Global Economy and Development at BROOKINGS

DECEMBER 2025

WORKING PAPER #196

THE MARKET VALUE OF NON-DEGREE CREDENTIALS

THE WORKFORCE OF THE FUTURE INITIATIVE

EDUARDO LEVY YEYATI
IAN SEYAL
SOPHIA HENN

The market value of non-degree credentials

Eduardo Levy Yeyati, Ian Seyal & Sophia Henn[1]

December 2025

[1] Corresponding authors: Eduardo Levy Yeyati (ely@utdt.edu), School of Government, Universidad Torcuato Di Tella, Av Figueroa Alcorta 7350, 1428, CABA, Argentina. Ian Seyal (aseyal@brookings.edu) Global Economy and Development Program, Brookings Institution. Sophia Henn (sghenn@uchicago.edu), The University of Chicago.

Acknowledgements

The authors are grateful to Marcela Escobari, Brahima S. Coulibaly, Greg Wright, Pierre Nguimkeu, Belinda Archibong, Annelies Goger, and Sean Murphy for their invaluable comments.

Abstract

Non-degree credentials (NDCs)—badges, certificates, certifications, licenses, and microcredentials—have proliferated as purported alternatives to traditional education, yet evidence on their labor market value remains limited. Using 37.7 million U.S. worker resumes, we employ machine learning to identify genuine NDCs and map them to a standardized taxonomy, enabling the first large-scale analysis of NDC wage returns. We find returns to NDC possession depend critically on job relevance: Workers' first job-relevant NDC yields a 3.8% wage premium, more than double the 1.8% premium for their first job-irrelevant NDC. And returns to accumulation depend entirely on relevance: Each additional job-relevant NDC increases wages by 1.0%, while irrelevant accumulation shows either no gains or a wage penalty. Returns vary substantially across worker characteristics: Non-college workers realize premiums one and a half to two times larger than college graduates, and early-career workers show similarly elevated returns. Disaggregating by NDC type reveals distinct mechanisms: Certifications exhibit returns to accumulation only when job-relevant, patterns consistent with human capital acquisition, while badges and certificates deliver one-off premiums independent of relevance, consistent with signaling. Our findings highlight both the promise and risks of NDC proliferation: Rigorous, job-relevant NDCs can narrow earning gaps for non-college and early-career workers, but absent quality assurance and transparent information, NDC market expansion risks exposing workers to low-value investments.

Keywords: Non-degree credentials, Labor market returns, Human capital, Wage differentials, Workforce development, Educational inequality

JEL Classification: J24, I26, J31, I21

1. Introduction

Non-degree credentials (NDCs)—badges, certificates, certifications, licenses, and microcredentials—are associated with significant labor market returns, but only when they are relevant to workers' occupations and meet threshold quality standards. Analyzing 37.7 million U.S. worker resumes, we find that workers' first job-relevant NDC is associated with a 3.8% wage premium relative to workers without an NDC—more than double the return to a first job-irrelevant NDC. More strikingly, returns to NDC accumulation depend entirely on job relevance: Each additional job-relevant NDC yields a 1.0% wage increase, while irrelevant NDCs show no marginal returns. These patterns vary dramatically across worker types: Non-college workers realize returns nearly twice as large as college graduates, suggesting that rigorous, well-targeted NDCs can serve as genuine alternatives to traditional education for workers who need them most.

NDCs have proliferated rapidly in U.S. labor markets. Recent estimates suggest over 1.5 million unique NDCs exist in the United States, and survey data indicates that over one-quarter of American adults held an NDC in 2016.[2] They have emerged as potential alternatives or complements to traditional educational pathways, offering more targeted, accessible routes to skill development and career advancement.

This proliferation responds to mounting concerns about traditional higher education's escalating costs and perceived disconnect from employer needs, alongside urgent demands for rapid reskilling driven by technological change and economic disruption.[3] NDCs position themselves as responsive alternatives, offering shorter, more targeted programs that directly address specific competencies demanded by employers, particularly for workers without bachelor's degrees or access to traditional degree pathways.

Yet, despite their growing prevalence and policy relevance, empirical evidence on the labor market value of NDCs remains limited and methodologically constrained. Most existing research relies on limited survey data or on small-scale studies of specific NDC types or programs, making it difficult to assess their broader economic impact or understand which NDCs deliver meaningful returns. The unstandardized nature of NDC data has posed significant challenges for large-scale empirical analysis, limiting researchers' ability to conduct comprehensive assessments of their market value.

This study makes three contributions. First, we develop machine learning methods to standardize 54.3 million unstandardized credential names from resume data, enabling the first large-scale analysis of NDC returns across the full spectrum of NDC types.

[2] See Cronen et al. (2017) and Credential Engine (2025).
[3] See HolonIQ. (2024) and World Economic Forum, (2025).

Second, we construct novel measures of credential-job relevance that allow us to distinguish productivity-related returns from pure signaling effects.[4] Third, we document substantial heterogeneity in returns across NDC types (certifications vs. badges vs. certificates vs. microcredentials) and worker characteristics (education and experience levels), revealing that NDC markets serve distinct functions for different populations.

This analysis reveals several key findings that advance our understanding of NDCs' role in labor markets. NDCs are associated with positive wage differentials, but the size of these differentials depends critically on job relevance rather than simple credential counts. Controlling for a variety of worker and labor market characteristics, we find that workers' first job-relevant NDC is associated with a wage premium of about 3.8% compared to workers without an NDC, more than double the 1.8% premium for a first job-irrelevant NDC. Additional NDCs generate gains only when they are relevant to the worker's occupation: Each additional job-relevant NDC is associated with roughly a 1.0% marginal increase in wages, while accumulating irrelevant NDCs yields no significant returns. These patterns suggest a baseline signaling value from NDC possession and additional productivity-related returns to NDC accumulation when they convey job-relevant skills and competencies.

NDC returns vary sharply across worker characteristics. For workers without a bachelor's degree, the first job-relevant NDC is associated with a wage premium of 6.8%, nearly double the premium for comparable college graduates, and additional relevant NDCs also yield larger marginal gains for non-degree holders.[5] Early-career workers likewise experience much stronger benefits than experienced workers: A first job-relevant NDC is associated with roughly a 6% wage premium and additional relevant NDCs with more than 2% higher wages per NDC, while accumulation effects for experienced workers are close to zero. These differentials by education and experience indicate that recent proliferation of NDCs may provide valuable alternative pathways for early-career and non-college workers, potentially helping to address educational inequality and expand access to skill development opportunities.

Our findings also reveal differences across NDC types. Certifications, which are often rigorously verified, exhibit patterns consistent with human capital accumulation: They are associated with strong, positive marginal returns to both possession and accumulation, but only when the certification is job-relevant. In contrast, badges and certificates exhibit the opposite pattern.[6] Their value comes only from initial possession, and returns to these NDC types do not depend on their job relevance. This

[4] We derive our measure of credential-job relevance from the relative concentration of NDCs in occupations. See section 3.4.
[5] Note that, because non-degree and early-career workers tend to earn lower baseline wages, their higher percentage returns may partially reflect base effects. Still, even in absolute terms, the estimated gains from job-relevant NDCs remain meaningful.
[6] Section 3.3 describes NDC types in detail.

is consistent with a signaling mechanism whereby a first badge or certificate effectively signals a worker's quality, but further accumulation yields diminishing or even negative returns.

These patterns suggest important differences in how various NDC types function in labor markets, though the precise mechanisms underlying these differences remain an important area for future investigation.

From a policy perspective, our findings suggest considerable potential for NDCs as tools for workforce development and social mobility, particularly for workers lacking experience and traditional educational credentials. However, substantial variation in returns across credential types and worker characteristics underscores the importance of quality assurance and careful targeting of NDC investments. If the proliferation of NDCs goes unchecked, particularly in the context of rising unemployment, rapid industrial transformation, and the disruptive effects of AI on job requirements and tasks, workers face risk. In the absence of mechanisms to verify credential quality and credible evidence on which NDCs support which workers and transitions, imperfect information in the credential market may expose individuals to low-value or even exploitative programs. Over-reliance on NDCs without clear evidence of their effectiveness also risks shifting the burden of training away from employers, neglecting the development of skills and capabilities that may be more effectively acquired through workplace learning.

2. Background and literature

2.1 Educational returns and NDCs: Theoretical frameworks

The labor market value of education has been explained through two primary theoretical frameworks with different implications for understanding NDC returns. Human capital theory posits that credentials directly enhance worker productivity by developing job-relevant skills and knowledge (Becker, 1964; Mincer, 1974), implying positive wage premiums reflect genuine productivity increases. Signaling theory argues that credentials primarily function as sorting mechanisms, allowing high-ability individuals to distinguish themselves without necessarily increasing productivity (Spence, 1973).

This distinction carries important implications for both individual decisionmaking and social policy. If NDCs primarily build human capital, then investments in NDC programs may generate positive spillovers and justify public subsidies. Conversely, if NDC benefits operate mainly through signaling, much of the investment in NDC programs may promote socially wasteful competition that simply re-sorts equally competent workers across jobs (Caplan, 2018).

