FEDERAL RESERVE BANK PHILADELPHIA
Consumer Finance Institute

Discussion Papers

Apprenticeship and Postsecondary Education Are Intertwined:

New Evidence on Apprenticeship Pathways in the United States

Rajeev Darolia
University of Kentucky and
Federal Reserve Bank of Philadelphia
Consumer Finance Institute Visiting Scholar

Lora Dufresne
Federal Reserve Bank of Philadelphia
Consumer Finance Institute

Tomas Monarrez
Federal Reserve Bank of Philadelphia
Consumer Finance Institute

Julia Turner
Northwestern University

DP 26-02

PUBLISHED
September 2026

FRB CFI PHILADELPHIA

DOI: https://doi.org/10.21799/frbp.dp.2026.02

Apprenticeship and Postsecondary Education Are Intertwined: New Evidence on Apprenticeship Pathways in the United States*

Rajeev Darolia† Lora Dufresne‡ Tomás Monarrez§ Julia Turner¶

August 31, 2026

Abstract

We use a large sample of online job postings and individual worker profiles to study apprenticeship in the United States. Counter to a view where apprenticeship and postsecondary education are substitutes, we find that these skill-building pathways are deeply intertwined for many: Nearly half of apprentices start their apprenticeships having already attended some college, and about 32 percent of apprentices arrive with prior college credentials. Similarly, about 40 percent of apprentices who started their apprenticeships with no prior education ultimately attain a bachelor's degree or higher. Pathways vary considerably across fields: Apprentices in the trades typically enter with little aligned prior education, suggesting that many of these students are using the apprenticeship to break into a new field. Apprentices in white-collar occupations, however, more often arrive already embedded in the relevant domain, suggesting that they use apprenticeship to deepen skills within an existing career trajectory. For many participants, apprenticeship serves as an intermediate step in a longer postsecondary trajectory, which carries important implications for the evaluation of apprenticeship programs within the broader postsecondary education system.

JEL codes: J24, J44, I23, I26, J21

Keywords: apprenticeships, postsecondary education, career pathways, human capital, work-based learning, occupational mobility, labor market

*Disclaimer.** The views presented in this study are those of the authors alone and do not represent the position of the Federal Reserve Bank of Philadelphia, the Federal Reserve Board, or the Federal Reserve System. Any errors or omissions are the responsibility of the authors. No statements here should be treated as legal advice.

†University of Kentucky, Email: Rajeev.Darolia@uky.edu

‡Federal Reserve Bank of Philadelphia, Email: Lora.Dufresne@phil.frb.org

§Federal Reserve Bank of Philadelphia, Email: Tomas.Monarrez@phil.frb.org

¶Northwestern University, Email: juliaturner@u.northwestern.edu

1 Introduction

Apprenticeship has received an unprecedented level of policy attention in the United States in recent years. Federal executive orders, state workforce initiatives, and high-profile employer programs have elevated apprenticeship, and work-based learning more generally, near the forefront of discourse about postsecondary pathways and workforce development.[1] Despite this prominence, the empirical foundation for systematically understanding the costs, benefits, and contexts of apprenticeship — including questions of who participates, how programs have evolved, and how they relate to the formal education system — remains thin. The absence of rigorous evidence constrains the ability to mobilize funding, target investment, and design accountability frameworks commensurate with the system's potential scale.

A central unresolved question in the evolving landscape is whether apprenticeships function as a substitute for, or a complement to, traditional educational systems. The conventional framing positions apprenticeship as an alternative to traditional postsecondary degree programs: a way for workers to acquire vocational skills and mentorship without incurring the time and financial costs of a college degree. However, modern apprenticeship models in the United States are unlikely to fit this stereotype. Registered apprenticeships typically require supplemental classroom education, and this instruction is often delivered through community colleges.[2] Moreover, numerous public policy and institutional initiatives emphasize the integration of apprenticeship with traditional higher education institutions.[3] Yet we currently know little about how frequently apprentices have earned postsecondary credentials before beginning an apprenticeship program, or pursued college degrees after completing one.

In this paper, we use a large sample of online job postings and individual worker profile data to provide novel evidence on the extent to which apprenticeship and postsecondary education are intertwined in the United States.[4] These data offer two key advantages over existing sources, with much of the prior, broad-

[1]As we describe in more detail later, federal guidelines define apprenticeship as an industry-driven career pathway combining paid work experience, mentorship, and classroom instruction leading to a portable credential (U.S. Department of Labor, 2026). Apprenticeships are long-term, structured work-based learning programs that lead to recognized occupational credentials, unlike typically shorter-term co-ops and internships that typically do not yield formal credentials.

[2]Registered apprenticeships are programs that are formally recognized by the U.S. Department of Labor or a state agency and require at least 144 hours of Related Technical Instruction (RTI), some of which is delivered through community college courses. See apprenticeship.gov.

[3]For example, the new Workforce Pell program under the One Big Beautiful Bill Act extends funding to eligible apprenticeship-attached instruction (see U.S. Department of Education press release), and some apprenticeships are eligible for Federal Work Study funds (see FSA Handbook). Prominent legislative proposals have also sought to expand the apprenticeship model and, more generally, to promote greater collaboration between higher education institutions and employers through apprenticeship programs (see, for example, the proposed Student Apprenticeship Act proposals of 2020 and 2022). For a broader discussion, see Inside Higher Ed. The U.S. system remains far smaller than those of peer countries: Apprentices account for roughly 0.3 percent of the U.S. workforce, compared with approximately 3.9 percent in Germany, 3.7 percent in Australia, and 3.7 percent in Switzerland — countries where apprenticeship is more tightly integrated into the formal postsecondary education system (Lerman, 2014).

[4]Lightcast provides a large proprietary database of online job postings and individual worker profiles widely used in labor economics research. Our sample draws on two components: U.S. job postings data covering 2010 to 2024, from which we identify roughly 400,000 apprenticeship-related postings using a URL-based classification approach, and U.S. worker profiles data, from which

ranging knowledge about apprenticeship available to researchers and policymakers deriving from administrative data on registered apprenticeships recorded in the Registered Apprenticeship Partners Information Database System (RAPIDS). First, they allow us to study both registered and unregistered apprenticeship opportunities, providing a potentially more complete picture of the market than RAPIDS data alone, which capture only formally registered programs. Existing estimates suggest that unregistered apprenticeships may account for as many as half of all participants nationally (Lerman and Jacoby, 2019). Our data reveal that only 26 percent of apprenticeship-related postings meet our criteria for registered status, underscoring the scale of potential activity operating outside the federal system. Second, beyond coverage gaps, the administrative RAPIDS data include no information on the educational and occupational histories of apprentices before or after program completion. Our sample, however, allows us to observe the educational and occupational histories of individual apprentices before and after their apprenticeship, enabling us to situate apprenticeship within broader career trajectories.[5]

We use these data to explore how apprenticeship intersects with the formal postsecondary education system in the United States. Apprenticeship has historically been concentrated in the skilled trades, with construction, manufacturing, and related occupations accounting for over 75 percent of registered apprentices as recently as 2015 (Darolia and Turner, 2026). However, recent work has also documented a rapid expansion of apprenticeship into white-collar fields, with apprenticeships in management, business, sciences, and the arts growing substantially in recent years. Consistent with this, we find that the occupational composition of apprenticeship has broadened well beyond the skilled trades, with white-collar apprenticeships now constituting an equal or larger share of the apprenticeship market and outpacing the growth of skilled trade apprenticeships since 2019.

We then turn to our central contribution: two new stylized facts about how apprenticeship fits within individuals' broader postsecondary trajectories. First, and contrary to a conventional framing of apprenticeship as a substitute for college, apprenticeship is not a terminal alternative to college for many participants but an intermediate step in a longer, sometimes indirect postsecondary journey. Nearly half of apprentices start their apprenticeships having already attended some college. Many apprentices also continue on to earn postsecondary degrees after completing their apprenticeship. Across all occupation groups, roughly 30 percent of apprentices with no observed prior education ultimately attain a bachelor's degree as their

we identify 280,000 distinct individuals with at least one observed apprenticeship spell.

[5]While our data and approach are uniquely positioned to provide a novel perspective on the evolving relationship between apprenticeship and postsecondary education, our analysis has important limitations. Most prominently, we only observe individuals who maintain an online professional profile, which likely overrepresents workers in white-collar and technical occupations relative to those in traditional trades. In addition, the profiles data are self-reported, which likely leads to selection bias in the professional experiences workers choose to report. To ameliorate these concerns, we assess the data coverage in more detail and review the strengths and weaknesses of our data relative to existing aggregate sources.

highest credential, and an additional 10 percent reach the graduate level. Second, these apprenticeship–postsecondary education–occupation pathways are highly heterogeneous across fields. Apprentices in the skilled trades typically enter apprenticeships that do not align with prior occupational or educational experiences, suggesting that they are using the apprenticeship as a vehicle for entering a new field. On the other hand, white-collar apprentices — those who apprentice in business, science, and adjacent fields — more often arrive already embedded in the relevant occupational domain, suggesting that many are using the apprenticeship to deepen skills and stack credentials within an established career trajectory.

Understanding how students navigate apprenticeship and postsecondary education pathways is critically important for understanding the challenges and opportunities faced by apprentices, employers, educational institutions, and workforce development systems — and more broadly evaluating the public and private return on apprenticeship investments. The existing data infrastructure, however, is particularly ill-suited to answer these questions: Aggregate records on registered apprentices fail to capture the educational histories that precede program entry as well as credentials and careers that may follow. The data we introduce here do not fill that gap entirely, but they do offer a new look at individual pathways to and through apprenticeships that have not previously been available at scale. Our findings underscore the importance of considering apprenticeships within a broad, integrated ecosystem in which higher education experiences are prevalent before, during, and after apprenticeships. This prevalence raises key questions about coordination across funding streams, credit recognition, and program design that are difficult to answer when apprenticeship is treated as a self-contained workforce training program.

The rest of the paper proceeds as follows. Section 2 summarizes the recent history and existing academic literature on apprenticeship. Section 3 describes the two data sets used in our analysis: job postings and worker profiles, and describes our methodology for identifying apprentices, their field of occupation, and their postsecondary education. Section 4 presents our main findings, and Section 5 provides concluding remarks.

2 Background

While models vary across settings, apprenticeships encompass programs that combine training and experience in the workplace with some part-time formal education (Wolter and Ryan, 2011). In the United States, the Department of Labor defines recognized apprenticeships as combining "paid on-the-job training with classroom instruction to prepare workers for highly-skilled careers" (U.S. Department of Labor, 2026). This dual structure distinguishes apprenticeship from purely school-based vocational education (as often seen in community college certificate or associate degree programs) or unstructured on-the-job training, positioning it as a hybrid model that aims to combine theoretical knowledge with practical skill development (Lerman, 2014).

The focus of this paper is on apprenticeships, although the absence of standardized definitions across states and the use of varied program terminology surrounding “earn-and-learn” and “work-based learning” opportunities can complicate identification. Although lines can blur across contexts, the longer-term commitment that culminates in a recognized occupational credential distinguishes apprenticeships from shorter-term or less structured programs that are typically directly or implicitly complementary to postsecondary pathways such as cooperative education (co-op) and internship programs. Co-op programs typically alternate between academic terms and employer placements, whereas internships are generally exploratory and time-limited. From a practical perspective for this paper, we use narrowly bounded search terms in an effort to identify apprentices as cleanly as possible. However, internships, co-op programs, and work-based learning are all commonly understood to share features of the apprenticeship model (U.S. Government Accountability Office, 2025), creating confusing overlap for students looking to distinguish between options as well as researchers aiming to study these models. In future work, we expect to expand our inquiry to understand a broader array of experiences.

The apprenticeship model has attracted significant research attention, although results have been largely mixed. Although empirical evidence from European countries — where apprenticeship is both more popular and more seamlessly integrated into the existing postsecondary education system (Darolia and Turner, 2026) — shows positive effects on youth employment rates and school-to-work transitions (Ryan, 2001), there is a distinct lack of rigorous evidence from the United States (Lerman, 2014; Lerman et al., 2009). Recent U.S. studies have provided descriptive evidence on lifetime earnings differences between apprenticeship completers and comparable workers, but there has been little causal evidence of the returns to these programs. Descriptive work tends to find large, positive earnings gains for apprenticeship completers but does not account for selection into these programs; Reed et al. (2012), for example, found that individuals who completed registered apprenticeship programs experienced average earnings gains of $240,037 over a 36-year career ($301,533 including employer benefits), while more recent analyses show apprentices experiencing 43 percent wage growth compared with only 16 percent for matched nonapprentices (Katz et al., 2022).

Advocates of the system note that apprenticeship can provide a more efficient mode of skill development than formal postsecondary education as it allows for a more direct relationship between skill development and the needs of employers (Wolter and Ryan, 2011). From an employer perspective, apprenticeship offers multiple benefits beyond simply training workers: Survey data show that firms report improvements in productivity, reduced turnover, lower recruitment costs, and enhanced workplace culture (Lerman et al., 2009; Helper et al., 2016). Moreover, surveys of U.S. employers involved in registered apprenticeship programs indicate that 87 percent would strongly recommend these programs, with nearly all reporting that apprenticeship helps them meet skill demands (Lerman et al., 2009). Cost-benefit analyses from the American Apprenticeship Initiative found that employers received a median return on investment of 44.3 percent, generating $144.30 in benefits for every $1,000 invested (U.S. Department of Labor, 2022).

However, the apprenticeship calculus for employers varies significantly across institutional contexts. Comparative research on German and Swiss apprenticeship systems — two countries in which apprenticeship is deeply embedded into the postsecondary education system and that train a significant number of apprentices each year (Lerman, 2014) — highlights striking differences in training costs and benefits (Dionisius et al., 2009). German firms face substantial net costs during the training period (upward of €7,000 per apprentice per year), whereas Swiss firms generate net benefits (€900 per apprentice per year) despite operating similar programs. Comparative studies largely attribute this difference to the higher share of productive tasks allocated to apprentices in Switzerland (83 percent versus 57 percent in Germany) and lower relative apprentice wages (Dionisius et al., 2009; Wolter and Ryan, 2011). These findings suggest that labor market regulations, wage structures, and the organization of work fundamentally shape employers' willingness to invest in apprenticeship training (Muehlemann and Wolter, 2014).

Despite these potential benefits, apprenticeship in the United States represents a far smaller share of the workforce (0.3 percent) compared with countries like Germany (3.9 percent), Australia (3.7 percent), and Switzerland (approximately 3.7 percent) (Lerman, 2014).[6] Policymakers and researchers are divided over the implications of the limited popularity of apprenticeship in the U.S. Proponents note that some research suggests that apprenticeship can enhance innovation — studies from Germany find that firms engaged in apprenticeship training demonstrate higher rates of incremental innovation, as workers with production-specific training can better understand production processes and can identify improvements (Bauernschuster et al., 2009). Critics, however, draw on traditional economic theory to note the potential downsides of firm-specific human capital (Acemoglu and Pischke, 1998). Hyperspecific development of skills can limit the mobility of workers and make both workers and firms more vulnerable to rapid changes in labor market circumstances, leading to slower adoption of new technology (Krueger and Kumar, 2004; Wolter and Ryan,

[6]Note that these statistics are slightly outdated, but even given the significant growth in apprenticeship over the last decade in the U.S., more recent estimates from the Department of Labor show that apprentices continue to make up a relatively small share of the workforce (0.4 percent) (U.S. Department of Labor, Employment and Training Administration, 2021).

