifts) to be more plausible, since local baseline employment shares may reflect historical sorting, regional economic structure, or other unobserved factors that could correlate with individual earnings. Under the assumption of exogenous shifts, the variation in local mismatch arises primarily from national-level changes in job demand, interacted with predetermined regional employment shares.

Heterogeneous Job-Skill Match impacts on earnings

Finally, to examine heterogeneity in the causal effect of mismatch, we estimate two-stage least squares models with individual fixed effects (2SLS-FE) for key subsamples. Specifically, we stratify the analysis by (1) gender—men and women/non-binary; (2) race and ethnicity—White, Black, Asian, Hispanic, and Other (3) highest degree attainment—undergraduate certificate (UC), associate's (AA), bachelor's (BA), master's (MA), and doctoral/professional (Doc) degrees; (4) major and (5) industry fields—manufacturing, STEM, education, and healthcare; and (6) labor-market tightness, distinguishing between slack and tight markets as defined by our MSA-level tightness measure. These subsample analyses allow us to evaluate whether the effects of horizontal mismatch on earnings vary across sectors, demographic groups, levels of educational attainment, and labor-market conditions.

3.2 Data

Our research examines the impact of local labor-market demand on individuals' credential attainment and employment outcomes between 2017 and 2023. We draw on four primary datasets—credential enrollment and attainment records, employment and income data, National Center for

Education Statistics and Bureau of Labor Statistics data, and County Business Patterns (CBP)—to build an integrated analytic framework.

National Student Clearinghouse (NSC) provides detailed information on formal degree attainment, including associate's (AA), bachelor's (BA), master's (MA), and doctoral/professional degrees, along with the year each degree was earned. The NSC also records non-degree credential attainment, such as school-based undergraduate certificates (UC). To construct individual-level educational attainment, we treat attainment cumulatively. For example, if an individual earned a bachelor's degree in May 2019, they are coded as a bachelor's degree holder from 2019 onward.

A major U.S. credit reporting agency provides individual earnings as well as demographic, location, and employment data. This dataset, which covers payroll information from more than 2.8 million businesses, provides high-fidelity measures of employment and income. The data include job start and termination dates, annualized gross income (measured each December), industry codes (NAICS), and complete employment histories. In this study, we focus on income from each individual's primary job as of December, which we use to construct annualized earnings.

National Center for Education Statistics (NCES) and **Bureau of Labor Statistics (BLS)** data capture job-skill alignment. We developed a crosswalk linking educational programs, occupations, and industries. This crosswalk was created by merging two data sources: (1) the CIP-SOC (Classification of Instructional Programs to Standard Occupational Classification) crosswalk from the National Center for Education Statistics, and (2) SOC employment counts by NAICS industry from the U.S. Bureau of Labor Statistics. Merging these sources on SOC codes yielded a comprehensive and consistent mapping of degree fields to occupations and industries for our study period.

The U.S. Census's County Business Patterns (CBP) dataset constructs measures of local industry employment. These data provide the baseline county-level employment shares and national industry employment shifts that underlie our Bartik instrument.

Our **analytic sample** had four main selection requirements:

- To ensure that employment data was collected by the credit rating agency, individuals had observable labor force participation reported any earned income during the study period (2017-2023).
- To ensure the heterogeneous effects for a specific CIP-NAICS match, individuals had to have just one income source at the time of measurement;
- To ensure our sample was reflective of a broad array of geographic and economic contexts, individuals had to be working in one of nine metropolitan areas across the U.S. (San Francisco, CA; Denver, CO; Austin, TX; St. Louis, MO; Chicago, IL; Nashville, TN; Boston, MA; Philadelphia, PA; and New York City, NY);
- To ensure reasonable comparisons and adequate earnings trajectories, individuals had to be born in 1981 or later.

3.3 Measures

Earnings, our primary outcome, is annualized individual income as of December of each year, constructed from the credit bureau's records. We focus on the monthly earnings of each individual's "main" job in December, which we multiply by twelve to generate an annualized measure. All values are expressed in constant dollars and standardized across individuals to allow comparability over time. To avoid conflating temporary fluctuations during schooling with post-schooling

returns, we restrict the analysis to post-graduation periods, beginning only after an individual has completed their highest degree. We further limit the sample to individuals with a single job in December, ensuring that the annualized measure reflects a clear and consistent employment outcome. This approach allows our estimates to capture changes in income associated with field-job alignment and labor-market shocks, rather than transitions in and out of schooling.

Educational attainment is measured as the highest degree earned by each individual at the time of observation. We distinguish between sub-baccalaureate credentials (e.g., certificates, associate's degrees), bachelor's degrees, and graduate degrees (master's, doctoral, and professional degrees). Crucially, the National Student Clearinghouse (NSC) data provide Classification of Instructional Programs (CIP) codes, which identify the field of major for each credential. These CIP codes allow us to construct field-level indicators that are directly comparable across institutions and cohorts, and they form the basis for our horizontal mismatch measure. To focus on the long-term consequences of mismatch and labor-market conditions, we analyze only income trajectories following completion of the highest degree, excluding interim or lower-level credentials earned earlier in the educational pathway.

Major and Industry Fields. Academic majors are identified using the Classification of Instructional Programs (CIP) codes provided by the National Student Clearinghouse. We use the full six-digit CIP code to capture fine-grained distinctions across fields of study. Industry (NAICS codes). Employment industries are identified using the North American Industry Classification System (NAICS) codes reported in the credit bureau's employment data. For our analysis, we focus on the first two digits of the NAICS code, which provide consistent sector-level classifications (e.g., NAICS 62 = Health Care and Social Assistance). This aggregation helps to reduce noise while retaining meaningful industry distinctions that align with our horizontal mismatch

construction.