While distinguishing these mechanisms empirically is challenging (Huntington-Klein, 2020), recent work suggests both operate simultaneously with varying importance across contexts (Bedard, 2001; Arteaga, 2018). This paper does not formally disentangle these mechanisms, but our estimates of returns to job-relevant NDC accumulation lend a tentative interpretation: If NDCs primarily build human capital, we would expect positive returns to job-relevant NDC accumulation and smaller or negligible returns to job-irrelevant NDC accumulation. If NDCs operate mainly through signaling, we would expect large initial premiums followed by minimal returns to additional NDCs of the same type, since additional signals would be redundant, with smaller differentials between returns to job-relevant and job-irrelevant NDCs as both can signal intelligence, trainability, conscientiousness, and other commonly cited traits.[7]

2.2 Empirical evidence on NDC labor market outcomes

The most extensively studied alternative credentials are occupational licenses. Kleiner and Krueger (2013) estimate that nearly 30% of U.S. workers hold occupational licenses and that licensed workers earn substantially higher wages. More recent estimates suggest that, after adjusting for observable differences, licensed workers earn roughly 5% to 8% higher hourly wages than otherwise similar unlicensed workers (Nunn, 2018). Professional certifications—also awarded by authoritative bodies following performance-based assessment—similarly occupy a middle ground between formal education and newer alternative credentials (Section 3.3 gives an overview of NDC

[7] See Neugebauer et al. (2025), Spence (1973), Deming and Sillman (2024), and Caplan (2018).

types). Using Current Population Survey (CPS) data, Cunningham (2019) finds that workers with a professional certification or license had earnings about 35% higher than those without, though this comparison does not control for education, occupation, and other worker characteristics.

Research on newer NDC types such as certificates, digital badges, and microcredentials remains limited due to data constraints. Surveys point to growing employer recognition, with 77% of hiring managers viewing microcredentials as equal to or more valuable than traditional degrees. [8] But systematic wage evidence is sparse, with most studies focusing on completion rates and short-term employment rather than comprehensive labor market returns.

2.3 Heterogeneity in NDC returns

A key finding across studies is substantial heterogeneity in returns, both across credential types and worker characteristics. This heterogeneity is central to understanding NDC value and market function.

Heterogeneity across credentials

Sigelman et al. (2025) examined over 23,000 credentials using data from 65 million career records, finding that only 12% of credentials deliver significant wage gains. Top-decile credentials yield average annual wage premiums of nearly $5,000.00, while bottom-tier credentials provide minimal benefits. This variation exists even within fields and providers, creating substantial uncertainty for learners in markets lacking quality assurance mechanisms. Our analysis extends this work by examining not just which credentials matter, but how their value depends on job relevance and the characteristics of who holds them.[9]

Heterogeneity across worker characteristics

Understanding who benefits from NDCs is essential for both equity considerations and policy design. If NDCs serve primarily as complements to formal education, benefiting college graduates who can stack additional credentials, they may exacerbate rather than reduce educational inequality. Conversely, if NDCs provide larger returns for workers without traditional degrees, they may offer genuine alternative pathways to skill development and wage growth.

Extensive research documents heterogeneous returns to formal degrees based on worker characteristics, reflecting the topic's importance to debates on efficiency of

[8] See Stoller (2024).

[9] Along with the mechanism by which NDCs generate value in the labor market (signaling versus human capital), these are important considerations for any data-driven evaluation of efficacy, particularly those aspiring to undergird funding models that hold NDC providers to account.

public spending, college access, and inequality.[10] As NDCs grow in prevalence, understanding whom they benefit carries similar importance. Ecton et al. (2025) document heterogeneous returns to NDCs using National Student Clearinghouse data across gender and ethnicity. Our analysis examines heterogeneous returns across prior education levels and work experience. Higher returns for workers without traditional degrees would suggest that NDCs may, at least partially, substitute for formal education. Similarly, stronger effects for less experienced workers may indicate NDCs are particularly valuable early in careers when workers have fewer opportunities to demonstrate capabilities through work history.

The interaction between credential type and worker characteristics remains underexplored in existing research. Baird, Bozick, and Zaber (2022) use credential attainment of peers as an instrumental variable, finding stronger wage effects for sub-baccalaureate workers, suggesting licenses may function as alternative pathways for workers without traditional degrees. Our analysis extends this by examining whether different types of NDCs (certifications, badges, certificates, microcredentials) serve different functions for different worker populations.

2.4 Research gaps and this study's contributions

Despite growing policy interest in NDCs, empirical evidence on their labor market value remains limited due to two key challenges. First, most existing research relies on small-scale studies or limited survey data, making it difficult to assess broader economic impact or detect heterogeneous effects across NDC types and worker populations. Second, the unstandardized nature of NDC data has posed significant challenges for large-scale empirical analysis.

This study makes three contributions that address these gaps. First, we develop machine learning methods to classify and standardize 54.3 million credentials from resume data, enabling analysis at a scale and order of magnitude larger than prior work. This scale is essential for detecting heterogeneous effects across the many credential types and worker subpopulations we examine.[11]

Second, we construct novel measures of credential-job relevance that weight credentials by their prevalence in specific occupations relative to overall prevalence. This weighting helps separate productivity-related returns (which should depend on job

---

[10] See Brand and Xie (2010), Bovenberg and Jacobs (2005), or Hout (2012).

[11] Recent advances in large-scale resume data have enabled new methodological approaches in labor economics research: Revelio Labs data has been employed by Li et al. (2020) for research on firm-level employment dynamics, by Nguyen and Sila (2025) on strategic hiring responses to political uncertainty, by Tambe (2025) on technological change and skill diffusion patterns, by Hampole et al. (2025) on AI task exposure effects, and by Frank et al. (2024) on career mobility through skill-based networks.

relevance) from pure signaling effects (which may not). When additional relevance-weighted NDCs show positive returns while unweighted counts do not, this suggests genuine human capital accumulation rather than pure signaling.

Third, we provide the most comprehensive examination to date of how NDC returns vary across both credential types and worker characteristics. By estimating separate effects for certifications, badges, certificates, licenses, and microcredentials, and by examining how returns differ for workers with and without college degrees and for early-career versus experienced workers, we move beyond "do NDCs matter?" toward understanding when, how, and for whom they matter.

Table 2.1 Summary of theoretical predictions that guide our empirical analysis

Dimension	Human capital theory	Signaling theory
Returns to first NDC	Larger if job-relevant	Positive for all
Returns to NDC accumulation	Positive if job-relevant; zero if not	Diminishing/zero regardless of relevance
Returns by credential type (controlling for relevance)	Similar if equally rigorous	Similar across types
Returns by worker education	Similar across education levels	Larger for those needing signals
Returns by work experience	Similar across experience levels	Larger for those needing signals

Note: *These theoretical predictions guide our empirical analysis. Human capital theory predicts returns depend on skill acquisition, particularly for job-relevant credentials. Signaling theory predicts returns depend on information asymmetries, with larger effects for workers needing quality signals (non-college, early-career). Our findings in Section 5 allow us to assess which mechanisms appear most important for different credential types and worker populations.*

The patterns we document in subsequent sections allow us to test these competing predictions. Returns that depend on job relevance suggest human capital mechanisms; returns that depend on worker characteristics (education, experience) suggest signaling mechanisms; and variation across credential types suggests different NDCs operate through different channels. This framework helps us move beyond aggregate effects toward understanding the mechanisms through which different credentials generate value for different workers.

3. Data and methodology

3.1. Data sources and sample construction

Revelio Labs data

Our analysis draws on a large-scale dataset of resumes compiled by Revelio Labs, a platform that aggregates and standardizes information from various online sources including professional profiles, company career pages, and job board aggregator sites. The dataset contains 156.5 million individual worker resumes processed through July 2025. The scale enables analysis of 54.3 million credentials matched to a common taxonomy and the construction of detailed measures at the worker level.

Each resume provides information on workers' employment histories, educational attainment, demographic characteristics (predicted by Revelio based on names and validated against Census distributions), and crucially for our analysis, NDCs listed by workers. The data spans all industries, geographic regions, and experience levels, offering comprehensive coverage of the U.S. labor market.

However, the dataset overrepresents workers with higher education levels, those in business and technical occupations, and residents of digitally-intensive labor markets (California, New York, Massachusetts). We address these potential biases by accounting for selection on observables and by applying post-stratification weights based on state × occupation cells from the American Community Survey (detailed in Appendix A1). Our base specifications use unweighted data. Weighted results and selection-correction estimates indicate that our findings are not driven by sample composition.

A limitation of resume-based data is that NDCs are self-reported and selectively listed. Workers may choose to display NDCs they believe are valuable and omit those perceived as low quality or irrelevant, which could bias estimated returns upward if high-value NDCs are disproportionately reported. Importantly, this concern strengthens rather than weakens one of our core findings: Even among NDCs that workers voluntarily choose to display, accumulation of job-irrelevant NDCs exhibits no positive wage association and, in some cases, negative associations. This pattern suggests that the absence of returns to irrelevant NDC accumulation is unlikely to be driven by underreporting of low-value NDCs but instead reflects genuine limits to their labor market value.

3.2. NDC data processing

Two steps for NDC standardization

We develop a two-step approach to ensure only genuine, standardized NDCs enter our analysis. The first methodological challenge lies in the highly unstandardized nature of self-reported, raw NDC entries in resume data, ranging from formal NDCs ("Certified Public Accountant") to irrelevant entries ("painting," "subject matter expert").[12] Appendix A2 describes the two steps of the approach in detail.

Step 1: Genuine NDC classification

Raw NDC entries from the resume data are first cleaned through standard text preprocessing (lowercasing, punctuation removal, duplicate word elimination), abbreviation expansion (e.g., CNA → Certified Nursing Assistant), and removal of vague common terms. We then classify all preprocessed NDC entries from the resume data as likely NDCs or non-NDCs using a pre-trained, instruction-tuned sentence transformer model (Su et al. 2023) combined with human-in-the-loop review.[13]

A random forest classifier is trained iteratively on text embeddings, with human reviewers updating model training examples to distinguish genuine NDCs from occupations, organization names, or irrelevant entries. Of approximately 7.8 million unique, raw NDC entries, 850,000 (about 11%) are classified as non-NDCs and excluded from analysis.