2011). This has become a particularly salient concern, given the rise of artificial intelligence technologies in recent years.

Moreover, while apprenticeships can potentially provide pathways to skill development and the labor market benefits of high-skill jobs, apprenticeship participation and experiences have varied across groups. Women remain underrepresented in apprenticeships, comprising only 14.5 percent of active apprentices as of 2024, despite being 47 percent of the overall labor force (Council of Economic Advisers, 2024). Within apprentices, there is significant occupational segregation that contributes to wage gaps across gender and race: Women who completed apprenticeships in 2017 earned median hourly wages of $17.84 compared with $26.28 for men, while Black apprenticeship completers earned median wages of $14.35 per hour compared with $26.14 for White completers (Bahn and Halpin, 2018). These gaps persist even after controlling for occupational choices, suggesting that expansion efforts must address not only the quantity but also the quality of apprenticeship opportunities (Institute for Women's Policy Research, 2024). Further research will also be important to understand the extent to which apprenticeships can increase or decrease wage differentials.

Despite recent expansions, the U.S. system remains structurally distinct from its European counterparts: Rather than being embedded within formal education pathways, American apprenticeships are layered atop a fragmented set of institutions, including community colleges, workforce training providers, and employers, which each operate under separate funding streams and regulatory frameworks. A feature of this fragmentation is the relative scarcity of data with which to study the performance of apprentices and apprenticeship programs in the United States. The primary administrative data source for studying registered apprenticeships is the Registered Apprenticeship Partners Information Database System (RAPIDS), which aggregates individual-level apprentice records submitted quarterly by the 28 states operating their own State Apprenticeship Agencies (SAAs) and the 21 states registering programs through the federal Office of Apprenticeship. Despite strong coverage of registered apprentices across the country, RAPIDS captures only formally registered programs, and existing estimates suggest that unregistered apprenticeships may account for as many as half of all participants nationally (Lerman and Jacoby, 2019). Additionally, RAPIDS data do not include individual-level information, rendering it difficult to draw lessons about pathways or to understand for whom and under what conditions apprentices have benefits and costs. The partial coverage and lack of detail introduce concerns that analyses using only RAPIDS data will not capture the full scope of the apprenticeship market or apprentice experiences. Taken together, gaps in administrative data coverage and the absence of individual-level detail compound the measurement challenges facing apprenticeship researchers and limit the evidence available to policymakers.

A related and underexplored question in the U.S. context is the relationship between apprenticeship and postsecondary education. Whereas European systems tend to treat apprenticeship as its own postsecondary track, the U.S. system is more ambiguous. The structure of the American system layers apprenticeships on top of existing community colleges and workforce training providers, creating institutional conditions in which apprenticeship and traditional postsecondary degrees (associate and bachelor's degrees, for example) may function as complements rather than substitutes. Whether apprentices in the U.S. pursue postsecondary education at meaningful rates is an open empirical question that existing data sources have not been well-positioned to address.

3 Data

This paper aims to address the empirical gaps in the literature by introducing a new data source for studying apprenticeships. Lightcast (formerly Burning Glass Technologies) provides access to proprietary databases on the U.S. labor market. Our analysis makes use of two Lightcast data sets: U.S. Job Postings Data and U.S. Worker Profiles Data. U.S. Job Postings Data (henceforth, "Postings") provide information on job postings in the United States starting January 2010, including date posted, occupation, industry, and full informational body of the post. U.S. Worker Profiles Data (henceforth, "Profiles") include resume-style information on a worker's job history and education, including start and end dates, company name, school name, occupation, college major, and geography. We use both of these samples to study the supply and take-up of apprenticeship programs in the U.S. labor market.

3.1 Postings Data

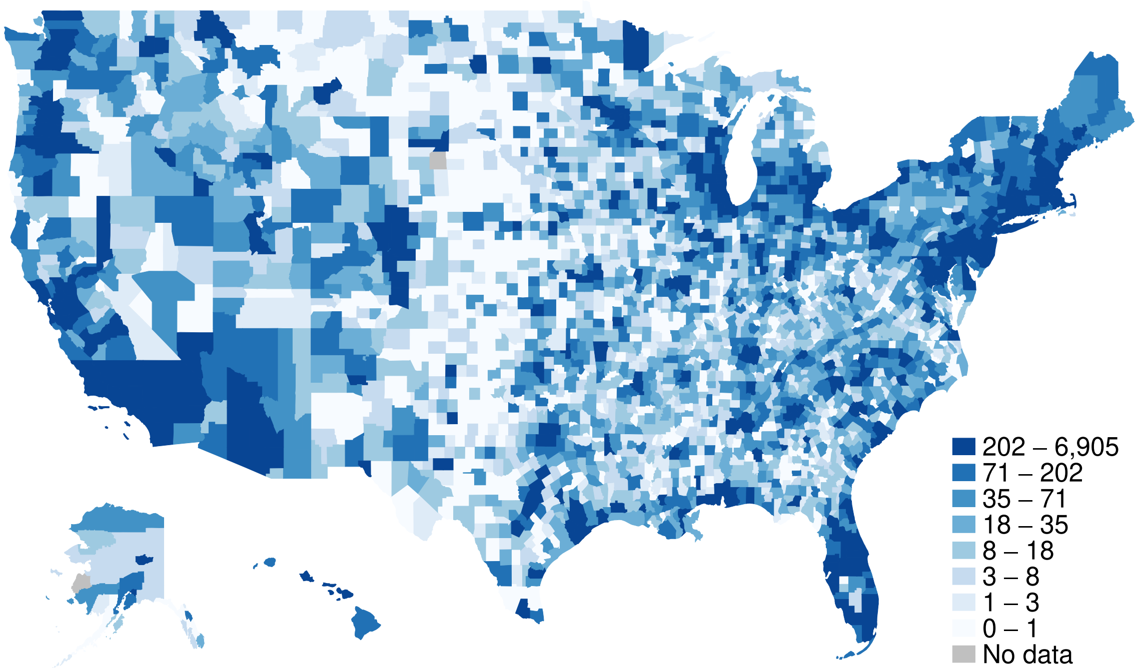
Lightcast collects and de-duplicates job postings from roughly 40,000 websites, capturing most U.S. job vacancies posted online; only new postings are counted, and vacancies posted on multiple sites are represented just once. Each posting includes geographic information such as city, state, county, and metropolitan statistical area, as well as multiple variables defining the vacancy's industry (based on North American Industry Classification System (NAICS) codes), occupation (based on Standard Occupational Classification (SOC) codes), standardized job title, employer name, and the sources from which the job posting was pulled. The data span 2007 to the present, and previous assessments of representativeness show that regional coverage is generally strong, although white-collar roles tend to be overrepresented relative to official sources, while manual and service occupations recruited through offline channels are underrepresented (Tsvetkova et al., 2024). We discuss these limitations with respect to the study of apprenticeships below.

To be included in the job postings data, a listing must appear on at least one job search website covered by Lightcast. All findings from postings data are based on aggregated job levels and thus refer to the number of unique apprenticeship postings. In contrast, profiles data focus on apprentices at the person level, which is a key improvement over existing aggregate data sources. In order to be included in the profiles data, an individual must have an online profile on one of Lightcast's data sources. While the sample is limited to profile creators, these data are useful as they allow us to study pathways over time and to track an individual's educational and professional career.

We test several potential approaches to identifying apprenticeships in the job postings data, each of which involves keyword searching different variables for words related to "apprentice" (e.g., apprentice, apprenticeship, apprentices, etc.). The most straightforward version of this search is to use the "raw title" variable, which provides the title of the job posting, uncleaned by Lightcast. This is the narrowest method of capturing apprenticeship-related postings in the data and returns roughly 11,800 postings out of 440 million (less than 0.003 percent of the sample). In comparison, the broadest definition of apprenticeship-related postings searches the entire body of the posting for apprentice-related keywords. This search returns over 1.7 million postings (roughly 0.4 percent of the sample) but could potentially overcharacterize some postings as being apprenticeship-related. For example, many of the jobs captured using this classification are those open to hiring those with apprenticeship training, but occasionally postings use "apprentice" descriptively; one such example describes the ideal candidate as having an "apprentice mindset." Our preferred method employs a keyword search in the URL variable, which contains the Lightcast-cleaned source website URLs of the job postings. Importantly, this source variable includes all URLs where the job appeared (including duplicates). We find that this is the cleanest way to capture apprenticeship-related postings, as in many cases it captures the website name as well as the title of the posting. For example, this method captures jobs posted by employers to the official apprenticeship.gov job posting board as well as jobs posted to traditional job boards (Indeed, ZipRecruiter, etc.) that have apprentice-related keywords in the job title (i.e., "ziprecruiter.com/....apprentice-electrician"). This approach returns just under 400,000 postings (just under 0.1 percent of all postings) and minimizes — although does not eliminate — the probability of false negatives, given the requirement that postings be found on apprenticeship.gov or use apprenticeship in the title. If anything, this approach is likely a conservative estimate of the total number of apprenticeship-related job postings advertised online. In Figure 1, we show the geographic distribution of these postings across U.S. counties between 2010 and 2024.[7]

[7] A comparison of discussed approaches is shown in Appendix Figure A1.

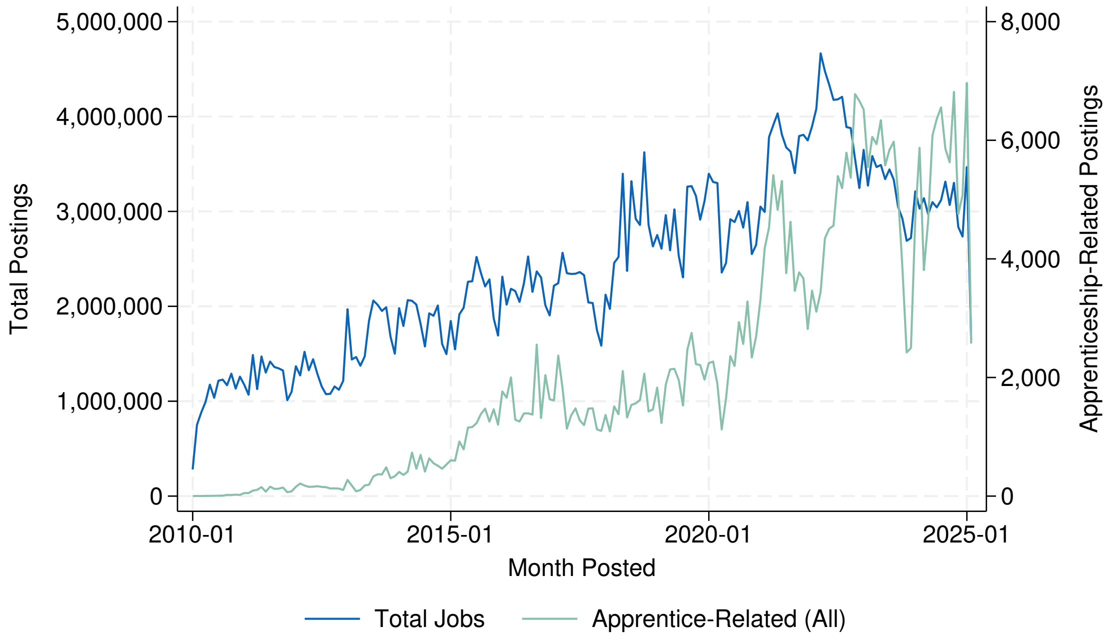
Figure 1: Number of Apprenticeship Postings in the Workforce by County: 2010–2024



Source: Lightcast U.S. Job Postings
Note: This figure shows the number of apprenticeship-related postings by location across counties in the United States. Apprenticeship-related postings are defined using the URL method described in Section 3.1. The figure uses aggregated counts between 2010 and 2024.

Furthermore, the use of URL data to identify apprenticeship-related job postings allows us to proxy for those postings that are registered apprenticeships and would likely be captured by RAPIDS versus those that are likely unregistered and would otherwise be likely to go unreported in federal data sets. We proxy for registered status by using the apprenticeship.gov location: Any job posted by an employer to apprenticeship.gov we assume to be formally registered and captured by RAPIDS, whereas apprenticeship-related jobs posted by an employer to other job search websites and not found on apprenticeship.gov are likely unregistered. Across all apprenticeship-related postings observed between 2010 and 2024, only 26 percent meet our registered definition. This does not necessarily mean that only 26 percent of apprentices are enrolled in registered apprenticeships, as unregistered apprenticeships are more likely to be small programs hiring only one or two apprentices, whereas registered apprenticeship programs are likely to be larger. That said, these estimates indicate that reliance on solely registered apprenticeship data may miss a large number of apprenticeship opportunities across the country. In Figure 2, we show trends in apprenticeship-related postings over time alongside total postings, and in Section 4, we further discuss how registered and unregistered apprenticeships vary across industry.

Figure 2: Postings Over Time (All vs. Apprenticeship)



Source: Lightcast U.S. Job Postings
Note: This figure shows the number of apprenticeship-related postings over time compared with all postings from Lightcast. Apprenticeship-related postings are defined using the URL method described in Section 3.1. The figure aggregates counts to the monthly level. Apprenticeship-related postings are plotted on the right-hand side axis and total postings are plotted on the left-hand side axis.

3.2 Profiles Data

The worker profiles data contain information on the job history and educational attainment of nearly 86 million workers. Each row corresponds to a job with a start and end date.[8] We first filter the job history data to include only individuals with an observed apprenticeship. To identify these individuals, we implement an open-ended keyword search on the appearance of "apprentice" (allowing for "apprentice," "apprenticeship," "apprentices," etc.) over the raw job title in a worker's profile. This approach returns about 282,000 distinct individuals with at least one observed instance of an apprenticeship. We next collect static characteristics at three points in the timeline of the profile — the start of the first observed apprenticeship and jobs directly before and after.[9] Additional variables in this sample include occupation type information (Lightcast-assigned SOC codes) as well as start and end dates for each job observed. Among apprentices in our sample, the median profile age (i.e., the time elapsed between the first and last observed job for a worker) is nine years, with the start of the apprenticeship taking place five years in.

[8]We drop spells with jobs that do not fall within the employed population, including unemployment, stay-at-home parenting, retirement, etc. Refer to Appendix B for additional details.
[9]For those with multiple apprenticeships observed, we use information from the first instance for all calculations.