Horizontal job-skill match rate is measured following an approach that is conceptually aligned with Odle & Russell (2024), who construct education-industry match indicators by combining CIP-SOC (Standard Occupational Classification) and SOC-NAICS crosswalks. The construction proceeds in three steps. First, we obtain national employment counts by SOC-NAICS combinations from the Bureau of Labor Statistics employment projections, collapsed into major industry groupings (e.g., STEM, education, healthcare, manufacturing, and all other industries). This provides the baseline distribution of occupations across industries. Second, we merge these SOC-NAICS employment distributions with the NCES CIP-SOC crosswalk, which links academic majors to potential occupations. This produces a CIP-level distribution of employment opportunities across industries. Third, for each CIP, we collapse the SOC-level records to create CIP-industry match profiles. We then express these profiles as probabilities, calculated as the share of all workers from a given CIP employed in a particular industry relative to the total

Formally, the horizontal match rate for major CIP c in industry f is:

$$MatchRate_{cft} = \frac{Employment_{cft}}{\sum_j Employment_{cjt}} \tag{3}$$

where $Employment_{cft}$ is the number of employees with occupations linked to major m who are employed in industry f in a given year, t. For example, a graduate in data science (CIP: 11.0802) maps through the CIP-SOC crosswalk to occupations such as data managers and statisticians. Using SOC-NAICS employment counts, we find that 134,123 workers with these occupations are employed in STEM-related industries out of 257,098 total employees across all industries. The resulting *match rate* is 0.52, indicating that graduates with a data science degree have a 52 percent

likelihood of entering a STEM-related industry.

Construction of Bartik Instrument. To capture exogenous variation in local labor demand, we construct a Bartik (shift-share) instrument at the MSA-by-field-by-year level. The instrument interacts with the baseline employment structures with subsequent national industry shocks. Specifically,

$$\text{Bartik}_{mft} = \sum_{j \in J_f} \left(\text{Share}_{mjt_0} \times \text{Shift}_{jt} \right) \tag{4}$$

where,

$$\text{Share}_{mjt_0} = \frac{n(\text{Jobs}_{jmt_0})}{N(\text{Jobs}_{mt_0})}$$

and

$$\text{Shift}_{jt} = \frac{n(\text{Job}_{jt}) - n(\text{Job}_{jt_0})}{n(\text{Job}_{jt_0})}$$

Here, Share_{mjt_0} represents the share of employment in industry j within MSA m at the baseline year (2017), and Shift_{jt} captures the national growth rate of industry j between the baseline year (t_0) and year t. We define fields of study c (based on CIP codes) as mapping onto sets of industries f, so that each field is exposed to multiple relevant industries. This construction exploits the idea that areas more specialized in certain industries at baseline are more exposed to national shocks in those industries. For example, if 15% of jobs in St. Louis in 2017 were in healthcare (NAICS 62), and national healthcare employment subsequently grew by 16.7% between 2017 and 2019, then the Bartik instrument predicts a 2.5% local demand shock for healthcare graduates in St. Louis in 2019.

Labor-market tightness at the metropolitan statistical area (MSA) level is from two data sources.

From the Census County Business Patterns (CBP), we calculate the number of newly created jobs in each MSA by differencing total employment counts between one year and the next. From the Bureau of Labor Statistics' Local Area Unemployment Statistics (LAUS), we obtain the total number of employed individuals in each MSA and year. We then define tightness as the ratio of newly added jobs to the employed population. This measure reflects the intensity of labor demand relative to the available workforce: higher values indicate markets where job creation is strong relative to labor supply (tight markets), whereas lower values indicate slack conditions. Each individual in our dataset is assigned the tightness value corresponding to their MSA and year.

Demographic attributes. In addition to our primary measures, we incorporate several demographic characteristics as controls, as well as for subsample analyses. These include gender, age, and race/ethnicity, all of which are drawn from credit record data. Including these covariates allows us to account for systematic differences in educational attainment, labor-market outcomes, and mismatch incidence across demographic groups.

Table 1 provides descriptive statistics of the variables used in our sample as of the earliest and the latest year of observations.

4 Empirical Findings

4.1 Descriptive Patterns of Horizontal Job-Skill (Mis)match

Figure 1 shows variation in job-skill match rates across demographic groups, degree levels, majors, industries, and local labor-market conditions. Across all comparisons, the distributions reveal substantial heterogeneity in how effectively postsecondary education aligns with actual em-

ployment.

Demographic and credential/degree-based disparities emerge clearly. Gender (Panel A) differences are statistically significant ($F = 973.212$, $p < 0.001$), with men slightly less likely to secure aligned jobs than women and non-binary individuals, though the gap is modest relative to educational or industry differences. Race and ethnicity (Panel B) also matter: White and Asian graduates exhibit marginally higher alignment rates than Black and Hispanic graduates, pointing to structural inequities in job sorting ($F = 73.774$, $p < 0.001$). Degree level (Panel C) further differentiates outcomes. Doctoral graduates show the highest match rates, reflecting the specialized nature of advanced training, while associate's degree holders are most often mismatched, underscoring the difficulty of translating general or short-cycle credentials into aligned employment ($F = 74.669$, $p < 0.001$).

Majors and industries provide complementary perspectives on alignment. On the supply side (Major, Panel D), Education stands out, with more than 75 percent of graduates working in aligned jobs and a left-skewed distribution clustered at high match rates. By contrast, Manufacturing and STEM majors show right-skewed distributions with long tails: most graduates are mismatched, but a smaller share demonstrate strong alignment. Healthcare presents a bimodal pattern, with graduates split between moderate and strong alignment ($F = 6084.405$, $p < 0.001$).

On the demand side (Industry, Panel E), low match rates in sectors such as Manufacturing indicate that most workers enter from outside fields. By contrast, industries like Education draw heavily from aligned majors but still demonstrate relatively low overall match rates, potentially because universities and schools employ faculty and staff across a wide array of disciplines (e.g., engineers in professional schools, physicians in medical schools). Across industries, these structural differences are highly significant ($F = 5419.424$, $p < 0.001$).

Labor-market conditions (Panel F) play only a limited role. While mismatch rates differ significantly between tight and slack markets ($F = 51.681$, $p < 0.001$), the distributions are nearly identical. This suggests that local demand conditions influence alignment only modestly, with structural factors such as demographic characteristics, degree attainment, and educational fields demonstrating far stronger effects.

4.2 Impacts of Horizontal Job-Skill Matching on Earnings

Overall horizontal job–skill alignment is a powerful and robust predictor of earnings. Table 2 reports the estimated effects of horizontal job–skill match rates on annual earnings using three two-stage least squares (2SLS) panel specifications: a pooled model (Column 1), a fixed effects (FE) model (Column 2), and a random effects (RE) model (Column 3). In all models, both the dependent variable (annual earnings) and the key explanatory variable (match rate) are log-transformed. As such, the coefficients represent elasticities—the percentage change in earnings associated with a 1 percent change in horizontal job-skill alignment.