Step 2: Credential Engine matching

Genuine NDCs are matched to the Credential Engine taxonomy using semantic embeddings and cosine similarity. Credential Engine maintains the most comprehensive U.S. registry of credentials (~100,000 verified entries) with standardized type classifications and metadata including issuer, credential description, and associated industries and occupations (See section 3.3 below for details on credential types).

Each genuine NDC is assigned to the Credential Engine entry with highest cosine similarity score. Visual inspection of matches confirms match quality improves with cosine similarity. We omit matches with a cosine similarity below the 20th percentile. This process yields 54.3 million NDC observations across 30,450 unique standardized NDCs, with 16.5 million workers (10.5%) holding at least one matched NDC.

3.3. Credential typology and prevalence

Following Credential Engine's classification, we analyze five NDC types:

---

[12] Additional examples of non-NDCs identified and removed include: junk or irrelevant entries ("painting," "subject matter expert"), job titles or positions ("ski instructor," "superintendent of schools"), organization names or affiliations ("the oxford consortium for human rights"), and ambiguous course or training titles ("poverty 101," "performance and reward management").

[13] We select this model over alternatives like TF-IDF or simple embeddings because: (1) instruction-tuned architecture that allows task-specific guidance through natural language prompts, (2) superior performance on informal, noisy text compared to generic embeddings, and (3) ability to distinguish subtle patterns like "AWS Certified" (credential) versus "Amazon Certified Organic" (non-credential).

Badges: Digital markers of achievement or participation, often awarded for completing online courses or demonstrating specific competencies (e.g., Google Analytics Badge, AWS Cloud Practitioner Badge)

Certificates: Credentials awarded upon completion of academic or training programs, typically institution-based (e.g., Project Management Certificate, Technical Writing Course)

Certifications: Formal credentials validated by industry bodies, often renewable and revocable, requiring ongoing maintenance (e.g., Certified Public Accountant, Cisco CCNA)

Licenses: [14] Legal authorizations required to practice specific occupations, typically regulated by government agencies (e.g., Registered Nurse, Real Estate Broker License)

Microcredentials: Sub-degree modular credentials targeting specific skills, often stackable toward larger qualifications (e.g., edX MicroMasters in Data Science, Udacity Nanodegree)

Distribution across NDC types

Our analysis reveals significant variation in NDC prevalence across these categories. Certificates and certifications dominate the landscape, comprising over 90% of all NDCs in our sample and held, respectively, by 7% and 5% of all individuals. The most common specific NDCs include Project Management Professional certifications (329,841 occurrences), BLS Basic Life Support certificates (293,010), and CompTIA security+ certifications (262,896). Badges are rare, comprising only 0.41% of all credentials and held by less than 0.1% of individuals (about 130,000 individuals list them). Microcredentials are somewhat more common. About 1% of individuals list them on their resumes.

Recent NDC proliferation

NDCs are rapidly proliferating, and uptake is highest among the least common types. Between 2024 and 2025 share of people listing at least one NDC grew from 6.5% to 7.5%.[15] The number of NDCs in our population-weighted sample (Appendix A1) grew by nearly 35%, and individuals acquired badges and microcredentials at the fastest rate, increasing by 51.3% and 37.6%, respectively.

---

[14] Though we observe many licenses in the data, we do not report results on license value due to a measurement problem: observed prevalence of licenses is much lower than actual prevalence of licenses likely because many jobs require a license, so workers listing work experience in those jobs safely assume their possession of the necessary license is implied to employers.

[15] To accommodate the possibility that Revelio scraped more resumes, we limit analysis over time to individuals that appear in both our 2024 and 2025 datasets.

3.4. Credential-job relevance measures

Recognizing that credential value likely depends on job relevance, we develop credential-job relevance (CJR) measures that quantifies whether credentials are over- or under-represented in specific occupations relative to overall prevalence (Appendix A3 describes the procedure in detail).

Since Credential Engine treats similar credentials with slightly different names or from different providers as distinct,[16] we implement a clustering procedure using DBSCAN on enhanced credential embeddings to group functionally equivalent credentials.[17] This yields 18,919 clusters: 2,250 contain multiple credentials (median size = 2, mean size = 6), while the rest contain a single credential.

The CJR for credential cluster c in occupation j is computed as:

$$CJR_{j,c} = \frac{\frac{Workers_{j,c}}{\sum_c Workers_{j,c}}}{\frac{\sum_j Workers_{j,c}}{\sum_j \sum_c Workers_{j,c}}}$$

where the numerator represents the share of workers in occupation *j* holding a credential in cluster *c*, and the denominator represents the share of all workers holding a credential in cluster *c*. Values greater than one indicate that a credential in cluster *c* is more prevalent among workers in occupation *j* than in the overall sample of workers.

The computed CJR values are transformed to a 0-1 scale for use as weights in our regression analysis. Values greater than 2 are capped to 2 (approximately the 90th percentile of all CJR values) and min-max normalization is applied to scale values between 0 and 1. Approximately 32% of non-zero credential-job relevance scores take the maximum value of 1, while the remainder are distributed between 0 and 1, with highest density between 0.1 and 0.4 (See Appendix A3).

A sample of job-credential relevance scores is shown in Appendix A3 for Software Developers, Nurses, and Management Analysts. For example, Software Developers are 10.66 times more likely to hold a JavaScript certification than the overall sample of workers, and Management Analysts are 3.82 times more likely to hold a Project Management certification.

For each individual, relevance-weighted credentials are defined as the sum of the individual's $CJR_{j,c}$ across all credential clusters held in their current occupation. This

[16] E.g., Spanish Medical Interpreter Certificate from Walla Walla College and Medical Interpreter Spanish Certificate from Highline College. See Appendix Table A3.1.

[17] Enhanced meaning credential embeddings as well as credential metadata on related industries, occupations, and instructional programs.

measure distinguishes possession and accumulation of job-aligned NDCs from those of diffuse or more general NDCs. We carry this distinction throughout the analysis for a richer interpretation, beyond simple NDC counts, of the mechanisms by which NDCs yield value (See Table 2.1).

3.5 Regression sample construction

To examine earnings premiums associated with NDCs, we construct a regression sample from the larger dataset by applying several filters to ensure data quality and model identification. We restrict the analysis to individuals with non-missing information on their sex, ethnicity, education, experience, occupation, industry and state. These filters yield a final regression sample of 37.7 million individuals holding 27.0 million credentials. Removing so many observations introduces potential for bias if data are not missing at random. Appendix B6 shows robustness of our main specification to exclusion of experience and experience and education controls (which are responsible for most excluded observations) and reintroduction of excluded observations). A selection correction robustness test (Appendix B4) further addresses potential for bias in our reduced regression sample.

We also apply conservative outlier removal. Specifically, we drop observations where cumulative work experience exceeds 960 months (80 years) or where credential counts exceed the 99.9th percentile (26 credentials). This procedure removes an additional 77,821 observations, representing approximately 0.2% of the initial regression sample. Appendix B7 shows main results are robust to tests varying controls and sample size.

For each individual in the regression sample, we construct measures across four domains:

Demographic characteristics: Education level (highest degree earned), cumulative work experience (sum of months across all positions listed on the resume), sex, and ethnicity (both predicted by Revelio Labs based on name patterns and validated against Census distributions)

Job characteristics: Occupation classification (6-digit SOC code), industry classification (2-digit NAICS code), and annual wage estimates provided by Revelio Labs based on job title, company, location, seniority, and other observable characteristics

Credential attainment: Individual-level counts of credentials by type, including both simple counts and relevance-weighted measures as described in Section 3.4. These counts only include credentials that meet a minimum threshold for a confident match to an existing credential in the Credential Engine taxonomy (Appendix A2)

Geographic location: State of most recent employment for fixed effects estimation

Table 3.1 tabulates summary statistics for continuous and binary variables in the base regression specification. Appendix Table C2 shows the same for college and non-college workers.

Table 3.1 Summary statistics of variables in the regression sample

	Mean	Median	St. Dev.	Min	Max
Salary	102,444	82,347.5	71,184	0	3,000,000
Sex (Male)	0.51	1.0	0.50	0	1
Experience (Years)	12.81	10.33	10.40	0	80
Education (BA or higher)	0.89	1.0	0.32	0	1
Has credential	0.25	0.0	0.44	0	1
Number of credentials	0.72	0.0	1.90	0	26
Number of relevance-weighted credentials	0.26	0.0	0.81	0	26

In the analysis that follows, our main outcome variable is individual earnings, which are estimated by Revelio based on company, location, seniority, and more.[18] Revelio's wage estimation methodology has been validated in academic research, with demonstrated accuracy against administrative wage records.[19] We similarly validate our core findings with earnings data from Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS) in Appendix B1. National average OEWS wages are assigned to individuals based on their occupation.

[18] See more details here.

[19] For example, see Dorn et al. (2025).

4. Empirical strategy

4.1 Main specification

Our primary empirical strategy estimates the association between credential attainment and log wages using a fixed-effects regression framework. The main specification is:

$$
\begin{aligned}
ln(wage_i) = {} & \beta_1(AnyCred_i) + \beta_2(NumberofCreds_i) + \beta_3(RelWeightedCreds_i) \\
& + \sum_t [\gamma_t(AnyCred_i \times Type_t) + \mu_t(NumberofCreds_i \times Type_t) \\
& + \delta_t(RelWeightedCreds_i \times Type_t)] \\
& + \sum_j [\theta_j(AnyCred_i \times Char_j) + \rho_j(NumberofCreds_i \times Char_j) \\
& + \lambda_j(RelWeightedCreds_i \times Char_j)] \\
& + \eta(Controls_i) + \alpha_s + \varphi_j + \psi_e + \varepsilon_i
\end{aligned}
$$

Dependent variable:
$\ln(wage)_i$ = Logarithm of estimated annual wages for individual *i*, provided by Revelio Labs based on job title, company, location, seniority, and other observable job characteristics.