Using the apprenticeship identifier and corresponding start and end dates in combination with the educational attainment data, we can identify educational pursuits before and after a worker's first observed apprenticeship. We also establish the highest education attained regardless of date achieved. Comparing highest attainment with pre-apprenticeship attainment allows us to provide new evidence on the relationship between apprenticeship take-up and subsequent educational upgrading and how this may vary by occupation type. We construct six education groups: no education listed, no degree listed, certificate/course, associate degree, bachelor's degree, and graduate degree.[10]

Additionally, we use field of study to examine industry alignment across education and apprenticeships. Assigned by Lightcast to any degree listed on a worker's profile, the field of study classifier is the Classification of Instructional Programs (CIP) code, a standardized six-digit code developed by the National Center for Education Statistics (NCES) to classify educational programs and fields of study at postsecondary institutions. CIP is prevalent in education data and can be linked to related occupation codes using the National Career Clusters Framework Crosswalk.[11] For expositional simplicity, we focus on occupation codes for our main analysis, which compares the field of study of an individual's educational experience with the occupation code(s) of the work experiences for the same individual. A parallel set of results using industry categories (NAICS classifications) is available in Appendix C.[12]

The final analysis data set is a cross-section at the worker level. To aid in the interpretation of results, we organize SOC codes into five broad categories following the practice from the U.S. Census Bureau:[13] (1) Natural Resources, Construction, and Maintenance, (2) Production, Transportation, and Material Moving, (3) Services, (4) Sales and Office, (5) Management, Business, Sciences, and Arts.[14] Within these occupational categories, we assess four types of matches between: (i) the occupation of the job held prior to the apprenticeship to the occupation of the apprenticeship itself; (ii) the occupation of the apprenticeship

[10] Lightcast categorizes educational attainment as one of: associate, bachelor's, master's, or doctorate. We then further classify individuals as either no education or no degree listed if they do not fall into one of these four categories. No education listed refers to individuals with no education observations. Those classified as no degree listed have an observed education experience but lack classifiers on education level and any additional attainment information. Individuals in the certificate/course group must explicitly note the education was for a certificate or course in their profile. Associate degree, bachelor's degree, and graduate degree groups contain individuals with observed educational level indicators for each respective degree.

[11] The NCCF Crosswalk may assign multiple occupation codes to one CIP.

[12] NAICS and SOC measure fundamentally different things: NAICS codes are a federal standard to classify business establishments (i.e., what the *business* does), whereas SOC codes are a federal standard to classify occupational categories, i.e., what the *worker* does. For the purposes of this analysis, we favor SOC codes for two reasons. The first is conceptual. Occupation codes are a closer reflection of employee tasks, and tasks are more easily connected to skills that employees can gain in apprentice or classroom experiences. For example, we might be more interested in knowing whether someone who learns software skills works in a software occupation, rather than whether they work in the healthcare or construction industry. The second reason is more practical for our context and related to avoiding introducing systematic bias in our data. Individuals in our data who are missing NAICS codes but not missing SOC codes are more likely to be in the skilled trades and less likely to be in business, management, or services. Therefore, using SOC codes instead of restricting the sample to those with observed NAICS codes provides better data coverage across fields.

[13] For a full breakdown of what occupations are included in each group, see Appendix A.

[14] Results including workers with unknown occupation codes can be found in Appendix A.

to the field of study of any postsecondary education pursued during or after the apprenticeship; (iii) the occupation of the apprenticeship to the occupation of the job held after; and (iv) the field of postsecondary study to the occupation of the post-apprenticeship job. In Section 4.2, we describe how these alignment rates vary across major occupation groups.

While the profiles data represent a meaningful improvement over the current data landscape by enabling observation of educational attainment, field of study, and career trajectories for individual apprentices, important limitations remain. We lack comprehensive information that is critical for evaluating apprenticeship programs, including wages and longer-run labor market outcomes, which means our data do not allow for a full assessment of the returns to apprenticeship or for causal analysis of program impacts. Moreover, we are transparent about selection into the data sample, both in terms of who maintains online profiles and what they choose to write in them (i.e., revisions of profiles by the participant, frequency of updates, addition and subtraction of contents), which means that these data are not well-suited to establish a comprehensive description of the market. With those caveats in mind, we believe our analysis moves the knowledge base forward by offering new descriptive insights into the structure and composition of apprenticeship pathways for those included in the sample.

4 Results

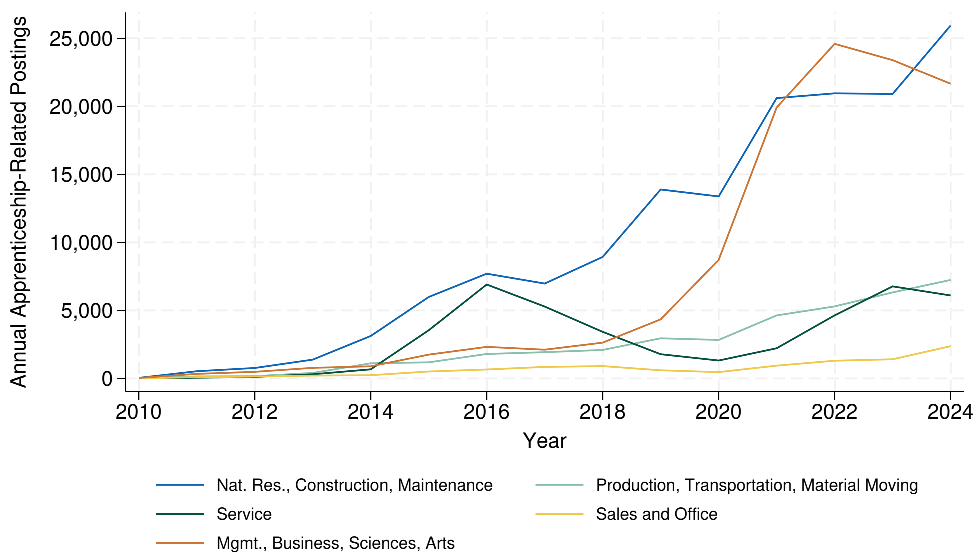
We organize our findings in three parts. We begin with the postings data, which we use to characterize the changing occupational composition of apprenticeship openings. This first set of results is largely confirmatory: It reproduces, in our novel data, an expansion of white-collar apprenticeship that recent work has already documented. We then use the profiles data to study the prevalence of traditional postsecondary education experience among apprentices, both before and after their apprenticeship spell, and finally analyze differences in apprenticeship-linked career pathways by occupation type, uncovering important patterns of heterogeneity in career-switching behavior across fields.

4.1 The Growth of White-Collar Apprenticeships

A notable recent trend, documented in prior work (e.g., Darolia and Turner, 2026), has been the broadening of the apprenticeship model to include a wider set of occupations and industries. Whereas apprenticeships, especially in the United States, were traditionally confined to the skilled trades, there has been a recent surge of white-collar apprenticeships in industries such as business, technology, and professional services. Notable examples of large corporations introducing these types of apprenticeships include IBM, Accenture, and Aon, which have all expanded apprenticeship opportunities across technical fields over the last decade. This represents a significant shift in the credentialing landscape of these fields, as many apprenticeship programs span cybersecurity, software engineering, and financial services roles, fields that would traditionally require applicants to have a college degree.

Figure A2 shows the evolution of apprenticeship posting types by broad occupation category over time. Notably, the annual count of apprenticeship-related postings has been increasing over time across all occupations, likely due in part to data collection practices (i.e., the growth in popularity of platforms like LinkedIn) and in part to the true growth of apprenticeships over the same period.[15] Postings in white-collar occupations (namely, management, business, science, and the arts) saw large increases in annual volume between 2018 and 2022, accounting for the largest number of postings across all occupations between 2021 and 2023. Since 2022, postings in white-collar occupations have largely stagnated, while other occupation types have seen significant growth. This tracks with an overall slowdown in hiring across these occupations, especially in the wake of the COVID-19 pandemic (U.S. Bureau of Labor Statistics, 2025). Expansion of apprenticeships into other fields such as production, transportation, and material moving can be seen in Figure A2, with especially sharp growth in service apprenticeships since 2021.

Figure 3: Annual Apprenticeship-Related Job Postings

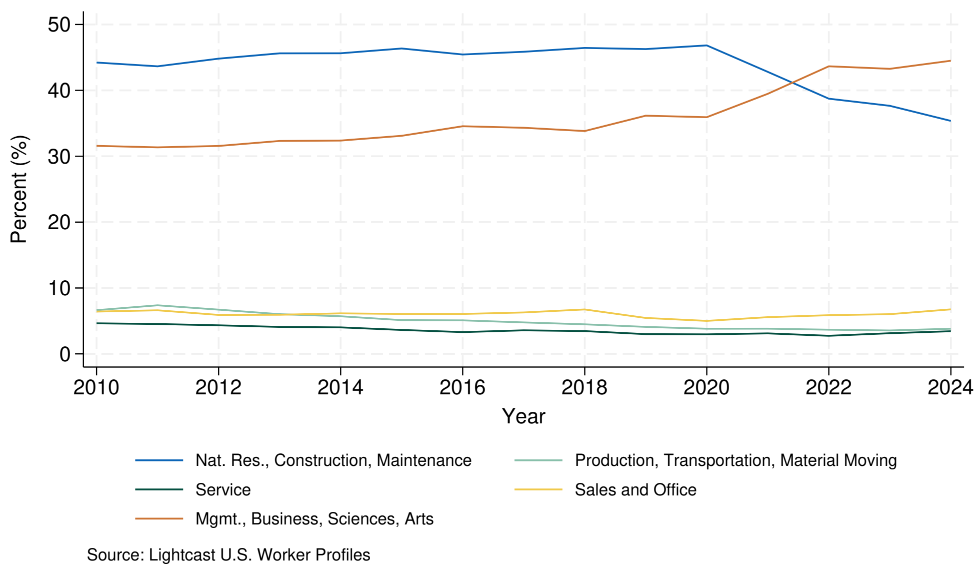


Source: Lightcast U.S. Job Postings
Note: This figure shows the number of apprenticeship-related postings over time by occupation grouping. A posting is considered apprenticeship-related using the URL method described in Section 3. Postings are reported in aggregated counts by year from 2010 to 2024. Apprenticeship-related job postings are binned into five occupation groups. Occupation group breakdowns can be found in Appendix B. There exists a sixth group of unknown occupation codes that makes up 2 percent of our sample. The breakdown of this group can be found in Appendix A.

[15]Similar growth in the number of active apprenticeships can be seen in Figure 1A of Darolia and Turner (2026).

These patterns are broadly mirrored in Figure 4, which shows the share of apprenticeship-identified profiles by occupation over time. This figure uses the profiles data to identify the occupation of apprenticeships listed on individual's job profiles. Until 2020, the "natural resources, construction, and maintenance" occupation group — largely considered to be comparable with the "skilled trades" category of jobs — is consistently the most common, with "management, business, sciences, and arts" (white-collar occupations) exhibiting slow but steady growth between 2010 and 2020, at which point we see a sharp uptick. In 2022, the white-collar share overtakes skilled trades as the most common occupation type listed and maintains this position up to the most recent data point available (2024).[16] These patterns follow those in Figure A2 with a slight lag — the timing we would expect, given the lag between firm-side posting of apprenticeship roles and trainee-side updating of their online profile. That the postings and profiles data independently reproduce the same documented expansion is reassuring: It corroborates patterns established in prior work and gives us confidence in the profiles data underlying the results that follow.

Figure 4: Share of Apprentices by Occupation Group



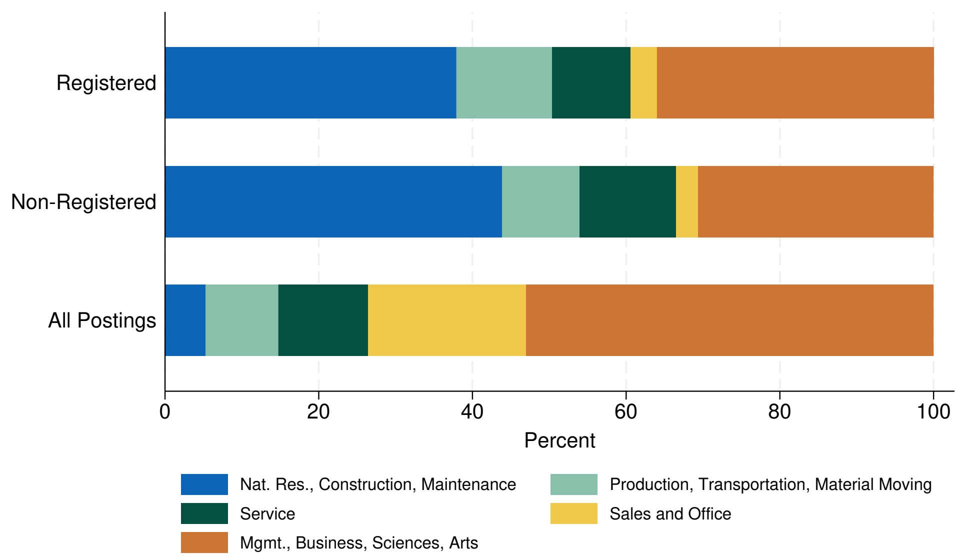
Source: Lightcast U.S. Worker Profiles
Note: Years 2010 to 2024. Percents calculated using year-aggregated apprenticeship and workforce counts. Occupation group breakdowns can be found in Appendix B. There exists a sixth group of unknown occupation codes that makes up 6 percent of our sample. The breakdown of this group can be found in Appendix A.

We next break down the composition of postings across three categories: registered apprenticeships, unregistered apprenticeships, and all apprenticeship postings (Figure A6). We determine whether an apprenticeship is registered based on whether it was posted to the government's website apprenticeship.gov. Un-

[16]The additional slowdown in skilled trades apprenticeships could be, at least in part, related to the declining enrollment in community colleges around the COVID-19 pandemic that was driven by supply-side impacts on courses of study requiring significant capital and experiential learning as documented in Schanzenbach and Turner (2022).

surprisingly, both groups have a significantly higher share of postings in natural resources and construction (a category that can largely be viewed as "skilled trades") than postings as a whole. Although registered and unregistered apprenticeships look similar in terms of occupational breakdown, apprenticeships in the skilled trades (natural resources and construction) are overrepresented in the unregistered category compared with registered apprenticeships. This suggests that there may be some apprenticeship programs, especially smaller programs in traditional fields, that are operating outside of the structured, federal system of apprenticeships. These programs may therefore not be systematically held to the same federal standards and requirements. Without this oversight, it becomes more difficult to verify whether participants receive comparable protections or pathways to credential recognition. These concerns may be especially salient for workers in rural areas or with fewer alternatives to larger, registered programs. This evidence also serves as a reminder that we are limited in our ability to track the true growth and evolution of apprenticeship programs and participants over time due to data constraints. Using solely federal data to track apprentices and apprenticeship programs may provide a misleading picture of apprenticeship growth in certain sectors.