Across all specifications, higher job-skill alignment is strongly and significantly associated with higher earnings. The pooled model (Column 1) yields an elasticity of 0.231 ($p < 0.001$), and the RE model (Column 3) yields a slightly higher estimate of 0.361 ($p < 0.001$). Meanwhile, the FE model (Column 2)—which controls for time-invariant individual traits—produces a much larger elasticity of 0.867 ($p < 0.001$). This implies that a 1 percent increase in horizontal job-skill alignment leads to approximately a 0.87 percent increase in annual earnings, on average. Put differently, improving alignment by 10 percent, for example, increasing a worker's match rate from 40% to 44%, is associated with an 8.7 percent increase in earnings. This effect size is economically substantial and suggests that improving the match between education and job

content is a key driver of labor market returns.

Crucially, the validity of the 2SLS estimation is supported by strong first-stage results. The F-statistics for the excluded instrument (Bartik-style shift-share variable) are 2431.88 (pooled), 308.53 (FE), and 1216.10 (RE), well above the conventional threshold of 10, indicating that the instrument is not weak. This reinforces the strength of the identification strategy and the reliability of the estimated elasticities.

The large gap between the FE estimate and those from the pooled or RE models further underscores the importance of addressing unobserved heterogeneity—not only as a statistical concern but also in terms of the empirical focus of each specification. Whereas the pooled and RE models primarily leverage between-individual variation in job-skill match rates, the fixed effects model isolates within-individual variation over time, capturing how changes in an individual's match rate influence their earnings trajectory. This distinction is crucial: pooled and RE estimates are more susceptible to bias from unmeasured individual characteristics—such as cognitive ability, motivation, or institutional background—that may simultaneously affect both mismatch and earnings. The fixed effects approach mitigates this concern by controlling for all time-invariant unobservables, thereby offering a more credible causal interpretation.

Also, the RE and pooled models do not fully account for systematic differences in baseline match rates across education majors and job industries. As shown in the previous section, these structural differences are substantial—some fields of study and sectors of employment are inherently more (or less) prone to horizontal mismatch. Because the RE and pooled models partially conflate these structural sources of variation with individual-level effects, their estimates may obscure the true within-person impact of improving match quality. In contrast, the fixed effects model abstrains from such between-individual and sectoral disparities and focuses on within-

person change, making it more robust to confounding and more directly informative for policy efforts aimed at improving job-skill alignment. For these reasons, we adopt the 2SLS-FE specification as our primary model of interest.

4.3 Heterogeneous Impacts of Job–Skill Matching on Earnings

Figure 2 (as well as Appendix A) reports 2SLS-FE models with subsets of our analytic sample, showing how the earnings returns to job-skill alignment vary across demographic attributes (gender and race/ethnicity), degree level, industries and majors, and labor market conditions. Across all comparisons, the estimates reveal meaningful heterogeneity in the elasticity of earnings with respect to alignment.

Demographic and credential-based patterns show that alignment is broadly beneficial, but its impact is conditioned by gender, race and ethnicity, and educational attainment in ways that reflect persistent labor-market inequalities. Women and non-binary individuals (0.980, $p < 0.001$) benefit slightly more from alignment than men (0.708, $p < 0.001$), suggesting that alignment may help narrow, but not eliminate, underlying gender disparities. Across racial and ethnic groups, White (1.057, $p < 0.001$), Asian (0.617, $p < 0.001$), and Hispanic (0.500, $p < 0.01$) graduates all experience significant positive returns to alignment, while the effect for Black graduates is smaller (0.385, $p < 0.05$), indicating that structural barriers may constrain the full payoff of alignment for this group. Returns also rise with degree attainment: bachelor's (0.987, $p < 0.001$), master's (0.900, $p < 0.001$), and doctoral graduates (0.765, $p < 0.001$) all see sizable benefits, whereas undergraduate certificate and associate's degree holders show no significant effect. Although the elasticity for doctoral degree holders is somewhat lower than for bachelor's or master's graduates, this likely reflects the concentration of PhDs in higher education (e.g., colleges and universities),

where returns may be shaped by institutional pay scales rather than field–industry alignment per se.

Majors and industries offer complementary perspectives on the returns to alignment. From the supply side, graduates in Manufacturing (0.680, $p < 0.01$) and STEM (0.464, $p < 0.001$) fields earn significantly more when aligned, while Education (−0.179, not significant) and Healthcare (−1.913, not significant) majors show no measurable benefits. From the industry side, however, the pattern is more muted: Manufacturing industries (−2.059, $p < 0.05$) exhibit a negative association between alignment and earnings, and other industries show no significant relationship. These heterogeneous findings suggest that the value of alignment is not uniform. For majors such as Manufacturing and STEM, alignment tends to be rewarded, but in some industries—particularly Manufacturing—structural factors such as occupational licensing or the salience of more general human capital skills may limit the payoff to field–industry alignment. By contrast, in sectors like Education, alignment is theoretically expected to yield stronger economic returns given the direct major-to-occupation pipeline. Yet our estimates show no significant effect, likely reflecting the heterogeneity of the Education industry itself, where universities and schools employ faculty and staff across diverse disciplines—for instance, STEM or healthcare professors in higher education—whose salaries are not tied to the Education major per se but to institutional pay scales.

Lastly, labor market conditions further amplify the effects of alignment. In slack markets, where jobs are relatively scarce, the return to alignment is positive but moderate (0.448, $p < 0.001$). By contrast, in tight markets, where labor demand is stronger, the effect nearly triples (1.333, $p < 0.001$). This suggests that job–skill alignment matters most when workers are in a stronger bargaining position, as aligned skills are more readily rewarded in contexts of robust

labor demand. Put differently, alignment generates consistent benefits, but those benefits are magnified in favorable labor market conditions, underscoring how macroeconomic context conditions the micro-level payoff to education–occupation matching.

5 Discussion

Research on the economic returns to education has typically focused on vertical differences in attainment—comparing incomes across various levels of credentials, such as differences across associate's, bachelor's, and graduate degrees. Here, differences in attainment assume that certain skills within a given level of credentialing lead to jobs with particular economic returns. Indeed, our prior work has demonstrated the significant effects of vertical differences in attainment (Jabbari et al., 2024). However, far less attention has been paid to differences in horizontal attainment—comparing incomes across various credential fields, such as differences across STEM, healthcare, and education fields. While recent research has demonstrated the significant effects of credential fields (Andrews et al., 2024; Arcidiacono, 2004; Bleemer & Mehta, 2022), these studies often assume that credential fields have certain embedded skills that lead to jobs within a given industry with particular economic returns. In other words, "matches" between credential fields and industries are often implied. Nevertheless, this is not always the case. As technology changes labor market demands (e.g., Deming & Noray, 2020), many credential holders find themselves without a match between their credential field and industry, which can often lead to lower wages. Here, a horizontal mismatch can depress the effects of vertical attainment, a phenomenon often described as "underemployment".