Note that Revelio's wage model is trained on external salary sources and uses job characteristics (title, company, location, seniority) rather than individual features such as gender, education, skills, or NDCs to impute wages. Since our dependent variable is an imputation based on these job characteristics, our estimates on β_1, β_2, and β_3 reflect the degree to which NDCs allow workers access to higher-valued job titles, higher seniority levels, and better-paying firms.

Because Revelio's model does not capture wage variation within these job characteristic cells (e.g., performance bonuses), our estimates likely understate the total effect of NDCs on wages. We confirm that key results are not artifacts of Revelio's wage model by re-estimating the main specification using an external occupation-based earnings measure (Appendix B1), which yields consistent findings: workers who hold job-relevant NDCs sort into higher-paying jobs. That said, the resulting regression uses a generated dependent variable, which may affect the precision of our standard errors. While we do not observe the first-stage residuals and therefore cannot fully correct for this, our results are robust to the use of alternate wage measures (Appendix B1), and we interpret our statistical inferences with appropriate caution.

Credential variables:
$AnyCred_i$ = Binary indicator equal to 1 if individual *i* holds at least one NDC
$NumberofCreds_i$ = Number of credentials held by individual *i*.
$RelWeightedCreds_i$ = $\sum_{k=1}^{N_i} r_{ik}$ = Sum of job-credential relevance weights across all credentials held by individual i (see Section 3.4), where individual *i* holds N_i credentials indexed by k_i, each with relevance $r_{ik} \in [0,1]$

Interaction terms:
$Type_t$ = Indicator variables for credential types where

$t \in \{badges, certificates, certifications, licenses, microcredentials\}$

$Char_j$ = Individual characteristic indicators where

$j \in \{bachelor's\ degree\ or\ higher, above\ mean\ experience\}$

Controls:
$Controls_i$ = Individual characteristics including predicted sex, cumulative work experience (months), experience squared, and education level

Fixed effects:
α_s = State fixed effects controlling for geographic wage differences
φ_j = Industry fixed effects (2-digit NAICS) controlling for sector-specific wage premiums
φ_j = Ethnicity fixed effects using predicted classifications

Error term:
ε_i = Individual-specific error term (standard errors clustered by state × industry)

Interpretation

The interpretation of our results require combining our three NDC variables, $AnyCred_i$, $NumberofCreds_i$, and $RelWeightedCreds_i$ to identify the returns to NDC possession versus accumulation, differentiated by job relevance.

Returns to possession:

Acquiring a first credential changes $AnyCred_i$ from 0 to 1 and increases both $NumberofCreds_i$ and $RelWeightedCreds_i$. The total wage effect depends on the credential's relevance to the worker's occupation. For a first credential, the estimated wage effect is given by: $\beta_1 + \beta_2 + \beta_3 \times r_{ik}$. Or, as reported in results: $\beta_1 + \beta_2 + \beta_3$ or $\beta_1 + \beta_2$ in the case of a worker's first fully relevant or fully irrelevant credential, respectively ($r_{ik} \in \{0,1\}$).

Returns to accumulation:

For workers who already hold at least one credential, acquiring an additional credential affects only the accumulation terms, and the interpretation again depends on relevance. For an additional credential, the estimated wage effect is given by: $\beta_2 + \beta_3 \times r_{ik}$. Or, as reported in results: $\beta_2 + \beta_3$ or β_2 in the case of a worker's additional fully relevant or fully irrelevant credential, respectively.

Our main results in Section 5 show combined coefficients as described above. Appendix E1 shows estimates of the main specification without combined coefficients.

Heterogeneity analysis

For credential type analysis, we estimate the main equation including the type interaction terms identified in Section 3.3. This specification estimates separate possession and relevance effects for each credential type, allowing us to test returns to different types of NDCs. We examine differential returns by educational attainment and work experience through interaction specifications, in turn including the respective interaction terms.

4.2 Robustness and sensitivity analysis

We conduct six robustness checks to assess the stability of our main findings across alternative specifications and modeling choices. Table 4.1 summarizes key coefficient estimates across all specifications, demonstrating that our core results remain stable in sign, magnitude, and statistical significance.

Table 4.1 Robustness checks: Key coefficient estimates

Specification	First relevant	Additional relevant	First irrelevant	N (millions)
(1) Base specification	0.038***	0.010***	0.018***	37.7
(2) OEWS wages	0.028***	0.023***	−0.003	37.6
(3) Sample weighted	0.049***	0.012***	0.029***	37.7
(4) + Occupation FE	0.019***	−0.001	0.013***	37.7
(5) IPW selection correction	0.038***	0.001***	0.018***	37.7
(6) + Number of Creds^2	0.038***	0.010***	0.018***	37.7

Specification	First relevant	Additional relevant	First irrelevant	N (millions)
(1) Base specification	0.038***	0.010***	0.018***	37.7
(2) OEWS wages	0.028***	0.023***	-0.003	37.6
(3) Sample weighted	0.049***	0.012***	0.029***	37.7
(4) + Occupation FE	0.019***	-0.001	0.013***	37.7
(5) IPW selection correction	0.038***	0.001***	0.018***	37.7
(6) + Number of Creds²	0.038***	0.010***	0.018***	37.7

Note: *Table shows key coefficients from main specification estimated under different robustness checks. 'First relevant' shows wage premium for first job-relevant NDC; "Additional relevant" shows marginal return per additional job-relevant NDC; "First irrelevant" shows premium for first job-irrelevant NDC. Full regression results for each specification appear in Appendix B. *** p<0.01, ** p<0.05, * p<0.1.*

The specifications in Table 4.1 address different potential concerns. Specification (2) uses Bureau of Labor Statistics OEWS median wages by occupation instead of Revelio's estimated individual wages, providing an external benchmark. Specification (3) applies post-stratification weights to align our sample with national employment distributions across state-occupation cells. Specification (4) includes occupation fixed effects, identifying credential effects from variation within job categories. Specification (5) employs inverse probability weighting to address potential selection into credential attainment. Specification (6) includes squared experience terms to capture non-linear age-earnings profiles. Specification (7) (shown with its relevant comparison in Appendix B6) uses an expanded sample that includes observations with missing education and experience data, so compares to a base specification without those controls.

Aside from specification (4), the core patterns remain consistent: Job-relevant NDCs show positive returns to both possession and accumulation, while job-irrelevant NDCs show substantially smaller, negative, or insignificant returns. Within occupations, we find no average returns to additional relevant NDCs. However, as discussed in Section 5, the broad result masks substantial heterogeneity. Consistent with the core patterns documented in the other specifications, Appendix B3 shows that additional job-relevant

NDCs yield positive returns for early-career workers, even after controlling for occupation (Accumulation of job-irrelevant NDCs does not yield positive returns for these groups).

In general, the key qualitative findings are robust. Full results including all control variables and fixed effects appear in Appendix B1-B6.

4.3 Identification and interpretation

Our empirical strategy identifies correlational relationships between NDC attainment and wages rather than causal effects. Selection concerns limit causal interpretation: Workers who acquire NDCs may differ from those who do not in ways that also affect wages. While our fixed effects, rich controls, and selection correction exercises address some forms of selection, unobserved heterogeneity remains a concern.

To further probe the role of selection, we explore an instrumental variables strategy following Baird, Bozick, and Zaber (2022), using local peer NDC attainment as a source of variation in individual NDC acquisition. This approach is intended as a robustness exercise rather than a primary identification strategy. While first-stage relationships are positive, the instrument is weak and second-stage estimates lack statistical precision. As a result, we do not interpret these estimates as causal and do not rely on them in drawing conclusions. Full details and results are reported in Appendix D for completeness.

Despite these limitations, our approach offers several advantages. The credential–job relevance weighting helps distinguish patterns consistent with productivity-related returns from those consistent with pure signaling. The scale of the data enables detection of heterogeneous relationships across worker characteristics and NDC types. Extensive robustness checks provide confidence that the documented associations are stable across specifications. Accordingly, the paper’s contribution lies in documenting robust and systematic descriptive patterns—particularly around relevance-weighted accumulation and heterogeneity—rather than in establishing causal treatment effects. These findings inform policy discussions about the value of NDCs while underscoring the need for future work that exploits exogenous variation in NDC acquisition.