Figure 5: Apprenticeship Postings by Registered Apprenticeship Status (SOC)



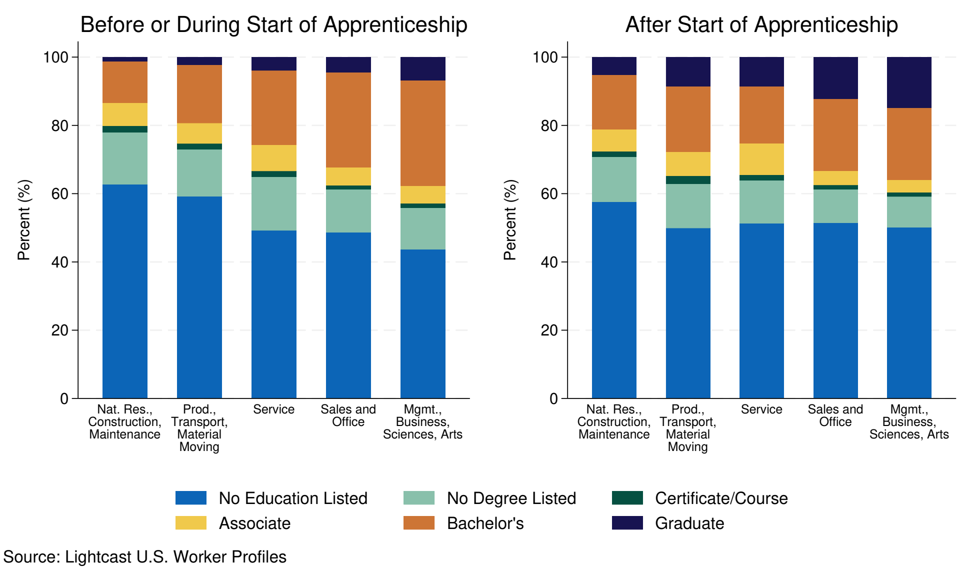
Source: Lightcast U.S. Job Postings
Note: This figure shows the number of postings by occupation grouping and apprenticeship status. A posting is considered apprenticeship-related and registered if it appears on apprenticeships.gov. Non-registered apprenticeships are those that are identified as apprenticeship-related using the URL method but do not appear on apprenticeship.gov. All postings include both apprenticeship *and* non-apprenticeship-related postings. More details on these classifications can be found in Section 3. Postings from 2010 to 2024 are reported in aggregated counts and are binned into five occupation groups. Occupation group breakdowns can be found in Appendix B. There exists a sixth group of unknown occupation codes that makes up 2 percent of our sample. The breakdown of this group can be found in Appendix A.

4.2 Apprenticeship Is Intertwined with the College Degree Pathway

We now turn to the central contributions of the paper. The expansion of apprenticeship into white-collar occupations complicates a framing of apprenticeship as an alternative to traditional postsecondary education. As apprenticeships grow in fields where degrees have historically been the norm for workers, understanding how apprenticeship intersects with the formal education system becomes a more interesting empirical question. We next turn to the educational trajectories of apprentices before and after program entry.

Figure 6 documents the distribution of educational attainment before and after the start of apprenticeship, disaggregated by broad occupation group. Comparing the two panels reveals a consistent pattern across fields: After their apprenticeship begins, a meaningful share of participants go on to earn bachelor's or graduate degrees. Aggregating across all occupation groups, roughly 30 percent of apprentices with no starting education ultimately attain a bachelor's degree as their highest credential, and an additional 10 percent reach the graduate level.

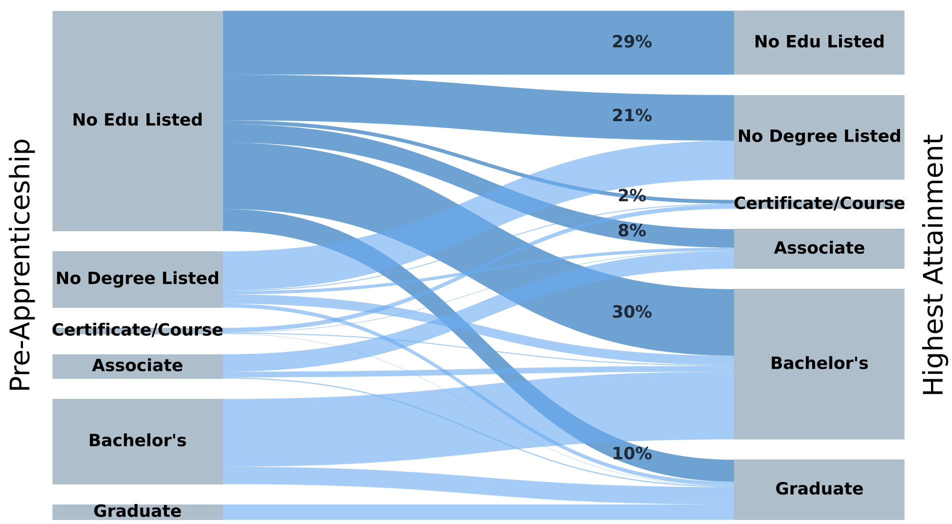
Figure 6: Educational Attainment: Before vs. After Start of Apprenticeship



Source: Lightcast U.S. Worker Profiles
Note: Educational levels for each apprentice are the most recent educational attainment after the start year of the individual's first observed apprenticeship. Each bar represents total apprenticeships in the indicated occupation group, with segments showing the percentage contribution of each educational attainment. Occupation group breakdowns can be found in Appendix B. There exists a sixth group of unknown occupation codes that makes up 6 percent of our sample. A chart including this group can be found in Appendix A.

Figure 7 presents the empirical flow of apprentices from their level of education observed before the apprenticeship spell (left-hand side), to their highest observed level of educational attainment (right-hand side) after the apprenticeship spell. The figure reveals that a large share of apprentices in our sample have no formal education listed in their profiles prior to the apprenticeship — the “No education listed” and “No degree listed” nodes together account for over half of the sample — yet substantial flows from these nodes reach the bachelor’s and graduate degree categories on the right. Apprentices for whom we observe no prior formal education nonetheless go on to earn college credentials at nontrivial rates. Many of those who enter with some prior credential also continue upward: Apprentices arriving with certificates or associate degrees frequently flow toward bachelor’s or graduate degrees as their eventual highest attainment.

Figure 7: Pre-Apprenticeship vs. Highest Educational Attainment: All



Source: Lightcast U.S. Worker Profiles
Note: Pre-apprenticeship educational levels are the most recent educational attainment before the start year of the individual’s first observed apprenticeship. Highest educational attainment refers to the highest observed education for an individual’s observed educational history. The width of each band corresponds to the share of individuals from the starting group pursuing different education options during or after their apprenticeship.

These findings are at first glance counterintuitive. The canonical framing of apprenticeship in the U.S. policy debate positions it as a substitute for traditional postsecondary education — an alternative pathway through which workers can acquire marketable credentials without incurring the time and costs associated with a college degree. Yet the evidence presented here suggests that for a substantial share of participants, apprenticeship functions less as a terminal alternative to college and more as an on-ramp toward it: Participants complete an apprenticeship and then continue along postsecondary educational trajectories, ultimately attaining credentials that are conventionally associated with the college track. This pattern is consistent with a view of apprenticeship as a complement to, rather than a substitute for, higher education, and complicates straightforward assessments of where apprenticeship sits within the broader postsecondary credentialing landscape. It also warrants caution in interpreting the effects of apprenticeship participation, since post-apprenticeship educational investment is itself a meaningful outcome that could mediate longer-run labor market returns.

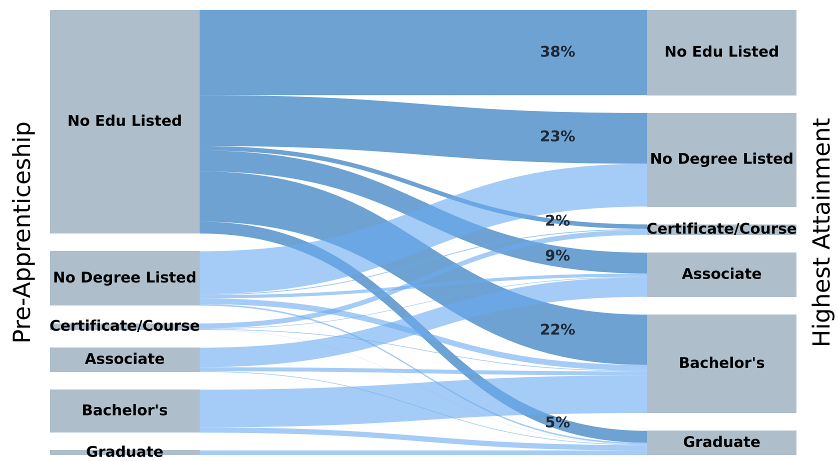
4.3 Heterogeneity and Apprenticeship Field Alignment

We now turn to differences in apprentice educational attainment by occupational field. Figure 8 decomposes attainment flows for two occupational archetypes: skilled trades (natural resources, construction, and maintenance) and white-collar occupation (management, business, science, and arts). At entry (left), skilled trade apprentices (Panel A) are heavily concentrated in the no-education and no-degree nodes; we observe field-aligned credentials for only 1.4 percent of these apprentices. Despite this, visible flows reach the bachelor's and graduate degree categories on the right, consistent with the 22 percent bachelor's and 5 percent graduate attainment rates for skilled trade apprentices with no prior credentials. For the skilled trades, the apprenticeship appears to be associated with further postsecondary enrollment after apprenticeship participation, even among those who enter with little or no formal educational background.

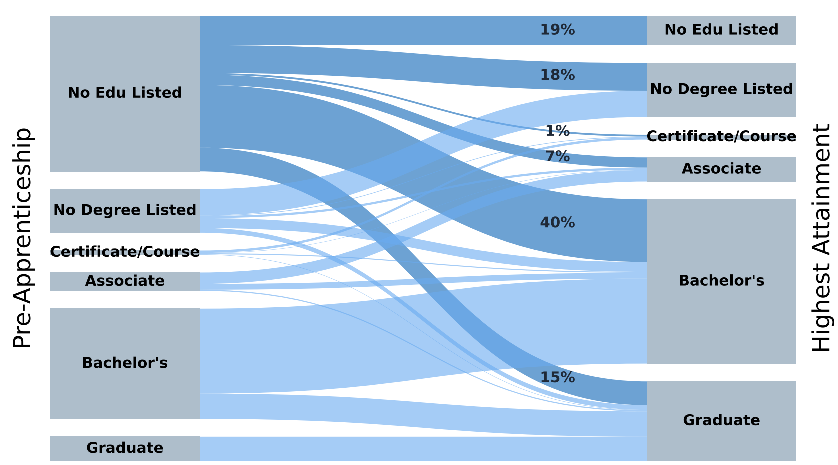
The picture is different for management, business, sciences, and arts apprentices (Figure 8, Panel B): The left-side nodes reflect a much more credential-rich starting point, with a larger share of entrants already having some postsecondary education. The flows toward bachelor's and graduate degrees are correspondingly stronger — among those entering with no prior education observed, 40 percent ultimately earn a bachelor's and 15 percent a graduate degree — and the overall pattern is one of credential stacking rather than credential pivoting. Together, the two figures make visually explicit that the apprenticeship-to-college pipeline exists across occupation groups, but its character varies fundamentally. For trades apprentices, it is an unexpected on-ramp for individuals who entered with little formal education; for white-collar apprentices, it is a continuation of a credential-accumulation trajectory that was already under way.

Figure 8: Pre-Apprenticeship vs. Highest Educational Attainment by Occupation Group

Panel A. Natural resources, construction, maintenance



Panel B. Management, business, science, and arts



Source: Lightcast U.S. Worker Profiles
Note: Pre-apprenticeship educational levels are the most recent educational attainment before the start year of the individual's first observed apprenticeship. Highest educational attainment refers to the highest observed education for an individual's observed educational history. The width of each band corresponds to the share of individuals from the starting group pursuing different education options during or after their apprenticeship.

Given this marked, and heterogeneous, overlap between apprenticeship and traditional postsecondary credentials, we now examine how workers actually use apprenticeships within their broader career pathways. An apprenticeship might serve as a bridge into a new field, drawing in workers whose prior jobs and studies lie elsewhere; alternatively, it might serve to deepen expertise within a field in which a worker is already established. To distinguish these possibilities, we measure the degree of alignment between the occupational field of the apprenticeship and the fields of a worker's activities before and after it — both prior and subsequent jobs and any postsecondary study.

We summarize this alignment using *occupational group match rates*. We assign every apprenticeship, job, and field of study to one of five broad occupation groups (Section 3), and a worker's activity is said to *match* the apprenticeship when the two fall in the same group. To fix ideas, consider two stylized apprentices. The first enters an electrician apprenticeship — part of the natural resources, construction, and maintenance group — after working in retail sales. Because that prior job belongs to a different group, this worker is counted as *unmatched* before the apprenticeship. The second enters a data-analytics apprenticeship in the business, management, sciences, and arts group after working as a junior analyst, an occupation in that same group; this worker is counted as *matched*. A group's match rate is simply the share of its apprentices who, like the second worker, were already active in the apprenticeship's own occupational group. A low pre-apprenticeship match rate therefore signals that apprentices arrive from outside the field — consistent with apprenticeship as a point of entry — while a high rate signals continuity within a field the worker has already begun.

Table 1 reports these match rates at two successive transitions along the career pathway. Column (1) gives the share of apprentices whose job immediately *before* the apprenticeship matched its occupational group ("Pre-Apprenticeship Job to Apprenticeship"),[17] and column (2) gives the analogous share for the first job observed *after* the apprenticeship ("Apprenticeship to Post-Apprenticeship Job"). The remaining columns summarize the movement between the two in complementary ways: Column (3) reports the absolute change in percentage points, and column (4) expresses that same change relative to the column (1) baseline. We report both because a given percentage-point gain represents a much larger proportional shift when it starts from a low base — an increase of 17 points on a base of 19 percent nearly doubles the match rate — and it is the relative change in column (4) that makes such differences in scale visible.

Reading across the rows reveals a contrast between the skilled trades and white-collar occupations. Consider first the natural resources, construction, and maintenance group. Only 19.3 percent of these apprentices held a matched occupation before entering the apprenticeship (column 1); afterward, 36.2 percent did (column 2) — a gain of 16.9 percentage points (column 3), or an 87.8 percent increase over the low starting base (column 4). Most trades apprentices, in other words, arrive from outside the field, and the appren-

[17] A related contextual question is whether the apprenticeship tends to represent an entry point into an apprenticeable profession or a career pivot after working in a different field. There is not a drastically different pre-apprenticeship to apprenticeship occupation match rate among those who entered an apprenticeship with a relatively short pre-apprenticeship career profile (match rate of 30.8 percent among those with less than five years of listed vocation prior to the apprenticeship) as compared with those who entered with a career profile of over five years (35.4 percent).

ticeship roughly doubles the share working within it. The business, management, sciences, and arts group looks entirely different: 54.5 percent already held a matched occupation beforehand and 66.7 percent did afterward, a smaller 12.3-point gain built on an already high base. The decisive contrast lies in the pre-apprenticeship column: Few workers entering a skilled-trades apprenticeship were already working in the trades, whereas a majority of those entering business and management apprenticeships came from within the same occupational field.