5.1 Summary of Findings

We start with a descriptive analysis of credential field (e.g., college major) and industry alignment. In doing so, we offer two complementary—and at times, competing—perspectives: a supply-side perspective (i.e., the proportion of a given credential field that work in an aligned industry) and a demand-side perspective (i.e., the proportion of workers in a given industry that have an aligned credential). Our analysis reveals that patterns of horizontal job–skill alignment differ sharply depending on the education (i.e., skill) field and job (i.e., industry), as well as whether we look from a supply-side or demand-side perspective. For example, from both a supply and demand side, manufacturing and STEM exhibit low overall match rates, indicating that students with manufacturing and STEM degrees tend to work in other industries, and—at the same time—these industries tend to draw heavily from outside fields. As these are often some of the highest-paying fields and industries, this finding may suggest the broad industry demands for those with manufacturing and STEM skills, which may create labor shortages in these fields. However, while credentials in the education field show high alignment, with most graduates entering the education industry, the education industry tends to draw from a variety of credential fields. These findings might be driven by the fact that high schools and colleges hire those with diverse—as opposed to education-specific (i.e., uniform)—skills. Moreover, healthcare demonstrated a bimodal distribution across both industries and credential fields, suggesting a mix of diverse and uniform skills.

Additionally, demographic differences also emerge: while differences across race and ethnicity were minimal, women and non-binary graduates exhibited moderately higher levels of alignment than men. This may be because women tend to work in fields with greater alignment or because they tend to achieve higher levels of education. Child rearing may also provide

women with less flexibility in the labor market. It is also important to note that women often get lower economic returns to job mobility than men, which may limit the incentives to switch jobs for women (Del Bono & Vuri, 2011). Finally, while differences across local labor market demands were minimal, doctoral degree holders exhibited the highest levels of alignment, while associate's graduates exhibited the lowest levels of alignment. Here, vertical education attainment, which often entails greater skills specialization, appears to guard against horizontal education misalignment.

Turning to our causal models, we find robust evidence that higher horizontal alignment substantially increases earnings. Across specifications, a one-percent increase in job–skill alignment is associated with an earnings gain of approximately 0.9 percent in the preferred fixed effects model. Put differently, improving alignment by just ten percentage points raises annual income by nearly nine percent. The magnitude of this effect is comparable to the well-documented returns to an additional year of schooling, which prior research typically estimates at 7–10% (Card, 1999; Deming, 2022; Oreopoulos & Petronijevic, 2013; Psacharopoulos & Patrinos, 2018). These findings confirm that alignment is not merely symbolic but constitutes a central determinant of postsecondary returns. Importantly, once mismatch is accounted for, the wage premium to higher degree levels diminishes, underscoring that how education is translated into the labor market can matter as much as what level of education is attained.

The benefits of alignment are not uniform, but vary across industries, majors, demographics, degree levels, and macroeconomic contexts. From the demand side, some industries, such as manufacturing, do not consistently reward alignment, likely due to the need for diverse skills as well as wide range of roles within it (e.g., accountants in manufacturing firms). From the supply side, however, graduates in these majors see large returns when working in aligned fields—potentially

because of the relatively high earning potential in these fields. These findings suggest that the economic returns to credential field and industry match depend on whether alignment is measured by where workers go versus where industries draw from. By degree level, bachelor's, master's, and doctoral graduates all benefit substantially from alignment, while those with associate's degrees and undergraduate certificate graduates show no significant gains. As expected, greater educational attainment and subsequently greater skills specialization benefit more from alignment. Additionally, White, Asian, and Hispanic graduates capture significant earnings premiums from alignment, while Black graduates receive more modest gains, pointing to enduring structural barriers. Women and non-binary workers benefit slightly more than men, but alignment alone does not close gender pay gaps, as seen in our random effect models. Finally, macroeconomic conditions amplify these patterns: alignment yields modest returns in slack markets but nearly triples in tight markets. This is consistent with a bargaining interpretation of supply and demand in which aligned skills are rewarded more when labor demand is strong.

5.2 Implications

These findings carry several implications for postsecondary education and labor market policy. First, improving transparency around education-to-career pathways in local labor markets is essential, as many students may not anticipate the long-term penalties of horizontal mismatch. In this regard, postsecondary institutions should provide data on the location and demand of skills offered by a particular major or area of study. Of course, greater transparency could bring about general equilibrium effects due to overcrowding in certain CIPs that may eventually dampen the effects of horizontal alignment. Thus, dynamic modeling and simulation models should also be pursued in this regard.

Second, postsecondary institutions should work to improve alignment at the point of graduation. Here, colleges and universities should strengthen partnerships with employers and expand work-based learning opportunities, so that graduates have clear education-to-employment pipelines to enter. Third, industries where alignment is undervalued may benefit from stronger connections to education institutions, so that education skills can adequately reflect industry needs. Given the rate of technological innovation and subsequent changes in labor market demands, these connections should be ongoing. Fourth, because returns to alignment are uneven across race and gender, targeted interventions—such as equity-focused recruitment pipelines, mentoring, and stronger anti-discrimination enforcement—are critical to ensure that all graduates benefit equally from educational investments.

Beyond policy implications, our study has implications for human capital theory and research. Concerning theory, we demonstrate that the returns to degree alignment rival that of the returns to degree attainment. Concerning methods, we demonstrate that alignment is not an either/or phenomenon, but rather a spectrum, and that modeling as such can yield important insights.

5.3 Limitations

Despite offering novel insights, our study is not without limitations. Concerning external validity, our sample is drawn from four industries and nine metropolitan areas, which may not fully represent the broader U.S. labor market, particularly in service sectors and rural areas, which are not prominent in our sample. Concerning internal validity, while our use of panel fixed effects and an exogenous Bartik instrument improves causal inference, dynamic selection into majors or industries may still bias results. Additionally, our alignment measure is defined at the field–industry level, which may obscure important variation in occupation-specific (i.e., job-

specific) skills. Finally, while we focus on pecuniary outcomes, alignment may also influence non-pecuniary dimensions of work such as satisfaction, stability, or occupational prestige, which remain important areas for future research.