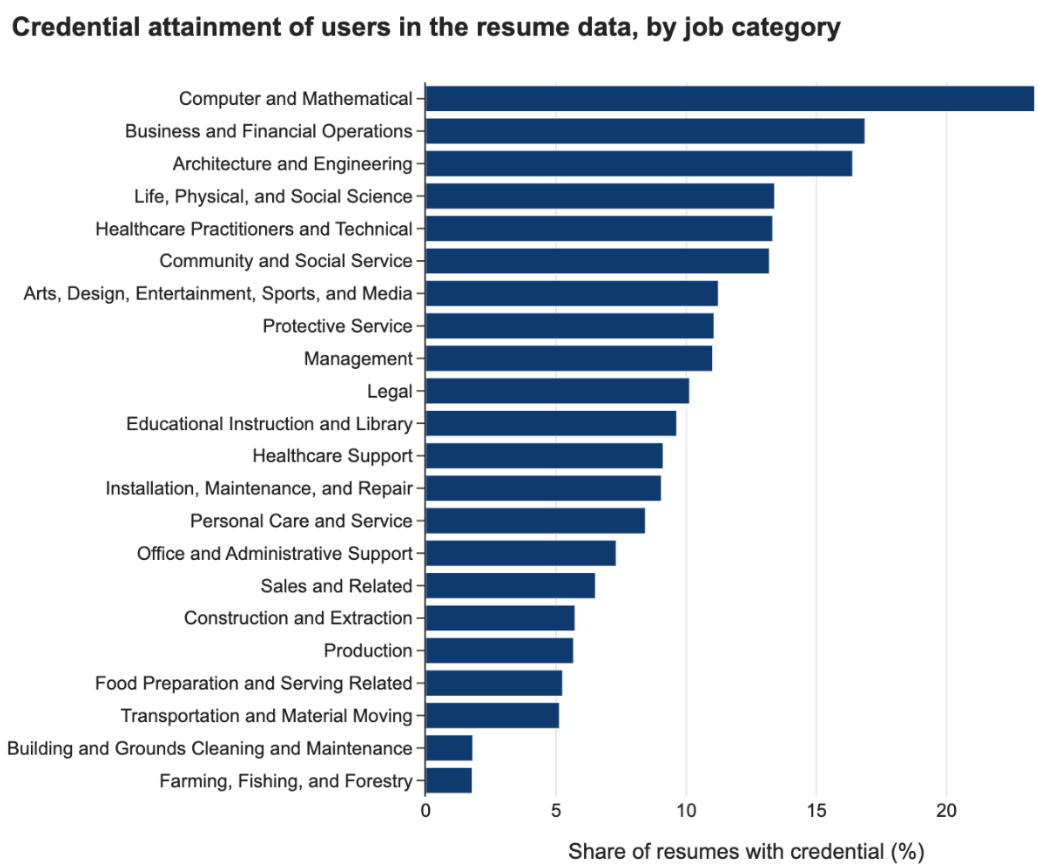
5. Results

5.1 Descriptive patterns

NDC prevalence by occupation

NDCs exhibit substantial variation in prevalence across occupational categories, reflecting the heterogeneous nature of skill requirements and professional development practices across industries. The descriptive figures in this section use sample weights (Appendix A1) to give population estimates. Figure 5.1 below shows the share of workers holding at least one NDC by major occupational groups.

Figure 5.1 Variation in NDC prevalence by occupation reflects rapid technological changes and professional certification requirements



NDCs are most prevalent among workers in knowledge-intensive occupations. NDCs are most common in Computer & Mathematical Occupations (23.4%, more than triple the overall weighted sample average of 7.2%), Business & Financial Operations (16.9%), and Architecture and Engineering (16.4%). These patterns likely reflect both established professional certification requirements and rapid technological change such as new software and methods that give rise to new NDC programs.

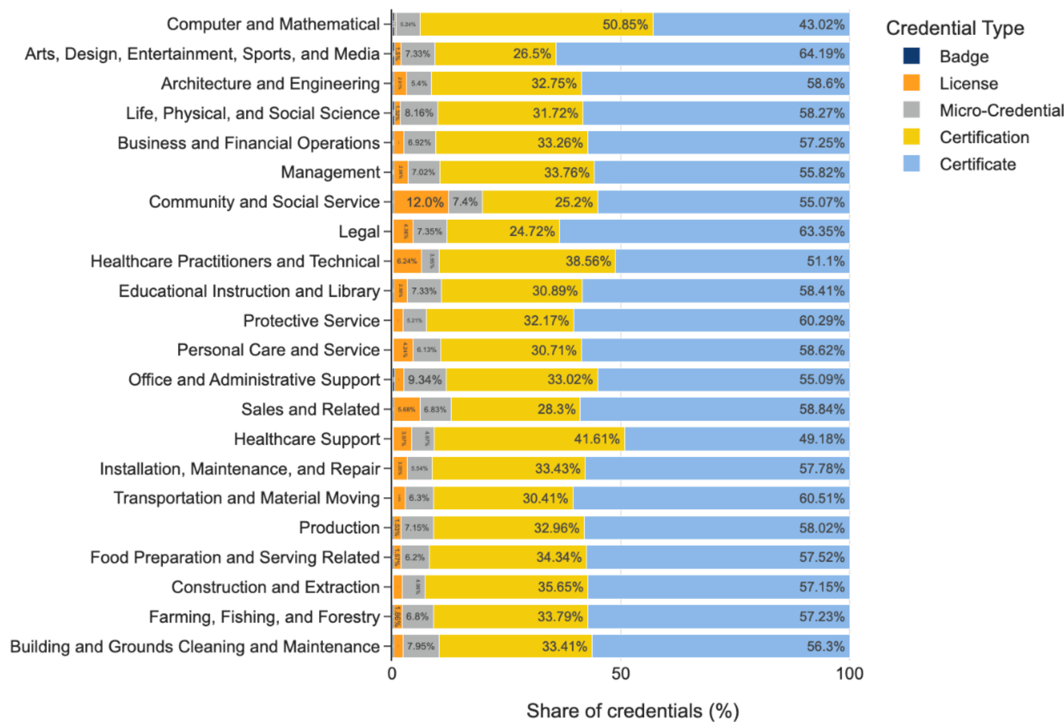
Less than 2% of workers in agriculture and cleaning and maintenance list NDCs on their resumes. This disparity may reflect different professional development practices in these industries.

NDC type prevalence by occupation

Figure 5.2 disaggregates NDC prevalence by type. Certificates represent the modal credential type across all occupations (43% to 64% of all NDCs), while certifications have a higher relative presence in Computer & Mathematical Occupations (51% of all NDCs in the occupation) and Healthcare Support, Practitioners and Technical Occupations (39% to 42%). As mentioned in Section 3.3, prevalence of licenses in our data is low due to a measurement problem: Since many jobs require a license workers often do not list them on their resume, safely assuming work experience implies their possession of the necessary license.

Badges constitute less than 0.6% of NDCs across each occupation but have the highest prevalence in Computer and Mathematical Occupations and Life, Physical, and Social Sciences.

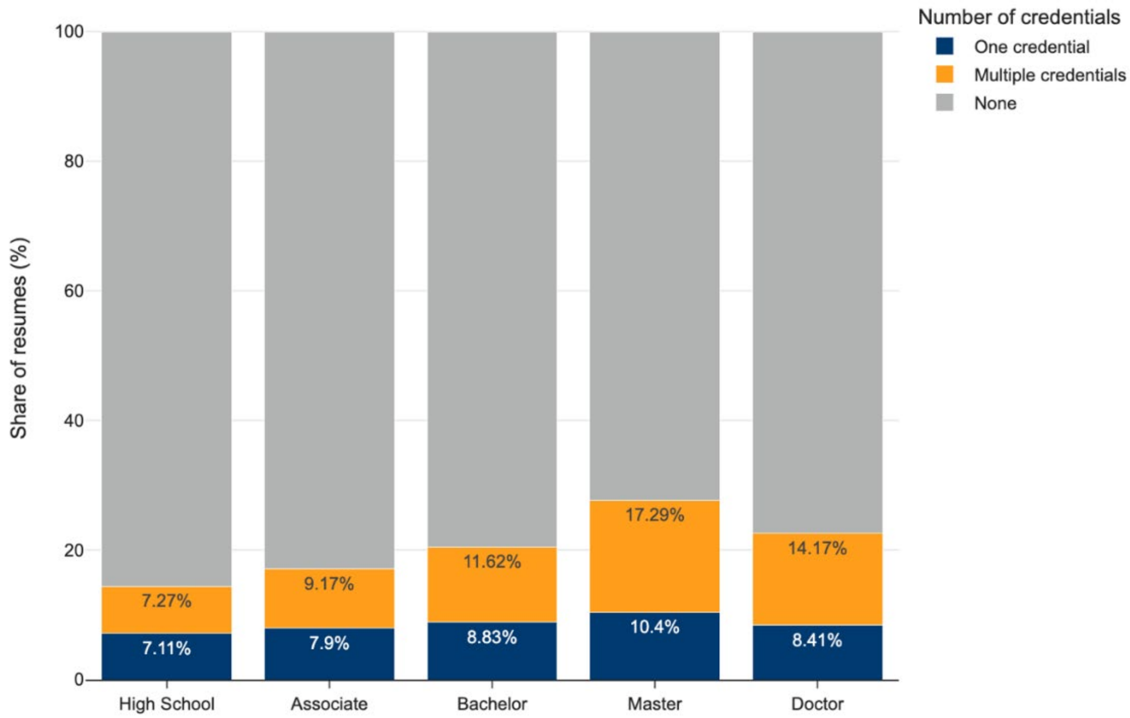
Figure 5.2 NDC prevalence across occupations, by type



NDC prevalence by type and formal educational attainment

Figure 5.3 shows that workers listing only a high school level of education on their resume are the least likely to hold a NDC (14.4%), while workers with a master's or doctorate degrees are the most likely (27.7% and 22.6%, respectively). This monotonic increase is consistent with findings of other studies.[20] It is also contrary to what might be expected if NDCs serve primarily as substitutes for traditional education or degrees. Instead, taken alone, this pattern suggests that NDCs primarily complement rather than substitute traditional degrees, at least in terms of who acquires them and displays them on their resumes.

Figure 5.3 NDC prevalence by education level suggests NDCs serve as complements to formal education and degrees



NDC prevalence by work experience

Figure 5.4 below demonstrates that NDC prevalence rises steeply from zero to ten years of experience, plateauing at approximately fifteen years and gradually declining thereafter.

This reflects: (1) early-career workers face greater uncertainty about their skills and career trajectories, so they use NDCs to signal competence before building extensive work histories. (2) cohort effects: the rapid proliferation of NDC offerings is a relatively recent phenomenon, so many NDCs did not exist when older workers entered the labor market. (3) experienced workers rely on work history rather than NDCs to convey their qualifications.

[20] See Horrigan (2016) and Christensen (2013).