Table 1: Apprenticeship Occupational Group Match Rates

	(1) Pre-Appr. Job to Apprenticeship (%)	(2) Apprenticeship to Post-Appr. Job (%)	(3) Absolute Change (p.p.)	(4) Relative Change (%)
All	35.6	48.5	12.9	36.1
Occupation Groups				
Nat. Res., Construction, Maintenance	19.3	36.2	16.9	87.8
Production, Transportation	21.6	27.7	6.1	28.3
Service	29.5	38.2	8.7	29.3
Sales and Office	25.8	27.4	1.6	6.3
Mgmt., Business, Sciences, Arts	54.5	66.7	12.3	22.5
N	146,031	146,031	–	–

Source: Lightcast U.S. Worker Profiles. *Note*: Sample includes all individuals with jobs preceding and following their first observed apprenticeship. Column 1 reflects occupation match rates from the position directly before the apprenticeship to the first observed apprenticeship. Column 2 reflects occupation match rates from the first observed apprenticeship to the position directly after the apprenticeship. Column 3 is the absolute change between Columns 1 and 2, in percentage points. Column 4 is the same change expressed relative to the Column 1 baseline, in percent.

This divergence points to fundamentally different roles that apprenticeship can play depending on occupation type. For construction and the skilled trades, the apprenticeship appears to serve frequently as a vehicle for occupational entry — a structured mechanism through which workers from outside the industry gain the credentials and experience needed to transition into the field. For white-collar occupations such as business and management, apprenticeship can more closely resemble an in-field advancement tool: Many participants are already embedded in the relevant occupational domain and use the apprenticeship to deepen skills, formalize expertise, or stack credentials within a career they have already begun. These contrasting patterns underscore that apprenticeship is not a monolithic institution and that interpreting its role in the labor market requires close attention to occupational context.

We next ask whether this pattern reflects prior *schooling* as well as prior work. Table 2 repeats the exercise for the subsample of apprentices who record some postsecondary fenrollment before their first apprenticeship, replacing the prior job in column (1) with the prior *field of study* as the measure of alignment; column (2) again reports the match between the apprenticeship and the first post-apprenticeship job. Returning to our two stylized apprentices, the question is no longer where each worked before the apprenticeship but what each studied: whether the electrician apprentice had previously enrolled in a construction-related program and whether the data-analytics apprentice had studied a business- or data-related field.

The educational baseline, reported in Table 2, reinforces and in fact sharpens the picture from Table 1. Among natural resources, construction, and maintenance apprentices, only 6.6 percent had studied in a field aligned with their apprenticeship — even lower than the 19.3 percent whose prior *job* was aligned (Table 1). The same holds in production and transportation (3.8 percent) and sales and office (6.0 percent). For the great majority of skilled-trades apprentices, then, neither prior work nor prior schooling was in the apprenticeship's field: The apprenticeship marks a genuine pivot. Business, management, sciences, and arts apprentices are once again the mirror image, with 97.6 percent having studied in a matching field — nearly double their already high 54.5 percent job-match rate. Their post-apprenticeship job-match rate (column 2) is 71.9 percent, 5.2 percentage points above the 66.7 percent in Table 1, confirming that the forward leg of the pathway looks much the same whether we begin from prior work or prior study.

Table 2: Occupational Group Match Rates: Pre-Apprenticeship Education to Post-Apprenticeship Job

	(1)	(2)	(3)	(4)
	Pre-Appr. Edu. to Apprenticeship (%)	Apprenticeship to Post-Appr. Job (%)	Absolute Change (p.p.)	Relative Change (%)
All	51.9	53.6	1.7	3.3
Occupation Groups				
Nat. Res., Construction, Maintenance	6.6	37.9	31.3	476.6
Production, Transportation	3.8	27.0	23.2	606.2
Service	22.2	43.3	21.1	94.7
Sales and Office	6.0	29.5	23.5	393.3
Mgmt., Business, Sciences, Arts	97.6	71.9	-25.7	-26.4
# of Individuals	64,443	64,443	–	–
N	403,563	403,563	–	–

Source: Lightcast U.S. Worker Profiles, National Career Clusters Framework (NCCF) Crosswalk. *Note*: Sample includes individuals with both pre-apprenticeship CIP and post-apprenticeship job observations. The NCCF crosswalk is used to map CIP to occupation. It is possible one CIP may match to multiple occupations. All occupation options are included in match rate calculations. Column 1 reflects occupation match rates from postsecondary education before the apprenticeship to the first observed apprenticeship. Column 2 reflects occupation match rates from the first observed apprenticeship to the position directly after the apprenticeship. Column 3 is the absolute change between Columns 1 and 2, in percentage points. Column 4 is the same change expressed relative to the Column 1 baseline, in percent.

Taken together, Tables 1 and 2 tell a story in which prior work experience and prior education point in the same direction. For trades apprentices, the apprenticeship is more typically an entry point and career pivot, drawing in participants from outside the field in both occupational and educational terms; for white-collar apprentices, it is more commonly the continuation and formalization of a pathway already well under way.

A final question turns the lens forward: When apprentices go on to further schooling, is that schooling in the apprenticeship's own field? Table 3 addresses this for the subsample who pursue postsecondary education during or after their first apprenticeship, with column (2) now measuring the match between the apprenticeship and the *subsequent field of study*. The contrast is at its starkest here. Business, management, sciences, and arts apprentices who continue their education overwhelmingly do so within the field: Their field-of-study match rate reaches 98.4 percent, a 48.3 percentage-point increase over the 50.2 percent whose prior job was aligned. The other groups move in the opposite direction. Only 5.4 percent of natural resources, construction, and maintenance apprentices who pursue further education do so in an aligned field, with similarly low rates in production and transportation (3.5 percent) and sales and office (5.3 percent). The on-ramp to college documented in Section 4.2 is, for trades apprentices, largely an on-ramp to *other* fields: When they continue their schooling, it typically leads away from the trade in which they apprenticed, whereas white-collar apprentices use additional schooling to deepen the field they are already in.

Table 3: Occupational Group Match Rates: Pre-Apprenticeship Job to Post-Apprenticeship Education

	(1) Pre-Appr. Job to Apprenticeship (%)	(2) Apprenticeship to Post-Appr. Edu. (%)	(3) Absolute Change (p.p.)	(4) Relative Change (%)
All	33.5	50.1	16.5	49.4
Occupation Groups				
Nat. Res., Construction, Maintenance	15.6	5.4	-10.2	-65.6
Production, Transportation	19.0	3.5	-15.5	-81.8
Service	28.1	14.8	-13.3	-47.2
Sales and Office	25.6	5.3	-20.3	-79.4
Mgmt., Business, Sciences, Arts	50.2	98.4	48.3	96.2
# of Individuals	54,869	54,869	–	–
N	372,623	372,623	–	–

Source: Lightcast U.S. Worker Profiles, National Career Clusters Framework (NCCF) Crosswalk. *Note*: Sample includes individuals with both pre-apprenticeship job and post-apprenticeship CIP observations. The NCCF crosswalk is used to map CIP to occupation. It is possible one CIP may match to multiple occupations. All occupation options are included in match rate calculations. Column 1 reflects occupation match rates from the position directly before the apprenticeship to the first observed apprenticeship. Column 2 reflects occupation match rates from the first observed apprenticeship to postsecondary education during or after the apprenticeship. Column 3 is the absolute change between Columns 1 and 2, in percentage points. Column 4 is the same change expressed relative to the Column 1 baseline, in percent.

5 Conclusion

In this paper, we use novel data to document new stylized facts about apprenticeship pathways in the United States — pathways that existing data sources have been poorly positioned to reveal. Unlike contexts from elsewhere in the world where apprenticeship is tightly integrated into formal postsecondary pathways and supported by standardized data infrastructure, basic empirical questions about who participates in U.S.

apprenticeship, how it relates to the broader postsecondary system, and how apprentices are compensated in the labor market have remained only partially answered.

Our analysis indicates that a substantial share of apprentices who arrive with no prior education on record — roughly 40 percent, and 55 percent among white-collar participants — ultimately attain a bachelor's degree or higher, challenging the conventional view of apprenticeship as a substitute for postsecondary education. Pathways differ fundamentally across sectors: Skilled trades apprentices often enter from outside their field and use the program as an occupational entry point, while white-collar apprentices more often arrive with aligned prior credentials and use it to stack qualifications within an ongoing career trajectory. Together, the evidence positions apprenticeship less as a monolithic alternative to college and more as a heterogeneous institution whose relationship to the formal education system depends critically on occupational context.

These findings have important implications for how apprenticeship programs continue to be evaluated and supported. Funding and accountability frameworks that fail to recognize the relationship between apprenticeship and other postsecondary degree options — treating apprenticeship as a self-contained workforce training program — miss the reality of how apprentices move through the postsecondary system. The prevalence of other postsecondary participation before, during, and after the apprenticeship raises key questions about how to coordinate funding streams across often disparate education and workforce systems, how to recognize on-the-job-training in educational credential systems and vice versa, how to design accountability systems that incorporate a multitude of skill-building pathways, and more generally, how to understand costs and benefits across different types of students and workers. Data on individual pathways to and through apprenticeship are key to answering these questions and have the potential to continue to provide important insights.

References

Acemoglu, D. and J.-S. Pischke (1998): "Why Do Firms Train? Theory and Evidence*," *Quarterly Journal of Economics*, 113, 79–119.

Bahn, K. and W. Halpin (2018): "Wage Gaps and Outcomes in Apprenticeship Programs," Tech. rep., Center for American Progress.

Bauernschuster, S., O. Falck, and S. Heblich (2009): "Training and Innovation," *Journal of Human Capital*, 3, 323–353.

Council of Economic Advisers (2024): "All Aboard the ApprenticeSHIP: Assessing the Changing Face of Registered Apprenticeships," https://www.whitehouse.gov/cea/written-materials/2024/11/20/all-aboard-the-apprenticeship/, accessed: 2026-02-08.

Darolia, R. and J. Turner (2026): "Apprenticeships in the United States: Emerging Opportunities and Evidence Gaps," *Journal of Policy Analysis and Management*, 45, e70082.

Dionisius, R., S. Muehlemann, H. Pfeifer, G. Walden, F. Wenzelmann, and S. C. Wolter (2009): "Cost and Benefit of Apprenticeship Training: A Comparison of Germany and Switzerland," Discussion Paper 3465, IZA.

Helper, S., R. Noonan, J. R. Nicholson, and D. Langdon (2016): "The Benefits and Costs of Apprenticeships: A Business Perspective," Tech. rep., U.S. Department of Commerce.

Institute for Women's Policy Research (2024): "Gender, Race, and the Wage Gap in Apprenticeship," Tech. rep., Washington, DC.

Katz, B., R. I. Lerman, D. Kuehn, and J. Shakesprere (2022): "Did Apprentices Achieve Faster Earnings Growth Than Comparable Workers? Findings from the American Apprenticeship Initiative Evaluation," Tech. rep., Urban Institute, Washington, DC.

Krueger, D. and K. B. Kumar (2004): "Skill-Specific Rather than General Education: A Reason for US-Europe Growth Differences?" *Journal of Economic Growth*, 9, 167–207.

Lerman, R. and T. Jacoby (2019): "Industry-Driven Apprenticeship What Works, What's Needed," Tech. rep., Opportunity America.

Lerman, R. I. (2014): "Do Firms Benefit from Apprenticeship Investments?" *IZA World of Labor*.

Lerman, R. I., L. Eyster, and K. Chambers (2009): "The Benefits and Challenges of Registered Apprenticeship: The Sponsors' Perspective," Tech. rep., U.S. Department of Labor, Employment and Training Administration, Washington, DC.

Muehlemann, S. and S. C. Wolter (2014): "Return on Investment of Apprenticeship Systems for Enterprises: Evidence from Cost-Benefit Analyses," *IZA Journal of Labor Policy*, 3, 1–22.

Reed, D., A. Yung-Hsu Liu, R. Kleinman, A. Mastri, D. Reed, S. Sattar, and J. Ziegler (2012): "An Effectiveness Assessment and Cost-Benefit Analysis of Registered Apprenticeship in 10 States," Tech. rep., Mathematica Policy Research, U.S. Department of Labor.

Ryan, P. (2001): "The School-to-Work Transition: A Cross-National Perspective," *Journal of Economic Literature*, 39, 34–92.

Schanzenbach, D. W. and S. Turner (2022): "Limited Supply and Lagging Enrollment: Production Technologies and Enrollment Changes at Community Colleges During the Pandemic," *Journal of Public Economics*, 212, 104703.

Tsvetkova, A., E. D'Amico, A. Lembcke, P. Knutsson, and W. Vermeulen (2024): "How Well Do Online Job Postings Match National Sources in Large English-Speaking Countries? Benchmarking Lightcast Data Against Statistical Sources Across Regions, Sectors and Occupations," Tech. Rep. 2024/01, OECD Publishing.

U.S. Bureau of Labor Statistics (2025): "Job Openings and Labor Turnover survey (JOLTS): Hires Level, Business and Professional Services (Series ID: JTU540099000000000HIL)," https://data.bls.gov/timeseries/JTU540099000000000HIL.

U.S. Department of Labor (2022): "Beyond Productivity: Employer Gains from Apprenticeship," Tech. Rep. ETAOP 2022-40, Employment and Training Administration.

——— (2026): "Apprenticeship," https://www.dol.gov/general/topic/training/apprenticeship, accessed: 2026-02-08.

U.S. Department of Labor, Employment and Training Administration (2021): "FY 2021 Data and Statistics: Registered Apprenticeship National Results," Fiscal Year 2021 (October 1, 2020 to September 30, 2021), 593,690 active apprentices.

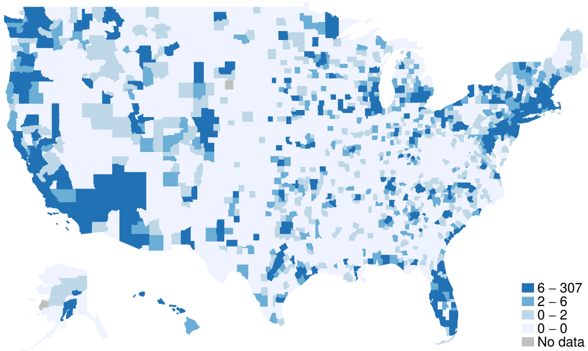
U.S. Government Accountability Office (2025): "Apprenticeship: Earn-and-Learn Opportunities Can Benefit Workers and Employers," Tech. Rep. GAO-25-107040, U.S. Government Accountability Office.

Wolter, S. C. and P. Ryan (2011): "Apprenticeship," in *Handbook of the Economics of Education*, ed. by E. A. Hanushek, S. Machin, and L. Woessmann, Amsterdam: Elsevier, vol. 3, chap. 11, 521–576.