6 Conclusion

In sum, this study demonstrates that horizontal alignment is a powerful but highly stratified determinant of economic returns. While higher education continues to yield economic benefits, those benefits are maximized when graduates secure jobs closely related to their field of study. At the same time, alignment interacts with race, gender, degree level, and labor market conditions in ways that can lessen, maintain, or exacerbate inequality. By moving beyond vertical attainment alone, this study offers a more nuanced understanding of how education structures opportunity in contemporary labor markets. These findings underscore the importance of designing educational and labor market policies that not only expand access to a wide variety of postsecondary education opportunities—particularly as it relates to majors—but also ensure that its benefits are realized through meaningful and well-compensated alignment in the labor market.

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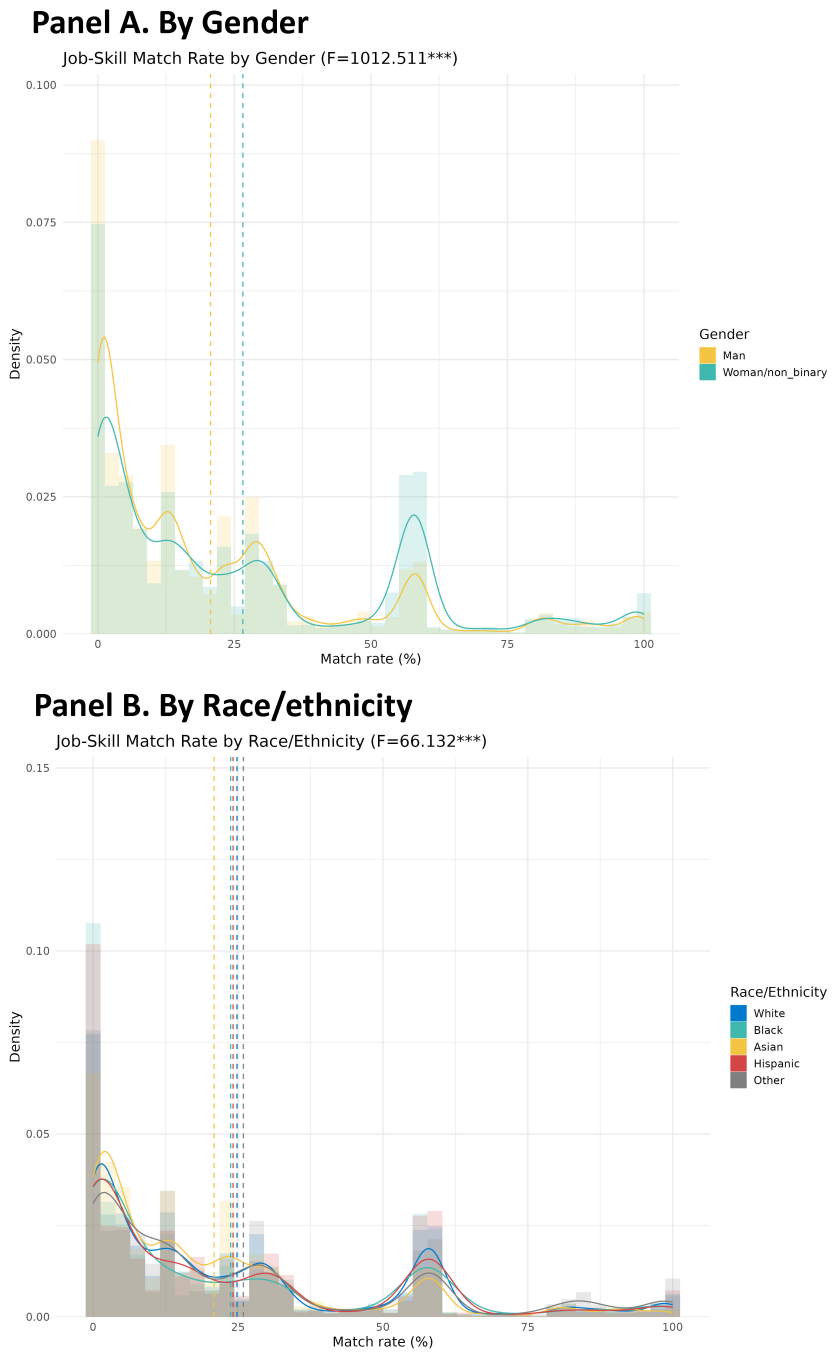
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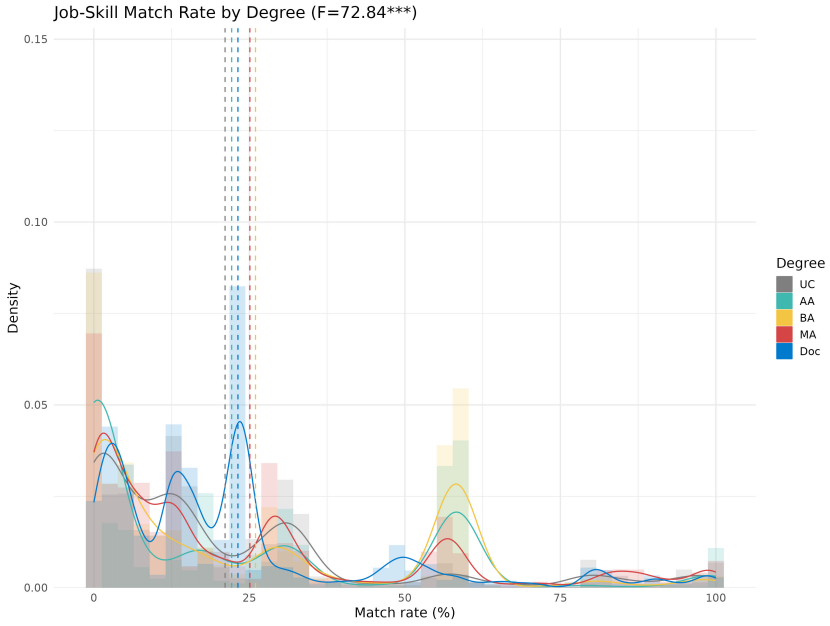
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Figures and Tables