Figure 5.4 NDC prevalence rises sharply early in careers

5.2 Main results

Overall effects

Table 5.1 below presents our baseline regression results examining the association between credential attainment and wages. The estimates reveal substantial returns to credential possession, with pronounced differences depending on credential relevance to the worker's occupation.

Returns to possession (first NDC):

Workers' first job-relevant NDC is associated with 3.8% higher wages compared to workers without NDCs.[21] In contrast, the first job-irrelevant NDC is associated with 1.8% higher wages. This difference of approximately 2.0 percentage points suggests that job relevance substantially enhances the value of initial credential acquisition. The gap suggests that possessing any NDC provides baseline signaling value about worker quality, but possessing a job-relevant credential conveys additional value: the productivity gains from job-aligned skills.

Table 5.1 Base specification

Dependent Variable:	Log Salary
First relevant credential	0.0376***
	(0.0077)
Additional relevant credentials	0.0104***
	(0.0024)
First irrelevant credential	0.0177***
	(0.0058)
Additional irrelevant credentials	-0.0094***
	(0.0012)
Sex (Male)	0.1360***
	(0.0106)
Education (BA or more)	0.3518***
	(0.0142)
Experience	0.0024***
	(0.0001)
Experience SQ	$-2.79 \times 10^{-6***}$
	(1.89×10^{-7})
Fixed-effects	
Ethnicity	Yes
State	Yes
NAICS Industry	Yes
Observations	37,730,478
R^2	0.2651
Within R^2	0.1280

*Reported coefficients correspond to combined marginal effects derived from the underlying regression specification, which separately estimates indicators for NDC possession, total NDC counts, and relevance-weighted NDC accumulation. "First credential" effects capture the wage association of acquiring a single NDC when total NDCs move from zero to one. "Additional credential" effects capture the marginal association of acquiring an additional NDC for workers who hold at least one. Relevance is defined using credential–occupation prevalence weights (Section 3.4). Standard errors clustered by state × industry. *** p<0.01.*

Returns to accumulation (additional NDCs):

The returns to additional NDCs are even more dramatically differentiated by job relevance. Each additional, fully job-relevant NDC is associated with an additional 1.0% increase in wages. Critically, additional NDCs that are not relevant to workers' occupations show no positive wage association, suggesting that once the signaling value of NDC possession is established, accumulating NDCs unrelated to the worker's occupation provide no additional labor market benefit.

Positive returns to job-relevant accumulation but not to irrelevant accumulation is consistent with a model where: (1) possessing any NDC provides signaling value about worker quality and commitment to professional development, and (2) accumulating job-

[21] Given the large sample size of our analysis, standard errors are naturally small, resulting in high statistical significance across most estimates. Throughout, emphasis is placed on economic significance and relative patterns (relevant vs irrelevant, possession vs accumulation) as well as robustness to alternative earnings measures (Appendix B1) and across specifications (Table 4.1).

relevant NDCs reflects genuine skill complementarity that enhances productivity. The asymmetry between relevant and irrelevant accumulation effects suggests that credential quality and alignment matter more than mere quantity.

Heterogeneity by NDC type

The market value of NDCs depends not only on job-relevance, but also on the NDC's type. In this respect, certifications stand out. Unlike the other NDC types analyzed here, they typically require proctored exams, regular renewal, and third-party validation.

Results shown in table 5.2 indicate a pattern for returns to certifications consistent with human capital accumulation. Possession and accumulation of certifications is associated with strong, positive marginal returns only when the certification is job relevant. This suggests that for certifications, value is derived not from the initial signal of "being certified," but from the specific, additive skills verified by each subsequent credential.

In contrast, badges and certificates exhibit the opposite pattern. Returns to these NDC types do not depend on their job relevance, and their accumulation is not associated with higher wages. Their value comes only from initial possession. This dynamic is consistent with a signaling mechanism: holding a first badge or certificate effectively signals a worker's "quality" or learning orientation to employers, separating them from non-credentialed peers. However, once this signal is conveyed, acquiring further badges or certificates yields diminishing or negligible returns.

Table 5.2 Heterogeneous effects by NDC type

Dependent Variable:	Log Salary
First relevant badge	0.01698
	(0.01174)
Additional relevant badges	-0.03044***
	(0.00715)
First irrelevant badge	0.05259***
	(0.01181)
Additional irrelevant badges	0.00520
	(0.00780)
First relevant certificate	0.00842*
	(0.00483)
Additional relevant certificates	-0.01613***
	(0.00283)
First irrelevant certificate	0.01409***
	(0.00421)
Additional irrelevant certificates	-0.01050***
	(0.00130)
First relevant certification	0.04067***
	(0.01240)
Additional relevant certifications	0.02227***
	(0.00260)
First irrelevant certification	0.00895
	(0.00865)
Additional irrelevant certifications	-0.00940***
	(0.00270)
First relevant micro-credential	0.04513***
	(0.01461)
Additional relevant micro-credentials	0.03438***
	(0.01160)
First irrelevant micro-credential	-0.00889
	(0.00679)
Additional irrelevant micro-credentials	-0.01960***
	(0.00510)

Note: Table shows combined wage effects by NDC type. Controls (not shown) match those of base specification.

Interestingly, the pattern exhibited by returns to microcredentials is consistent with that of certifications. This may reflect their recent emergence and their smaller sample size in our data. It may also their role as modular, skill-specific NDCs that function best when tightly aligned with job requirements.

By estimating separate possession and accumulation effects for each type, we document a dichotomy, between formal, rigorous credentials and those that function primarily as signals of interest or basic competency.

5.3 Heterogeneous effects by worker characteristics

Education

Table 5.3 examines whether NDC returns vary by educational attainment and career stage, testing whether NDCs serve different functions for workers with and without traditional degrees and for workers with more or less work experience.[22]

Across the board, table 5.3 shows that wage premiums associated with NDCs are significantly larger for workers without a bachelor's degree than for those with one. For workers without a college degree, possessing a first job-relevant credential is associated with a 6.76% wage premium, compared to a 3.42% premium for college-educated workers.

This pattern of diminished returns for more educated workers extends to credential accumulation. Each additional job-relevant credential yields a 1.54% marginal wage increase for non-degree holders, whereas the return for degree holders is significantly lower at approximately 1.0%.

These results are consistent with the view that NDCs function as high-value partial substitutes for formal education. For workers without a degree, relevant NDCs provide a substantial mechanism to close earnings gaps, offering returns that are economically large. For degree holders, NDCs appear to act as modest complements, providing additive value that is real but less transformative than for their non-college peers.

Paradoxically, NDCs are more prevalent among formal degree holders, as shown in Figure 5.3. Several reasons can explain why a worker without a formal two or four-year degree may not acquire a NDC despite their outsized returns. Bitar et al. (2024) show time and financial costs may be prohibitive. Poor data make it difficult to discern which NDCs will pay off. Escobari et al. (2019) show programs and institutions that grant NDCs are typically designed for advantaged groups. On the other hand, formal degree holders more often have their NDC costs paid by their employer, their professional

[22] The cutoff between less and more experienced workers is 12.8 years, the sample mean. In calculating years of work experience, when no end date of an individual’s most recent role is listed, we impute July 2025, effectively assuming the individual is still employed in that role.

networks may provide harder-to-access information on which NDCs pay off, and they face less risk investing time and money into earning NDCs.

Table 5.3 Heterogeneous effects by education and experience

Dependent Variable:	Log Salary	
	(1)	(2)
First relevant credential	0.0676***	0.0613***
	(0.0082)	(0.0095)
Additional relevant credentials	0.0154***	0.0232***
	(0.0030)	(0.0028)
First irrelevant credential	0.0535***	0.0294***
	(0.0048)	(0.0076)
Additional irrelevant credentials	0.0012	-0.0087***
	(0.0014)	(0.0015)
First relevant credential × BA or more	-0.0334***	
	(0.0072)	
Additional relevant credentials × BA or more	-0.0054**	
	(0.0025)	
First irrelevant credential × BA or more	-0.0396***	
	(0.0054)	
Additional irrelevant credentials × BA or more	-0.0115***	
	(0.0012)	
First relevant credential × Experienced		-0.0329***
		(0.0055)
Additional relevant credentials × Experienced		-0.0189***
		(0.0023)
First irrelevant credential × Experienced		-0.0145***
		(0.0052)
Additional irrelevant credentials × Experienced		-0.0005
		(0.0011)

Note: *Table compares combined wage effects of workers by experience level of formal education. Controls include gender and ethnicity as well as industry, location, and ethnicity fixed effects.*

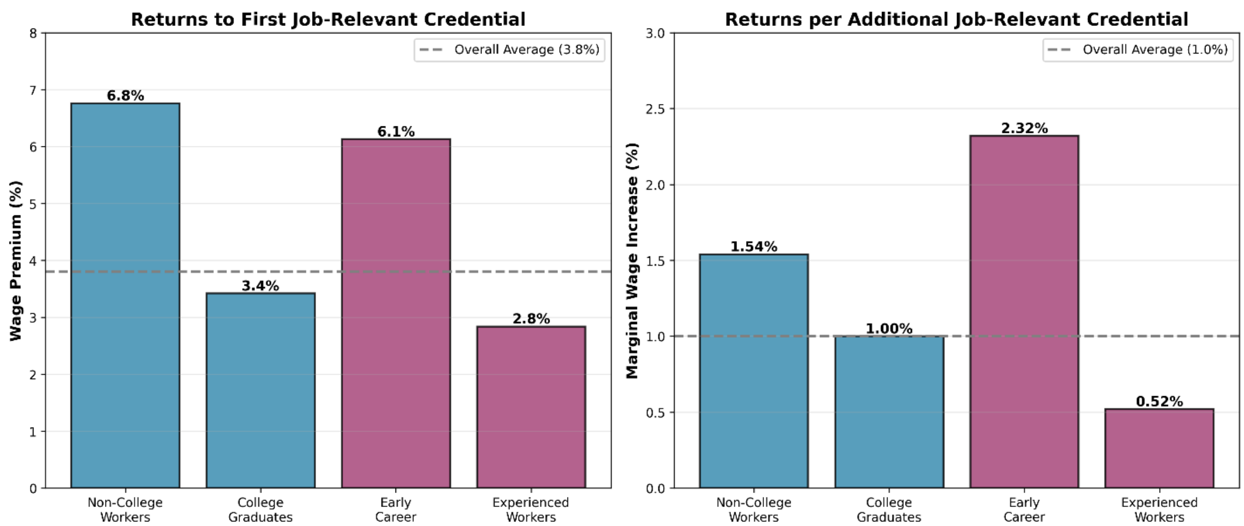
Experience interactions

Experience-based heterogeneity is even more pronounced. Early-career workers (those with below-mean experience) realize a 6.13% wage premium from their first job-relevant credential, whereas experienced workers see a significantly smaller premium of 2.84%.