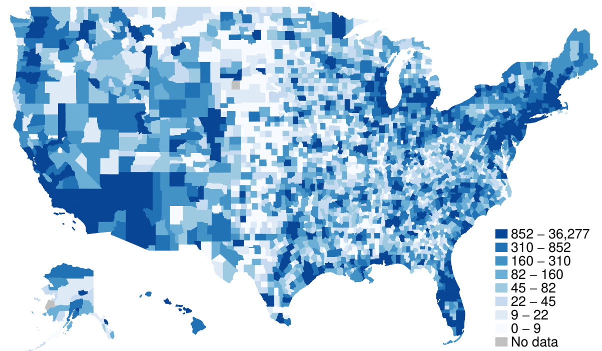
Appendix A: Additional Figures and Tables

Figure A1: Map of Apprenticeship Postings (County-Level)

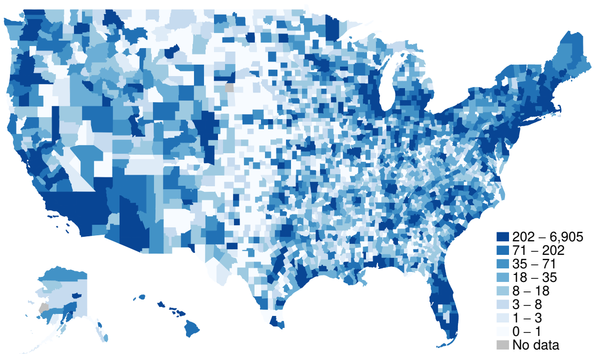
Panel A. Apprenticeship Using Title



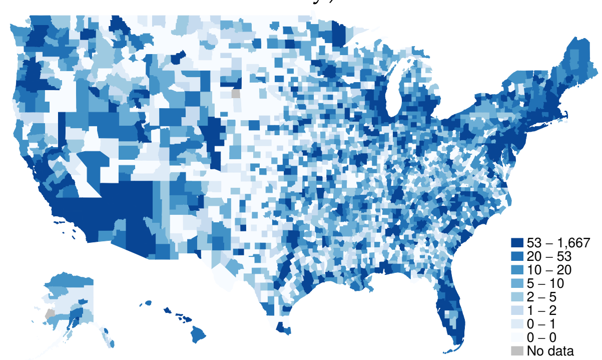
Panel B. Apprenticeship Using Text



Panel C. Apprenticeship Using URL (all)

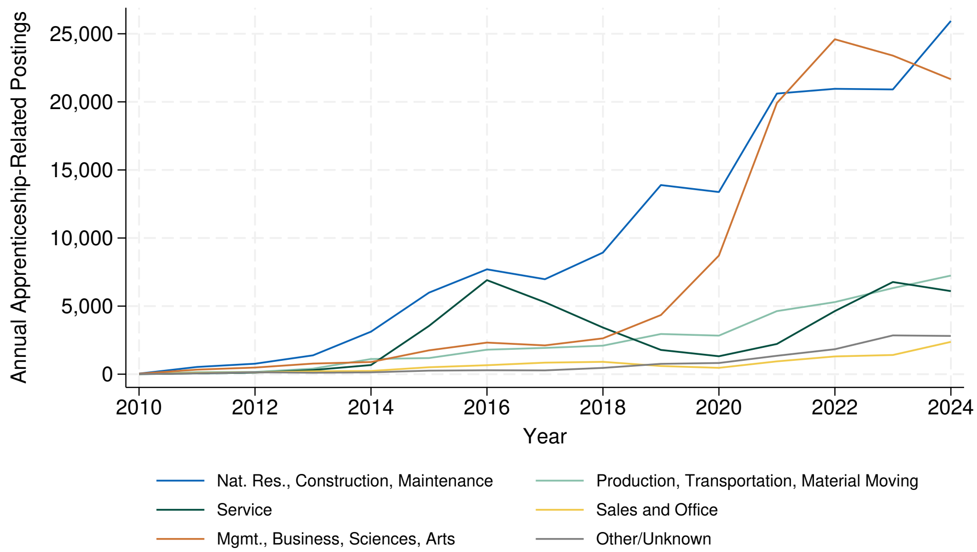


Panel D. Apprenticeship Using URL (Registered Only)



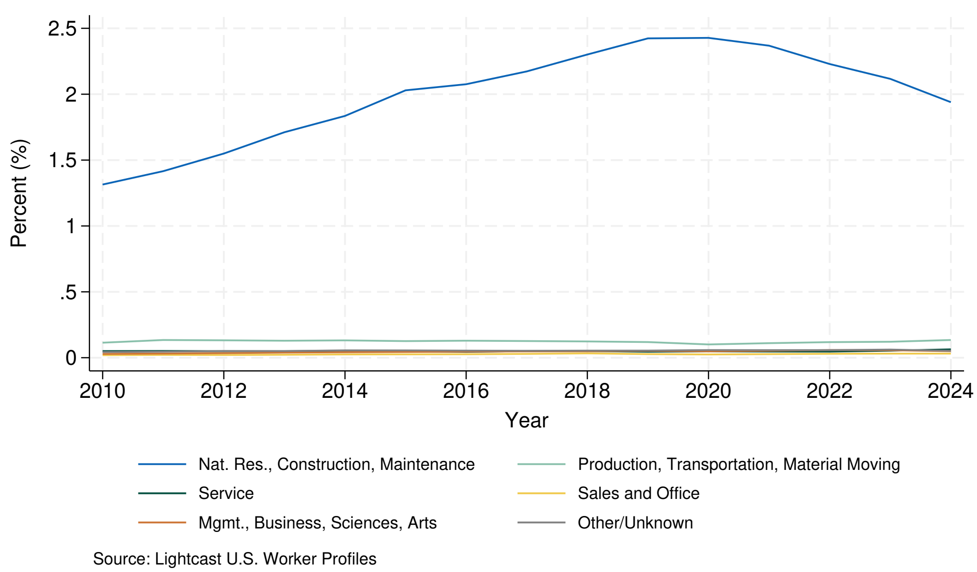
Source: Lightcast U.S. Job Postings
Note: Both figures show the number of apprenticeship postings in each county. In Panel A, apprenticeship postings are identified using the Lightcast variable title. Panel B identifies apprenticeship postings using Lightcast variable body text. Panel C and D identify apprenticeship postings using Lightcast variable URL, but Panel D restricts to only registered apprenticeships as proxied by posting to apprenticeship.gov.

Figure A2: Annual Apprenticeship-Related Job Postings



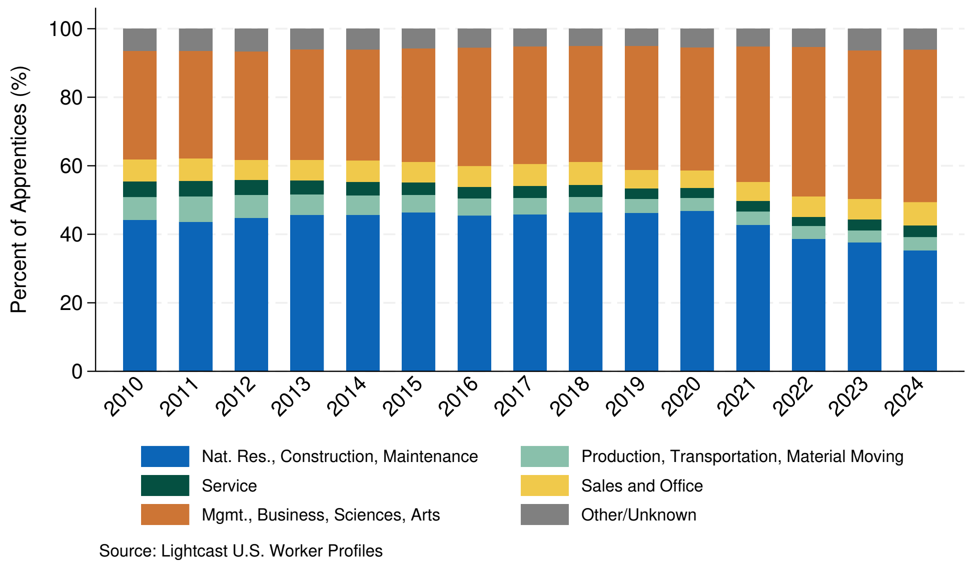
Source: Lightcast U.S. Job Postings
Note: This figure shows the number of apprenticeship-related postings over time by occupation grouping. A posting is considered apprenticeship-related using the URL method described in Section 3. Postings are reported in aggregated counts by year from 2010 to 2024. Apprenticeship-related job postings are binned into six occupation groups. Occupation group breakdowns can be found in Appendix B.

Figure A3: Percent of Workforce That Is an Apprentice by Occupation Group



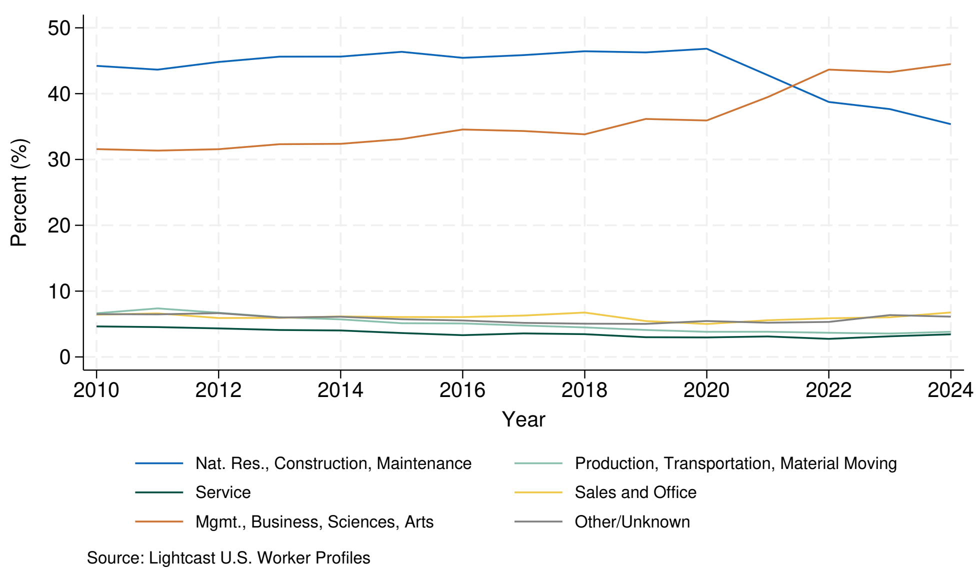
Source: Lightcast U.S. Worker Profiles
Note: Years 2010 to 2024. Percents calculated using year-aggregated apprenticeship and workforce counts. Occupation group breakdowns can be found in Appendix B.

Figure A4: Apprenticeship by Occupation Group



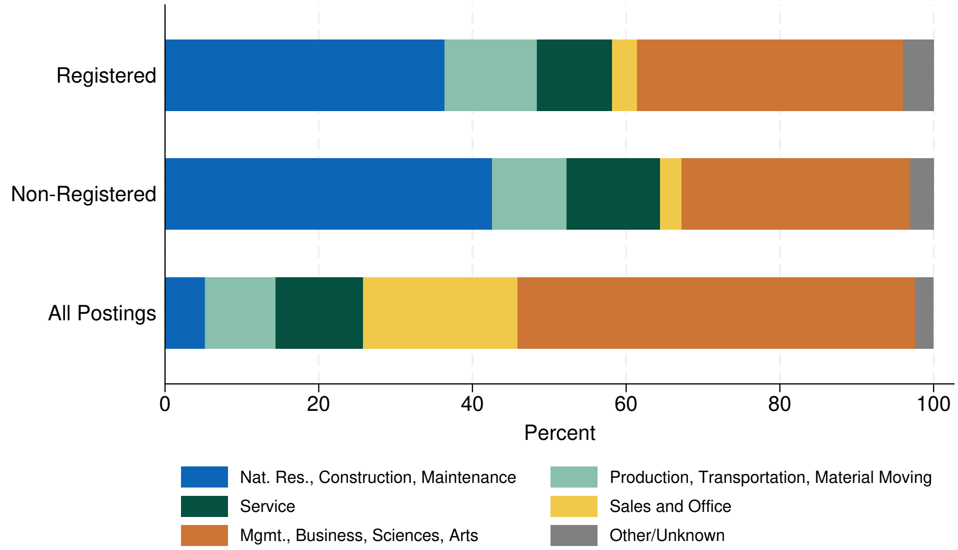
Source: Lightcast U.S. Worker Profiles
Note: Years 2010 to 2024. Percents calculated using year-aggregated apprenticeship and workforce counts. Occupation group breakdowns can be found in Appendix B.

Figure A5: Share of Apprentices by Occupation Group



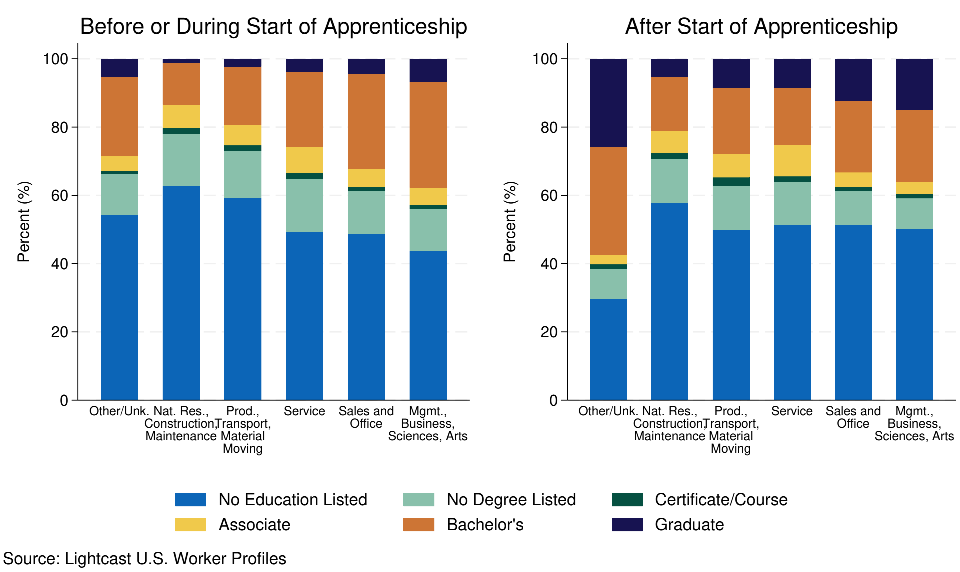
Source: Lightcast U.S. Worker Profiles
Note: Years 2010 to 2024. Percents calculated using year-aggregated apprenticeship and workforce counts. Occupation group breakdowns can be found in Appendix B.

Figure A6: Apprenticeship Postings by Registered Apprenticeship Status (SOC)



Source: Lightcast U.S. Job Postings
Note: This figure shows the number of postings by occupation grouping and apprenticeship status. A posting is considered apprenticeship-related and registered if it appears on apprenticeships.gov. Non-registered apprenticeships are those that are identified as apprenticeship-related using the URL method but do not appear on apprenticeship.gov. All postings include both apprenticeship *and* non-apprenticeship-related postings. More details on these classifications can be found in Section 3. Postings from 2010 to 2024 are reported in aggregated counts and are binned into six occupation groups. Occupation group breakdowns can be found in Appendix B.