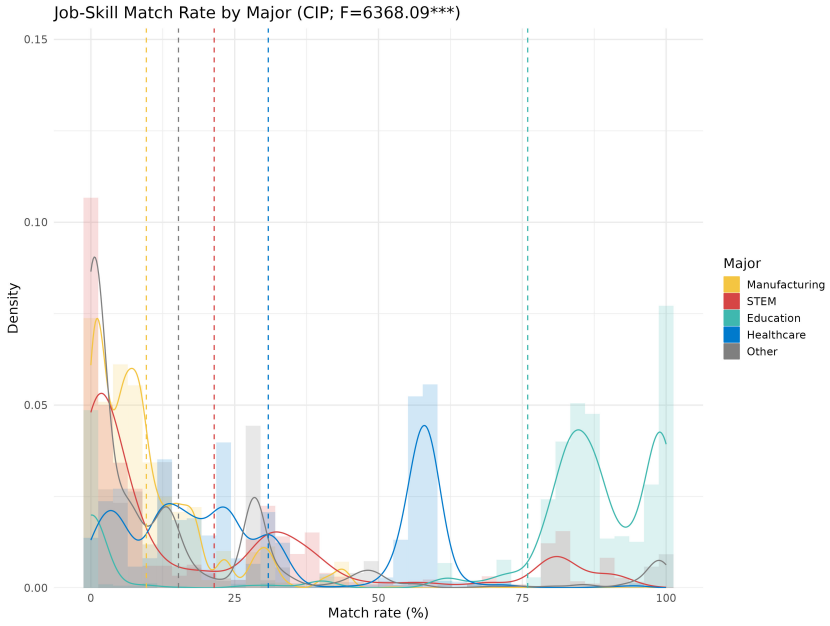
Figure 1: Distributions of Horizontal Skill-Job Matching Rate by Subsamples