The contrast is starkest in the returns to accumulation. For early-career workers, each additional job-relevant credential is associated with a robust 2.32% wage increase. However, for experienced workers, this return effectively vanishes.

This gradient suggests that NDCs play a critical role in the early stages of a career, in part by increasing productivity and in part by signaling competence; in both cases helping them differentiate themselves in the absence of a long track record. For experienced workers, whose resumes already contain rich signals of productivity through job history and tenure, the marginal information value of accumulating additional NDCs is negligible.

Figure 5.5 NDC returns are significantly higher for non-college and early career workers



Heterogeneous effects by worker characteristic and NDC type

Certifications demonstrate the clearest pattern consistent with human capital accumulation as well as the strongest returns for workers with less experience and without a bachelor’s degree. Among workers without a bachelor's degree, acquiring a first relevant certification is associated with a 7.06% wage premium, the largest coefficient in the entire specification. Each additional relevant certification yields an additional 3.49% return for this group. The pattern is similar for early-career workers, where the first relevant certification associates with a 5.22% premium and each additional relevant certification with 3.20%.

These results reinforce the hypothesis that certifications operate at least in part through human capital mechanisms, conferring returns to accumulation across worker types but only when job relevant. Their additional value to less experienced workers and workers without a bachelor’s degree suggests they may also provide a positive signal for those lacking a traditional one. Through both channels, they serve as viable alternatives to formal education and among those building competencies early in their careers.

Microcredentials display a distinctive complementarity with formal education. Unlike other credential types, which show negative or insignificant interactions with bachelor's degree attainment, additional relevant microcredentials are associated with 4.22 percentage points higher returns among college graduates. This positive interaction suggests microcredentials may function differently in labor markets than other NDC types. Rather than substituting for formal education, they appear to complement it, perhaps by providing specialized, current skills that enhance the productivity of workers with strong educational foundations. This pattern aligns with microcredentials' institutional form: Their design as modular, skill-specific offerings allows workers to rapidly update to reflect evolving technologies and employer demands. These attributes make microcredentials unique among NDC types for conferring amalgamable value to degree holders seeking to maintain cutting-edge expertise in their fields.

Certificates show limited accumulation returns that turn negative for some groups. While first relevant certificates associate with modest positive returns for workers without degrees (3.12%) and for early-career workers (3.43%), accumulating additional relevant certificates yields no significant wage gains for less experienced workers and negative returns (-1.88%) for non-college workers. This pattern suggests certificates primarily provide signaling value rather than additive human capital. Once workers have demonstrated commitment to professional development through initial certificate completion, additional certificates of this type offer limited marginal benefit and may even signal unfocused credentialing efforts.

Badge effects vary dramatically by relevance and worker characteristics. First irrelevant badges show surprisingly large positive associations with wages (5.77% for early-career workers and 5.45% for workers without degrees) suggesting substantial signaling value even when badges lack direct job relevance. However, accumulation of these lower-stakes NDCs carries risks for less experienced workers and degree holders alike, in both cases associated with a wage penalty greater in magnitude than -2.5%. Wage penalties from accumulation of badges, an NDC type often viewed as less rigorous, can only be interpreted as a negative signal, perhaps, in the case of workers that possess a formal degree, obfuscating its positive signal; or otherwise conveying poor judgement, a lack of deep expertise, or a fragmented skill set. However, these findings, while cautionary, may belie additional heterogeneity even within the NDC type: The category encompasses both rigorous professional badges and low-barrier participation markers, making aggregate effects difficult to interpret. Moreover, the small sample of badge holders in our data (approximately 130,000 individuals) also limits statistical precision for detecting differential effects across worker types.

These patterns collectively support a nuanced view of NDCs as heterogeneous signals that operate through different mechanisms. Certifications appear to build verifiable human capital that rewards accumulation particularly for workers lacking traditional educational credentials. Microcredentials may serve educated workers pursuing specialized skill development. Certificates and badges function as one-time quality signals that separate workers in early-career stages or non-degree pathways from their peers, but they offer limited marginal value beyond initial possession.

Significant differences across worker groups reinforce that NDC markets serve distinct functions for different populations, with the largest economic impacts accruing to non-college and early-career workers seeking alternative pathways to skill verification and wage growth.

5.4 Summary of results

Our analysis of U.S. resumes reveals three central findings that advance understanding of NDCs in the labor market.

First, NDC relevance emerges as a critical determinant of labor market returns. While workers holding any NDC earn higher wages on average, additional NDCs generate positive wage associations only when they are relevant to workers' occupations. Relevance-weighting opens the door to an interpretation that distinguishes between NDCs which may provide general signaling value versus those that may reflect job-specific human capital.

Second, we document substantial heterogeneity across NDC types. Certifications show strong positive associations with relevant accumulation but no possession premium, while badges and certificates exhibit the opposite pattern, large initial premiums but negligible accumulation effects, regardless of relevance. Returns to job-relevant NDC accumulation but not to job-irrelevant possession or accumulation is consistent with genuine skill complementarities. In contrast, returns to possession but not accumulation of both job-relevant and irrelevant badges and certificates is consistent with a signaling saturation.

Third, NDC returns vary dramatically across worker characteristics. Non-college workers realize larger earnings premiums of from NDC possession compared to college graduates, while early-career workers show larger premiums than experienced workers. These patterns suggest NDCs may potentially serve as substitutes for formal education among non-college workers and as early-career assets before work histories are established.

Findings are robust across multiple specifications, including alternative wage measures, sample weights, occupation controls, and inverse probability weighting for selection correction. While our approach identifies descriptive associations rather than causal effects, the consistency of results across robustness checks and the systematic patterns of heterogeneity provide confidence in the stability of these relationships. The results underscore both the promise of NDCs as alternative pathways to skill development and the critical importance of NDC quality and job relevance in determining their labor market value.

6. Discussion

This study provides the most comprehensive analysis to date of the labor market returns to NDCs in the United States. Drawing on 37.7 million worker resumes and 54.3 million NDCs, we document substantial heterogeneity in NDC returns that depends critically on three factors: job relevance, NDC type, and worker characteristics.

Our analysis yields three core findings that advance understanding of NDCs in labor markets:

1. **Job relevance is a critical determinant of NDC returns**. Workers' first job-relevant NDC is associated with a 3.8% wage premium, more than double the 1.8% premium for job-irrelevant credentials. More strikingly, returns to accumulation depend entirely on relevance: Each additional job-relevant NDC yields a 1.0% marginal wage increase, while accumulation of irrelevant NDCs shows no significant association with wages. This sharp distinction suggests that NDC markets reward specific human capital acquisition rather than mere NDC accumulation.
2. **NDC type matters fundamentally for how they function in labor markets**. Certifications—which typically require rigorous validation, ongoing maintenance, and third-party verification—exhibit returns consistent with human capital accumulation: positive, additive wage associations that depend critically on job relevance. In contrast, badges and certificates function primarily as screening devices, delivering one-time wage premiums regardless of relevance but with negligible returns to accumulation. This bifurcation reveals that the NDC market operates through distinct mechanisms depending on institutional form, with implications for both individual investment decisions and credential market design.
3. **NDC returns vary dramatically across worker characteristics in ways that suggest potential for reducing educational inequality**. Non-college workers realize a 6.8% wage premium from their first job-relevant NDC, nearly double the 3.4% premium for college graduates. Each additional relevant NDC yields 1.5 percentage points more for non-degree holders than for degree holders. Similarly, early-career workers experience a 6.1% premium from their first job-relevant NDC compared to 2.8% for experienced workers. These patterns indicate that rigorous, occupationally-aligned NDCs provide genuine alternative pathways to skill verification and wage growth for workers who lack traditional educational credentials or extensive work histories.

While our analysis identifies descriptive associations rather than causal effects, the systematic patterns across NDC types and worker characteristics offer insight into underlying mechanisms. The finding that only job-relevant certifications generate returns to accumulation while badges and certificates do not—regardless of relevance—suggests these NDC types operate through distinct channels. Certifications appear to function partially through human capital mechanisms, with each additional NDC conveying genuine, additive skills valued by employers. Badges and certificates, by contrast, appear to serve primarily as quality signals that separate workers from non-credentialed peers but provide limited marginal information once initial possession is established.

This interpretation gains support from the heterogeneity in returns. If NDCs operated purely through signaling mechanisms, we would expect similar returns across worker characteristics once we control for occupational sorting. Instead, substantially larger returns for non-college and early-career workers suggest these NDCs provide particular value when workers lack alternative signals of productivity—either through traditional educational credentials or extensive work experience.

The rapid proliferation documented in our data—35% growth in NDC prevalence in a single year, with badges and microcredentials growing fastest—occurs against this backdrop of heterogeneous mechanisms and returns. This proliferation creates both opportunity and risk.