Figure A7: Educational Attainment: Before vs. After Start of Apprenticeship



Source: Lightcast U.S. Worker Profiles
Note: Educational levels for each apprentice are the most recent educational attainment after the start year of the individual's first observed apprenticeship. Each bar represents total apprenticeships in the indicated occupation group, with segments showing the percentage contribution of each educational attainment. Occupation group breakdowns can be found in Appendix B.

Table A1: Educational Attainment Before and After Apprenticeship

Educational Attainment	Pre-Appr. #	Post-Appr. #	# Difference	Pre-Appr. %	Post-Appr. %	% Difference
No Education Listed	152,271	147,553	–4,718	54.07	52.40	–1.67
No Degree Listed	38,818	31,535	–7,283	13.78	11.20	–2.58
Certificate/Course	4,219	4,330	111	1.50	1.54	0.04
Associate	16,786	14,719	–2,067	5.96	5.23	–0.73
Bachelor's	58,879	54,077	–4,802	20.91	19.20	–1.71
Graduate	10,634	29,393	18,759	3.78	10.44	6.66
Total	281,607	281,607	-	100.00	100.00	-

Source: Lightcast U.S. Worker Profiles

Note: Pre-apprenticeship is defined as the most recent educational attainment before or at the start year of the individual's first observed apprenticeship. Post-apprenticeship is defined as the most recent educational attainment after the start year of the individual's first observed apprenticeship. Differences are calculated for each educational attainment level.

Table A2: Educational Attainment Before and After Apprenticeship: Construction, Maintenance, Natural Resources

Educational Attainment	Pre-Appr. #	Post-Appr. #	# Difference	Pre-Appr. %	Post-Appr. %	% Difference
No Education Listed	77,245	70,983	–6,262	62.77	57.68	–5.09
No Degree Listed	18,779	16,082	–2,697	15.26	13.07	–2.19
Certificate/Course	2,241	2,097	–144	1.82	1.70	–0.12
Associate	8,355	7,859	–496	6.79	6.39	–0.40
Bachelor's	14,848	19,718	4,870	12.07	16.02	3.95
Graduate	1,585	6,314	4,729	1.29	5.13	3.84
Total	123,053	123,053	-	100.00	100.00	-

Source: Lightcast U.S. Worker Profiles

Note: Natural Resources, Construction, and Maintenance occupation group only. Pre-apprenticeship is defined as the most recent educational attainment before or at the start year of the individual's first observed apprenticeship. Post-apprenticeship is defined as the most recent educational attainment after the start year of the individual's first observed apprenticeship. Differences are calculated for each educational attainment level.

Table A3: Educational Attainment Before and After Apprenticeship: Business, Management, Science, Arts

Educational Attainment	Pre-Appr. #	Post-Appr. #	# Difference	Pre-Appr. %	Post-Appr. %	% Difference
No Education Listed	42,923	49,232	6,309	43.70	50.12	6.42
No Degree Listed	12,011	8,840	–3,171	12.23	9.00	–3.23
Certificate/Course	1,155	1,255	100	1.18	1.28	0.10
Associate	5,061	3,535	–1,526	5.15	3.60	–1.55
Bachelor's	30,412	20,778	–9,634	30.96	21.15	–9.81
Graduate	6,664	14,586	7,922	6.78	14.85	8.07
Total	98,226	98,226	-	100.00	100.00	-

Source: Lightcast U.S. Worker Profiles

Note: Management, Business, Sciences, and Arts occupation group only. Pre-apprenticeship is defined as the most recent educational attainment before or at the start year of the individual's first observed apprenticeship. Post-apprenticeship is defined as the most recent educational attainment after the start year of the individual's first observed apprenticeship. Differences are calculated for each educational attainment level.

Appendix B: Additional Data Details

Before pursuing apprenticeship-specific data cleaning, we complete a general cleaning of both the jobs and educations tables in Profiles. In the job history data, we remove rows if they are missing dates and/or their corresponding job title is unintelligible to reduce noise (numbers, symbols, etc.). Examples include single letters or numbers such as "a" or "1." We also remove rows where individuals indicate they were not actively employed using an inclusive keyword search. Examples of such job titles are "retired," "parent," and "unemployed." In the education data, we remove rows if there was an observed exact duplicate. For some individuals, there exist rows with partially missing data that complete each other. We consolidate these rows into one row containing all available information.

Following general cleaning, we filter the jobs table to include only those with observed apprenticeships. We keep relevant variables at three points in time — at the time of the first observed apprenticeship and directly before and after. We then join the clean education table to obtain a full picture of an individual's pathway. We group education data into three categories — pre-apprenticeship, post-apprenticeship, and highest attainment regardless of apprenticeship timing. We generate variables based on the start year of an individual's apprenticeship. If more than one apprenticeship is observed for a single individual, we use the first occurrence observed. We restrict the final analytical data set to one apprenticeship per individual to promote comparability across observations.

Two-digit SOC occupation codes for each group:

1. Natural Resources, Construction, and Maintenance
   45: Farming, Fishing, and Forestry
   47: Construction and Extraction
   49: Installation, Maintenance, and Repair

2. Production, Transportation, and Material Moving
   51: Production
   53: Transportation and Material Moving
   55: Military Specific

3. Service
   31: Healthcare Support
   33: Protective Service
   35: Food Preparation and Serving Related
   37: Building and Grounds Cleaning and Maintenance
   39: Personal Care and Service

4. Sales and Office
   41: Sales and Related
   43: Office and Administrative Support

5. Management, Business, Sciences, and Arts
   11: Management

13: Business and Finance Operations
15: Computer and Mathematical
17: Architecture and Engineering
19: Life, Physical, and Social Science
21: Community and Social Service
23: Legal
25: Educational Instruction and Library
27: Arts, Design, Entertainment, Sports, and Media
29: Healthcare Practitioners and Technical

Appendix C: Industry Results

NAICS groups are based on five broad categories from (Darolia and Turner, 2026).

1. Skilled Trades, Manufacturing, and Utilities

   11: Agriculture, Forestry, Fishing and Hunting
   21: Mining, Quarrying, and Oil and Gas Extraction
   22: Utilities
   23: Manufacturing
   31-33: Construction

2. Transportation, Distribution, and Logistics

   42: Wholesale Trade
   44-45: Retail Trade
   48-49: Transportation and Warehousing
   51: Information

3. Health, Education, and Social Assistance

   56: Administrative and Support and Waste Management and Remediation Services
   61: Educational Services
   62: Health Care and Social Assistance

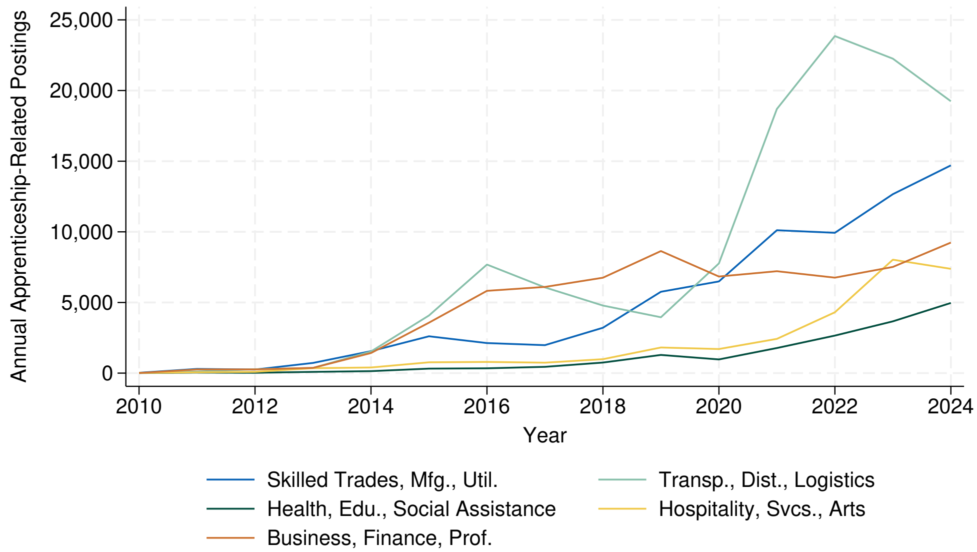
4. Hospitality, Services, and Arts

   71: Arts, Entertainment, and Recreation
   72: Accommodation and Food Services
   81: Other Services (except Public Administration)
   92: Public Administration

5. Business, Finance, and Professional

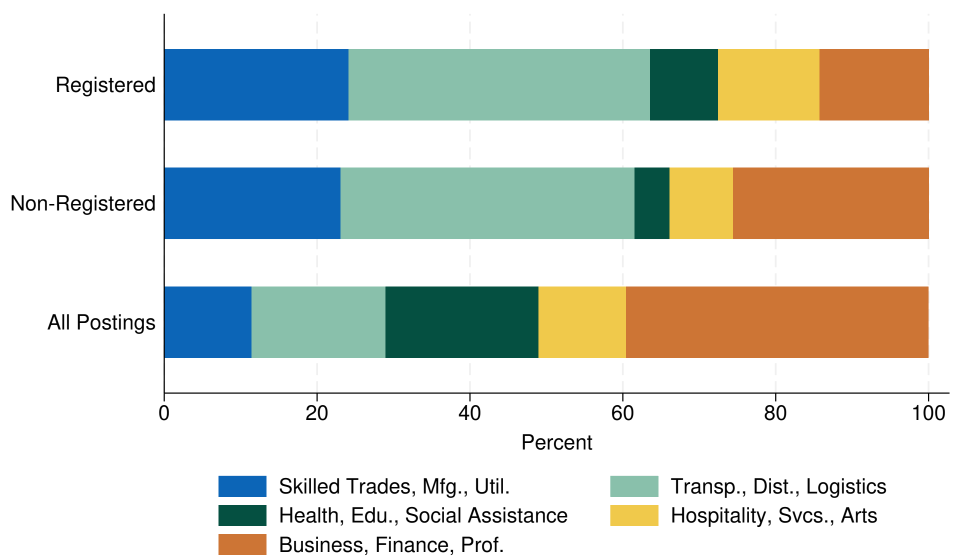
   52: Finance and Insurance
   53: Real Estate and Rental and Leasing
   54: Professional, Scientific, and Technical Services
   55: Management of Companies and Enterprises

Figure C1: Annual Apprenticeship-Related Job Postings (NAICS)



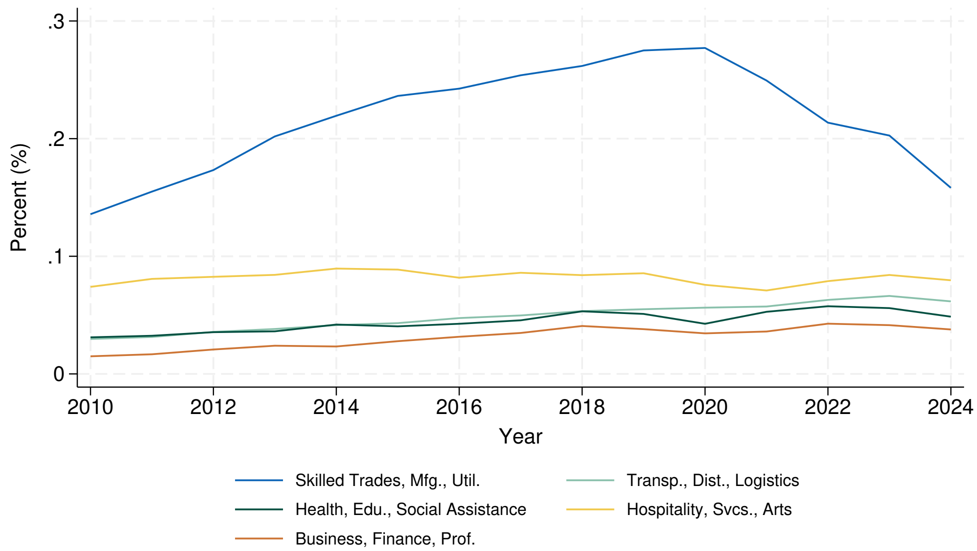
Source: Lightcast U.S. Job Postings
Note: A posting is considered apprenticeship-related if the URL contains an iteration of the keyword "apprentice." Postings are reported in aggregated counts by year from 2010 to 2024. Apprenticeship-related job postings are binned into five industry groups.

Figure C2: Apprenticeship Postings by Registered Apprenticeship Status (NAICS)



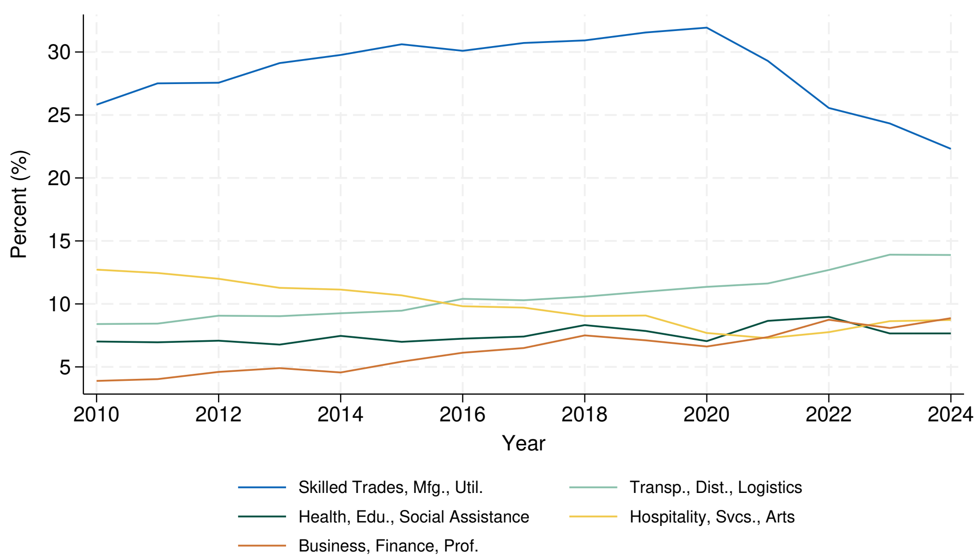
Source: Lightcast U.S. Job Postings
Note: A posting is considered apprenticeship-related if the URL contains an iteration of the keyword "apprentice." Postings are reported in aggregated counts by year from 2010 to 2024. Apprenticeship-related job postings are binned into five industry groups.