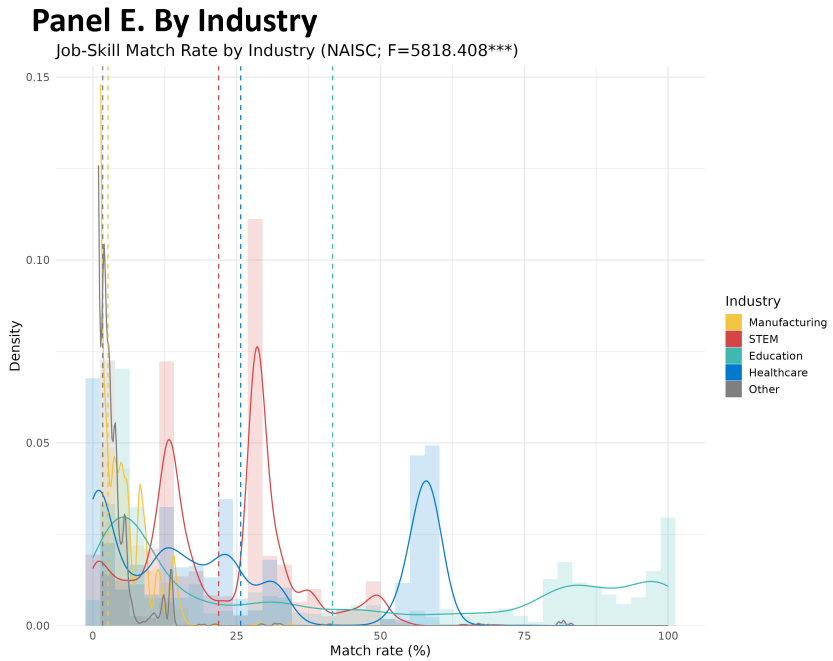


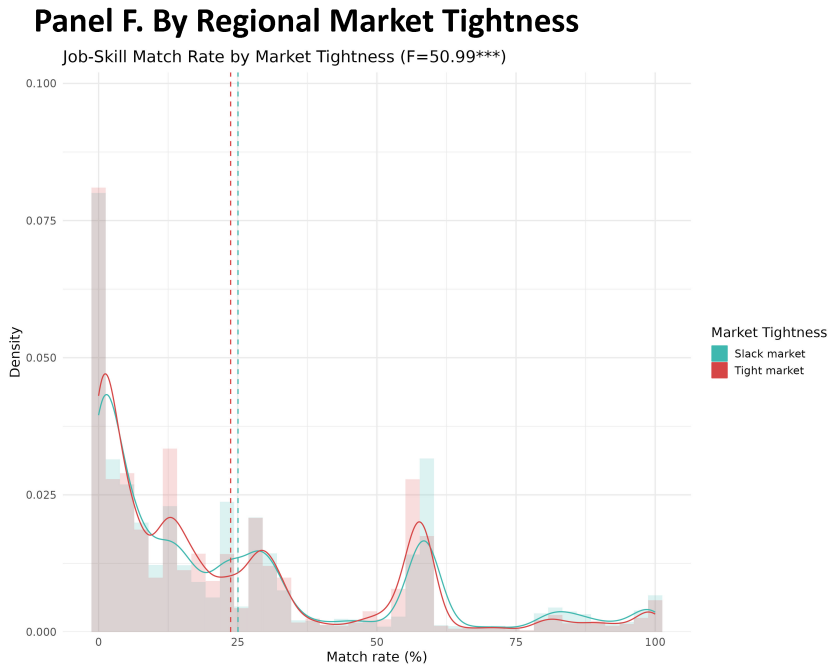
Panel C. By Highest Degree Attainment



Panel D. By Major

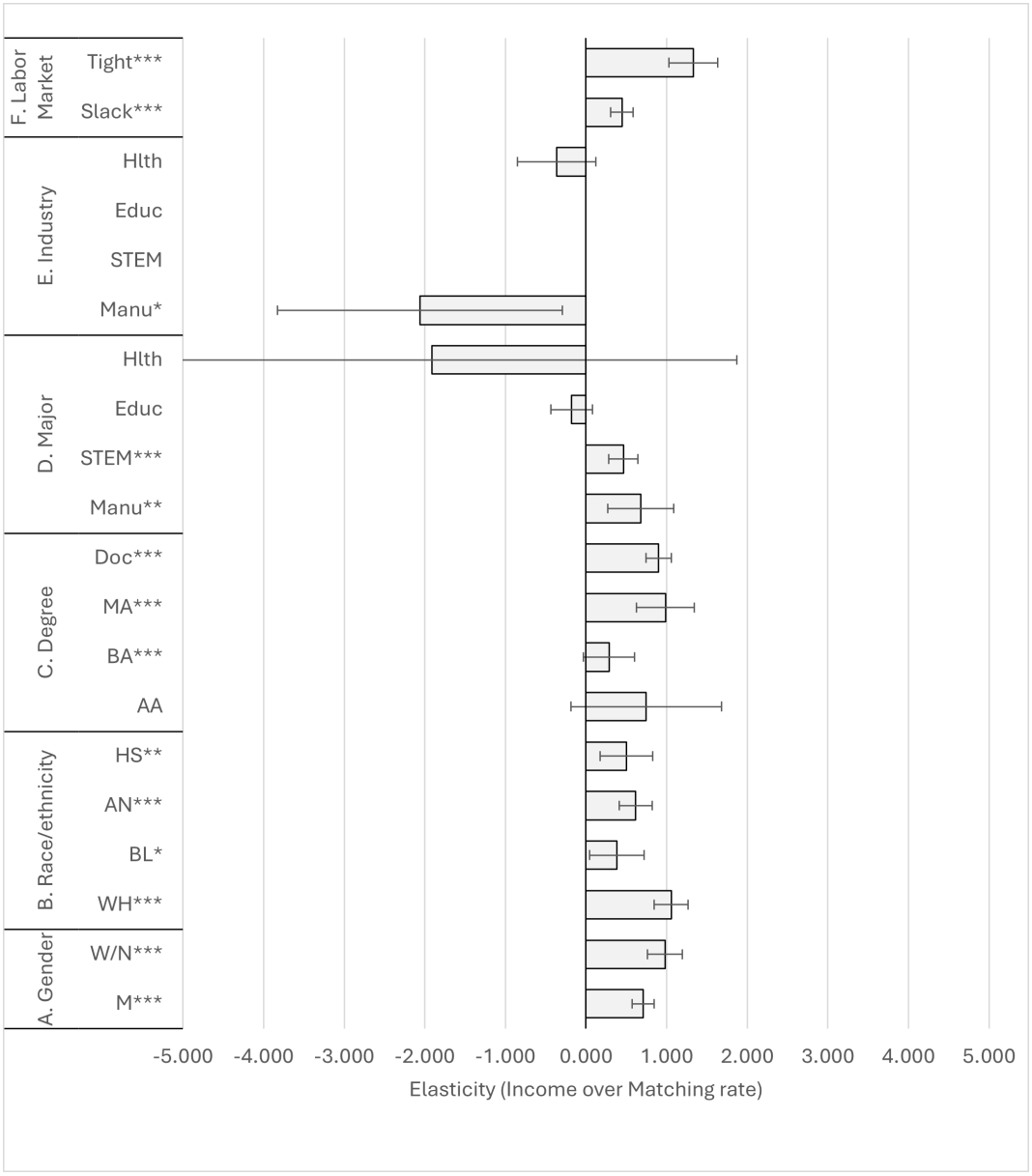






Notes: the dotted lines represent the median matching rate for each subgroup.

Figure 2: Heterogeneous Returns to Job–Skill Alignment by Industry, Major, Demographics, and Labor Market Conditions



Notes: + $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
Abbreviations: Manu = Manufacturing; Educ = Education; Hlth = Healthcare; WH = White (NH); BL = Black (NH); AN = Asian (NH); HS = Hispanic; AA = Associate degree; BA = Bachelor's degree; MA = Master's degree; Doc = Doctorate degree; M = Man; W/N = Woman/Non-binary.
STEM (B = −4.032, SE = 23.848) and Education (B = 34.134, SE = 550.198) in Industry are not reported due to excessively large standard errors.

Table 1: Descriptive Statistics for All and Industry-Specific Samples

Variables	Overall (1)	STEM (2)	Manufacturing (3)	Healthcare (4)	Education (5)	Other (6)
UC						
2018	0.0438	0.0183	0.0579	0.0504	0.0415	0.0412
	(0.2046)	(0.1341)	(0.2339)	(0.2189)	(0.1995)	(0.1990)
2022	0.0579	0.0395	0.0489	0.0683	0.0542	0.0562
	(0.2336)	(0.1949)	(0.2156)	(0.2523)	(0.2264)	(0.2305)
AA						
2018	0.1594	0.0251	0.0982	0.2437	0.0447	0.3206
	(0.3661)	(0.1567)	(0.2980)	(0.4295)	(0.2067)	(0.4674)
2022	0.1710	0.0565	0.1051	0.2574	0.0916	0.2608
	(0.3765)	(0.2309)	(0.3067)	(0.4372)	(0.2884)	(0.4393)
BA						
2018	0.2393	0.2763	0.3048	0.2513	0.1356	0.2647
	(0.4267)	(0.4477)	(0.4609)	(0.4339)	(0.3426)	(0.4418)
2022	0.2246	0.3130	0.2792	0.2043	0.1611	0.2895
	(0.4173)	(0.4638)	(0.4487)	(0.4032)	(0.3676)	(0.4538)
MA						
2018	0.4081	0.6164	0.4282	0.3025	0.5104	0.2971
	(0.4916)	(0.4868)	(0.4954)	(0.4595)	(0.5003)	(0.4576)
2022	0.3815	0.5143	0.4387	0.2808	0.4810	0.3206
	(0.4858)	(0.4998)	(0.4963)	(0.4494)	(0.4997)	(0.4670)
Doc						
2018	0.1494	0.0639	0.1108	0.1521	0.2679	0.0765
	(0.3565)	(0.2449)	(0.3143)	(0.3593)	(0.4432)	(0.2661)
2022	0.1650	0.0766	0.1281	0.1891	0.2122	0.0730
	(0.3712)	(0.2661)	(0.3343)	(0.3916)	(0.4089)	(0.2602)
Annual Wage						
2018	38,984.6	38,741.5	53,415.7	38,177.4	33,118.7	36,089.9
	(29,784.3)	(24,713.8)	(33,366.1)	(29,036.1)	(27,561.9)	(32,572.8)
2022	71,070.5	96,254.7	91,889.1	65,464.1	52,333.4	64,734.8
	(50,033.3)	(62,220.4)	(52,861.6)	(41,842.2)	(40,528.9)	(61,649.1)
Age	31.2934	29.4954	30.7179	31.9950	32.3971	29.7912
	(4.2836)	(3.8010)	(4.3165)	(4.2835)	(3.9478)	(4.1909)
Gender						
Men	39.3%	55.0%	57.9%	25.9%	39.2%	44.7%
Women/non-binary	60.7%	45.0%	42.1%	74.1%	60.8%	55.3%
Race/Ethnicity						
White	56.1%	59.6%	55.2%	58.3%	53.1%	50.3%
Black	7.6%	5.5%	4.8%	9.7%	6.4%	8.2%
Hispanic	10.3%	6.4%	10.3%	11.8%	7.5%	15.3%
Asian	14.7%	12.8%	19.1%	10.2%	20.9%	16.5%
Other	11.3%	15.8%	10.6%	10.0%	12.1%	9.7%

Notes: Standard errors are reported in parentheses. For educational attainments and annual wage, the table reports the earliest and the latest year of observations.