Figure C3: Percent of Workforce That Is an Apprentice by Industry Group



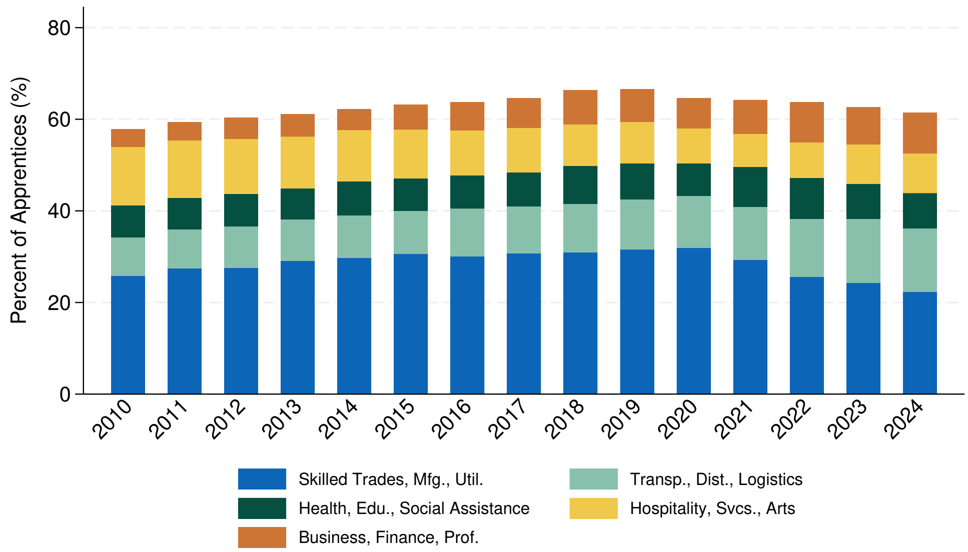
Source: Lightcast U.S. Worker Profiles
Note: Years 2010 to 2024. Percents calculated using year-aggregated apprenticeship and workforce counts.

Figure C4: Share of Apprentices by Industry Group



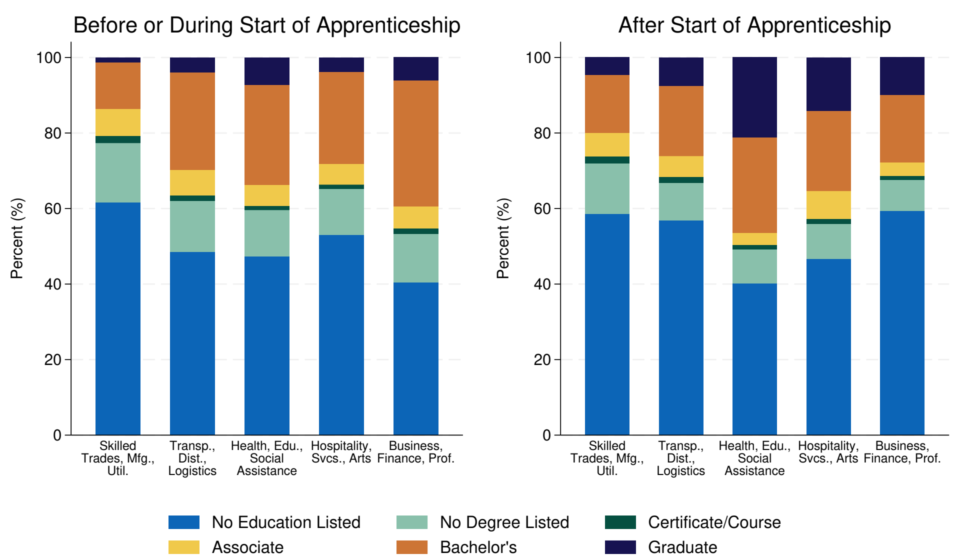
Source: Lightcast U.S. Worker Profiles
Note: Years 2010 to 2024. Percents calculated using year-aggregated apprenticeship and workforce counts.

Figure C5: Apprenticeship by Industry Group



Source: Lightcast U.S. Worker Profiles
Note: Years 2010 to 2024. Percents calculated using year-aggregated apprenticeship and workforce counts.

Figure C6: Educational Attainment: Before vs. After Start of Apprenticeship



Source: Lightcast U.S. Worker Profiles
Note: Educational levels for each apprentice are the most recent educational attainment after the start year of the individual's first observed apprenticeship. Each bar represents total apprenticeships in the indicated industry group, with segments showing the percentage contribution of each educational attainment.

Table C1: Industry Group Match Rates

	(1) Pre-Appr. Job to Apprenticeship (%)	(2) Apprenticeship to Post-Appr. Job (%)	(3) Absolute Change (p.p.)	(4) Relative Change (%)
All	23.1	43.9	20.8	90.2
Industry Groups				
Skilled Trades, Mfg., Util.	17.8	44.0	26.3	147.8
Transp., Dist., Logistics	28.0	41.6	13.6	48.6
Health, Edu., Social Assistance	32.8	42.6	9.8	30.0
Hospitality, Svcs., Arts	26.6	46.0	19.4	73.2
Business, Finance, Prof.	20.1	44.9	24.8	123.1
N	104,901	104,901	-	-

Source: Lightcast U.S. Worker Profiles
Note: Sample includes all individuals with jobs preceding and following their first observed apprenticeship. Column 1 reflects industry match rates from the position directly before the apprenticeship to the first observed apprenticeship. Column 2 reflects industry match rates from the first observed apprenticeship to the position directly after the apprenticeship. Columns 3 and 4 are the difference between Columns 1 and 2 in percentage points and percent, respectively.

Table C2: Industry Group Match Rates: Pre-Apprenticeship Education to Post-Apprenticeship Job

	(1) Pre-Appr. Edu. to Apprenticeship (%)	(2) Apprenticeship to Post-Appr. Job (%)	(3) Absolute Change (p.p.)	(4) Relative Change (%)
All	65.9	60.8	-5.1	-7.7
Industry Groups				
Skilled Trades, Mfg., Util.	45.5	61.1	15.6	34.4
Transp., Dist., Logistics	42.2	65.8	23.6	55.9
Health, Edu., Social Assistance	95.0	52.3	-42.7	-44.9
Hospitality, Svcs., Arts	96.6	57.0	-39.6	-41.0
Business, Finance, Prof.	68.2	68.1	-0.2	-0.2
# of Individuals	54,377	54,377	-	-
N	319,593	319,593	-	-

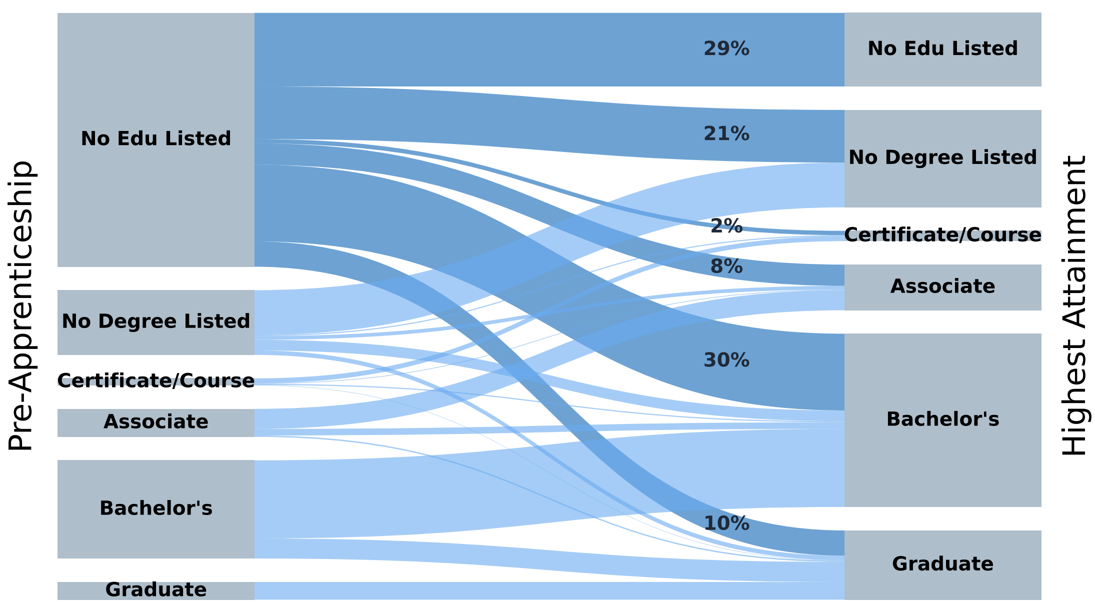
Source: Lightcast U.S. Worker Profiles, National Career Clusters Framework (NCCF) Crosswalk
Note: Sample includes individuals with both pre-apprenticeship CIP and post-apprenticeship job observations. The NCCF crosswalk is used to map CIP to industry. It is possible one CIP may match to multiple industries. All industry options are included in match rate calculations. Column 1 reflects industry match rates from postsecondary education before the apprenticeship to the first observed apprenticeship. Column 2 reflects industry match rates from the first observed apprenticeship to the position directly after the apprenticeship. Columns 3 and 4 are the difference between Columns 1 and 2 in percentage points and percent, respectively.

Table C3: Industry Group Match Rates: Pre-Apprenticeship Job to Post-Apprenticeship Education

	(1) Pre-Appr. Job to Apprenticeship (%)	(2) Apprenticeship to Post-Appr. Edu. (%)	(3) Absolute Change (p.p.)	(4) Relative Change (%)
All	42.4	74.5	32.2	76.0
Industry Groups				
Skilled Trades, Mfg., Util.	28.1	54.5	26.4	94.1
Transp., Dist., Logistics	42.3	46.8	4.5	10.6
Health, Edu., Social Assistance	56.5	97.0	40.6	71.8
Hospitality, Svcs., Arts	51.9	91.6	39.7	76.6
Business, Finance, Prof.	28.6	72.8	44.2	154.9
# of Individuals	104,901	104,901	-	-
N	291,729	291,729	-	-

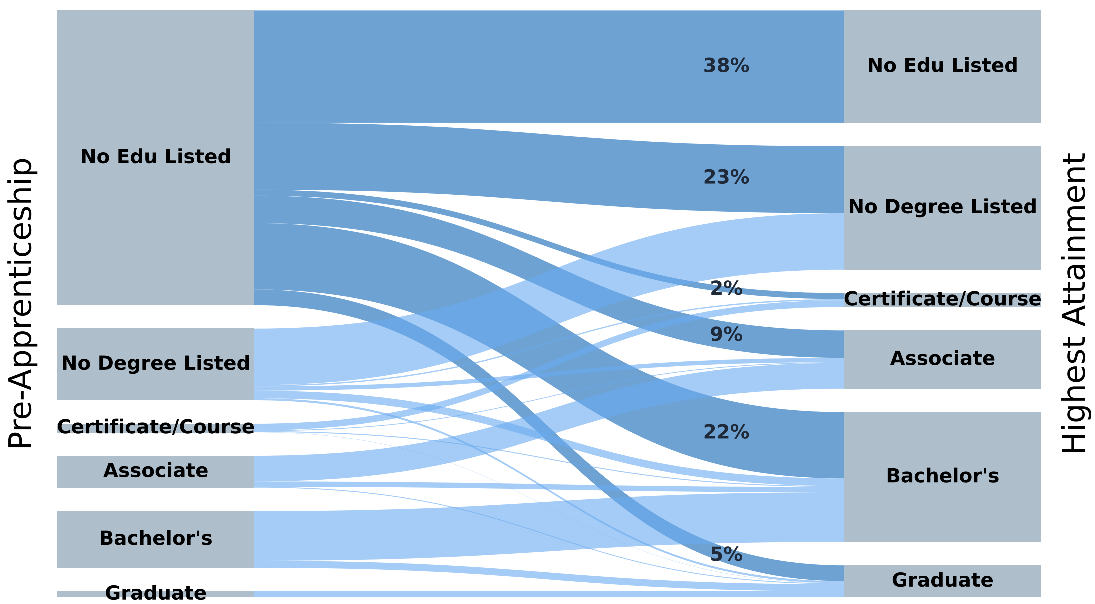
Source: Lightcast U.S. Worker Profiles, National Career Clusters Framework (NCCF) Crosswalk
Note: Sample includes individuals with both pre-apprenticeship job and post-apprenticeship CIP observations. The NCCF crosswalk is used to map CIP to industry. It is possible one CIP may match to multiple industries. All industry options are included in match rate calculations. Column 1 reflects industry match rates from the position directly before the apprenticeship to the first observed apprenticeship. Column 2 reflects industry match rates from the first observed apprenticeship to postsecondary education during or after the apprenticeship. Columns 3 and 4 are the difference between Columns 1 and 2 in percentage points and percent, respectively.

Figure C7: Pre-Apprenticeship vs. Highest Educational Attainment: All



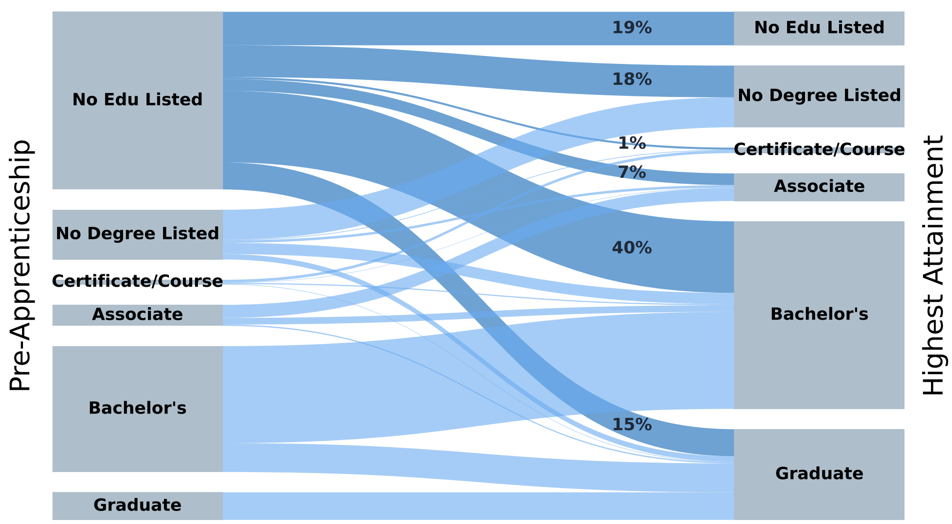
Source: Lightcast U.S. Worker Profiles
Note: Pre-apprenticeship educational levels are the most recent educational attainment before the start year of the individual's first observed apprenticeship. Highest educational attainment refers to the highest observed education for an individual's observed educational history. The width of each band corresponds to the share of individuals from the starting group pursuing different education options during or after their apprenticeship.

Figure C8: Pre-Apprenticeship vs. Highest Educational Attainment: Skilled Trades



Source: Lightcast U.S. Worker Profiles
Note: Pre-apprenticeship educational levels are the most recent educational attainment before the start year of the individual's first observed apprenticeship. Highest educational attainment refers to the highest observed education for an individual's observed educational history. The width of each band corresponds to the share of individuals from the starting group pursuing different education options during or after their apprenticeship.

Figure C9: Pre-Apprenticeship vs. Highest Educational Attainment: Business, Finance, Professional



Source: Lightcast U.S. Worker Profiles
Note: Pre-apprenticeship educational levels are the most recent educational attainment before the start year of the individual's first observed apprenticeship. Highest educational attainment refers to the highest observed education for an individual's observed educational history. The width of each band corresponds to the share of individuals from the starting group pursuing different education options during or after their apprenticeship.

FEDERAL RESERVE BANK PHILADELPHIA

Consumer Finance Institute

Consumer Finance Institute Discussion Paper Series

https://www.philadelphiafed.org/consumer-finance