Table 2: Impacts of Horizontal Job-Skill Match on Earnings (Panel 2SLS; IV: Bartik Instrument)

	Pooling (1)	Within (FE) (2)	Random (RE) (3)
Job-skill match rate	0.231***	0.867***	0.361***
	(0.011)	(0.064)	(0.013)
Age	0.033***		0.035***
	(0.001)		(0.001)
Gender (Ref: Men)			
Women/Non-binary individuals	-0.053***		-0.061***
	(0.007)		(0.008)
Race/Ethnicity (Ref: White)			
Black	-0.095***		-0.083***
	(0.014)		(0.015)
Asian	0.036**		0.040**
	(0.011)		(0.012)
Hispanic	-0.031**		-0.025*
	(0.011)		(0.012)
Other	0.007		0.002
	(0.014)		(0.015)
Highest educational attainment (Ref: UC)			
AA's degree	0.213***		0.190***
	(0.012)		(0.013)
BA's degree	-0.022*		0.007
	(0.011)		(0.012)
MA's degree	-0.123***		-0.112***
	(0.009)		(0.010)
Doc degree	0.044***		0.040***
	(0.007)		(0.008)
Individual FE/RE	-	FE	RE
Year FE	FE	FE	FE
MSA FE	FE	FE	FE
N (observations)	83,651	83,651	83,651
F-stat (First Stage)	2431.88***	308.53***	1216.1***
R^2	0.102	0.105	0.635
Sigma	0.7	0.5	0.6

Notes: + p<0.10; * p<0.05; ** p<0.01; *** p<0.001. Individual-clustered standard errors are in parentheses.

Internet Appendix for “From Major to Market: Causal Evidence on the Returns to Horizontal Job-Skill Match”

Appendix A Additional Results

Table A1: Heterogeneous Impacts of Horizontal Job-Skill Match on Earnings by Gender

	Men (1)	Women/Non-binary (2)
Job-skill match rate	0.708***	0.980***
	(0.069)	(0.110)
Individual FE	X	X
Year FE	X	X
MSA FE	X	X
N (observations)	32,423	51,228
F-stat (First Stage)	215.46***	119.71***
R^2	0.162	0.078
Sigma	0.4	0.5

Notes: + p<0.10; * p<0.05; ** p<0.01; *** p<0.001. Individual-clustered standard errors are in parentheses.

Table A2: Heterogeneous Impacts of Horizontal Job-Skill Match on Earnings by Race/Ethnicity

	White (1)	Black (2)	Asian (3)	Hispanic (4)
Job-skill match rate	1.057***	0.385*	0.617***	0.500**
	(0.107)	(0.172)	(0.105)	(0.166)
Individual FE	X	X	X	X
Year FE	X	X	X	X
MSA FE	X	X	X	X
N (observations)	46,452	5,531	11,806	9,152
F-stat (First Stage)	144.15***	16.43***	92.98***	22.01***
R^2	0.094	0.121	0.138	0.167
Sigma	0.5	0.4	0.4	0.4

Notes: + p<0.10; * p<0.05; ** p<0.01; *** p<0.001. Individual-clustered standard errors are in parentheses.

Table A3: Heterogeneous Impacts of Horizontal Job-Skill Match on Earnings by Highest Degree Attainment

	UC (1)	AA (2)	BA (3)	MA (4)	Doc (5)
Job-skill match rate	0.748	0.286	0.987***	0.900***	0.765***
	(0.477)	(0.161)	(0.183)	(0.080)	(0.114)
Individual FE	X	X	X	X	X
Year FE	X	X	X	X	X
MSA FE	X	X	X	X	X
N (observations)	4,542	13,439	18,904	31,919	14,847
F-stat (First Stage)	4.83*	11.67***	46.29***	209.48***	82.55***
R^2	0.067	0.196	0.142	0.110	0.132
Sigma	0.4	0.3	0.5	0.4	0.4

Notes: + p<0.10; * p<0.05; ** p<0.01; *** p<0.001. Individual-clustered standard errors are in parentheses.

Table A4: Heterogeneous Impacts of Horizontal Job-Skill Match on Earnings by Major

	Manufacturing (1)	STEM (2)	Education (3)	Healthcare (4)
Job-skill match rate	0.680**	0.464***	-0.179	-1.913
	(0.209)	(0.092)	(0.132)	(1.932)
Individual FE	X	X	X	X
Year FE	X	X	X	X
MSA FE	X	X	X	X
N (observations)	5,976	10,588	3,088	34,297
F-stat (First Stage)	25.25***	71.42***	10.98***	1.09
R^2	0.145	0.144	0.244	0.025
Sigma	0.4	0.4	0.3	0.7

Notes: + p<0.10; * p<0.05; ** p<0.01; *** p<0.001. Individual-clustered standard errors are in parentheses.

Table A5: Heterogeneous Impacts of Horizontal Job-Skill Match on Earnings by Industry

	Manufacturing (1)	STEM (2)	Education (3)	Healthcare (4)
Job-skill match rate	-2.059*	-4.032	34.134	-0.364
	(0.901)	(23.848)	(550.198)	(0.247)
Individual FE	X	X	X	X
Year FE	X	X	X	X
MSA FE	X	X	X	X
N (observations)	11,007	12,722	17,383	38,564
F-stat (First Stage)	9.57**	0.04	0	16.5***
R^2	0.198	0.257	0.001	0.255
Sigma	0.3	0.5	13.2	0.3

Notes: + p<0.10; * p<0.05; ** p<0.01; *** p<0.001. Individual-clustered standard errors are in parentheses.

Table A6: Heterogeneous Impacts of Horizontal Job-Skill Match on Earnings by Regional Labor Market Tightness

	Slack Market (1)	Tight Market (2)
Job-skill match rate	0.448***	1.333***
	(0.071)	(0.154)
Individual FE	X	X
Year FE	X	X
MSA FE	X	X
N (observations)	33,735	49,916
F-stat (First Stage)	101.73***	102.27***
R^2	0.138	0.082
Sigma	0.3	0.5

Notes: + p<0.10; * p<0.05; ** p<0.01; *** p<0.001. Individual-clustered standard errors are in parentheses.