Our findings suggest several priorities for NDC market development and regulation. The substantial returns to job-relevant certifications for non-college workers (7.1% for first relevant certification, 3.5% marginal returns to accumulation) indicate that well-designed, rigorously validated NDCs can serve as genuine alternatives to costly traditional education. However, the complete absence of wage associations with irrelevant NDC accumulation underscores the importance of matching mechanisms: Workers need better information about which NDCs yield returns in which occupations.

The NDC market currently lacks three elements necessary for efficient operation: (1) transparent quality signals distinguishing, for example, rigorous certifications from lower-stakes badges, (2) occupation-specific guidance on NDC relevance and returns, and (3) mechanisms to prevent exploitation of workers through low-quality programs in information-scarce environments. Addressing these gaps requires investment in NDC registries, return-on-investment tracking systems, and quality assurance mechanisms that help workers navigate an increasingly complex credential landscape.

The finding that NDC returns are largest for non-college and early-career workers suggests public subsidies for NDC acquisition may be justified on equity grounds, particularly for programs demonstrating strong job-relevant returns. However, the negative or null returns to accumulation of certain NDC types (particularly badges and certificates) indicates that quality standards and targeting are essential—indiscriminate subsidy of NDC programs risks public investment in NDCs with limited labor market value.

The strong differential between certification returns (which depend on relevance) and badge/certificate returns (which do not) suggests employers weigh these NDC types differently in hiring and promotion decisions. Training providers should recognize that market rewards for rigorous, validated certifications justify investments in quality assurance, proctored assessments, and renewal requirements. Conversely, the saturation effects observed for badges and certificates indicate limits to strategies focused on proliferation of low-barrier NDCs.

For employers, our findings suggest that credential-based hiring screens should account for both NDC type and job relevance rather than treating all NDCs equivalently. The fact that additional badges and certificates show no wage associations—and in some specifications, negative associations—indicates these NDCs provide limited signal value beyond initial possession. In contrast, accumulation of job-relevant certifications appears to reflect genuine skill development worthy of compensation.

Workers face an increasingly complex NDC market where the returns to investment vary dramatically by NDC type, job relevance, and worker characteristics. Our findings suggest several decision rules: (1) prioritize NDCs directly relevant to target occupations over general-purpose NDCs, (2) recognize that certified, validated NDCs provide more sustained returns than lower-barrier badges and certificates, particularly for accumulation, and (3) early-career and non-college workers stand to gain most from strategic NDC investment, suggesting these workers should prioritize NDC acquisition over workers with extensive experience or traditional degrees.

However, the information asymmetries documented here—particularly the difficulty workers face in assessing NDC quality and relevance—argue for policy interventions to improve market transparency rather than relying on individual navigation of opaque NDC markets.

Several limitations warrant acknowledgment.

- **Our analysis identifies correlational relationships rather than causal effects**. While extensive robustness checks including inverse probability weighting, occupation controls, and alternative specifications support the stability of our estimates, unobserved worker characteristics correlated with both NDC acquisition and wages likely influence our results. The instrumental variable strategy we employ using local peer effects proves too weak to isolate fully exogenous variation, indicating the need for alternative identification strategies such as policy discontinuities or natural experiments in credential availability.

- **Our data derive from worker resumes, which may selectively include credentials workers believe will benefit them and exclude credentials they view as irrelevant or low-value**. This selection potentially biases our estimates toward finding positive returns. However, this limitation strengthens our null finding regarding irrelevant NDC accumulation: Even among NDCs workers chose to display, accumulation of job-irrelevant NDCs shows no wage association.
- **Our credential-job relevance measures, while novel and informative, rely on observed credential-occupation patterns rather than direct measures of skill content or employer preferences**. Future research incorporating detailed skill requirements and employer validation would strengthen conclusions about the mechanisms through which relevant credentials generate returns.
- **We measure NDC prevalence at a point in time rather than tracking individuals before and after NDC acquisition**. Panel data following workers through NDC acquisition would enable estimation of within-person effects and more credible causal identification. Our ongoing work pursues such strategies using the longitudinal structure of the resume data.
- **Our analysis aggregates across credential providers within types, masking potentially substantial heterogeneity in quality and returns within categories**. Future research should examine specific NDC programs and providers to identify which characteristics of individual NDCs—program rigor, issuer reputation, industry recognition—drive the patterns we document.

Despite these limitations, our findings offer the most comprehensive evidence to date on the labor market value of alternative NDCs and how this value varies across NDC types and worker characteristics. The systematic patterns we document—particularly the sharp divergence between certification and badge/certificate returns, and the substantially larger effects for non-college and early-career workers—provide actionable insights for NDC market development and workforce policy.

The rapid proliferation of NDCs represents a potentially transformative shift in how workers acquire and signal skills. Our analysis suggests this transformation carries both promise and peril. Well-designed, rigorously validated NDCs that align with occupational skill requirements can provide genuine pathways to skill development and wage growth, particularly for workers without traditional educational credentials or extensive work experience. However, proliferation of low-quality, poorly aligned NDCs in the absence of transparent quality signals and effective guidance systems risks exposing workers to investments that yield limited returns.

As NDC markets continue to evolve—driven by technological change, shifting employer demands, and perceived limitations of traditional education—ensuring these markets serve workers effectively requires attention to quality assurance, information provision, and strategic targeting. The heterogeneity we document in NDC returns suggests that one-size-fits-all approaches to NDC policy will prove insufficient. Instead, effective NDC market development requires differentiation: Supporting rigorous, job-relevant certifications that build human capital while providing transparent information to help workers avoid low-value alternatives.

The finding that NDCs generate largest returns for workers who need them most—those without traditional degrees and those early in their careers—suggests the potential for NDCs to modestly reduce educational inequality if properly designed and targeted. Realizing this potential requires moving beyond NDC proliferation toward NDC quality and strategic alignment with labor market needs.

Appendix A: Methods

Appendix A1: Post-stratification weights

In general, Revelio data is biased towards workers with a higher level of education and in certain kinds of business and technical occupations (management, business and finance, sales, computer and mathematical, architecture and engineering, arts and media). Relatively lower representation in many traditionally “blue collar” jobs (food preparation, construction, cleaning, installation and maintenance, transport and material moving). In addition to these occupational and educational imbalances, the sample also exhibits geographic skew, with disproportionately high representation of states with more dynamic and digitalized labor markets (e.g., California, New York, Massachusetts, and Washington, D.C.).

To test whether these composition effects explain our regression results, we re-estimate our main models using post-stratification weights that recompose the sample to reflect the national distribution of employment across states and major occupational groups.

Each observation i is assigned a weight:

$$w_{i,so} = \frac{N_{so}}{n_{so}}$$

Where N_{so} is the number of workers in stratum(s, o)—defined by state and 2-digit SOC occupational group—according to the American Community Survey (ACS), and n_{so} is the corresponding count of users in Revelio resumes sample. Adding this variable as regression weight adjusts the sample so that state—occupation cells contribute to the estimates in proportion to their share of national employment.

We selected occupation and state as stratifying variables to strike a balance between bias control and data coverage—capturing key sources of variation without introducing excessive sparsity in the sample. Extending the adjustment to additional strata (e.g., education and sector) would have resulted in a larger number of unobserved cells in the resumes sample, limiting the reliability of the weights).

While this strategy does not eliminate all forms of selection bias, it serves as a focused robustness check. The fact that our key coefficients remain stable in sign, magnitude, and statistical significance after weighting supports the conclusion that the results are not driven by sample composition along state or occupational lines.

Figure A1.1 Education levels of workers in Revelio sample vs American Community Survey

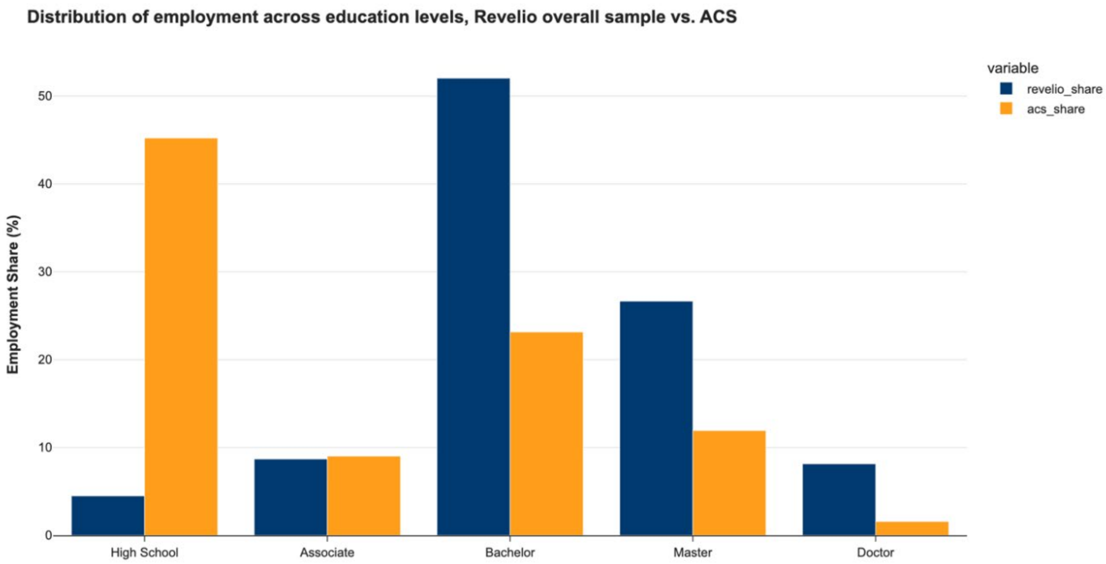
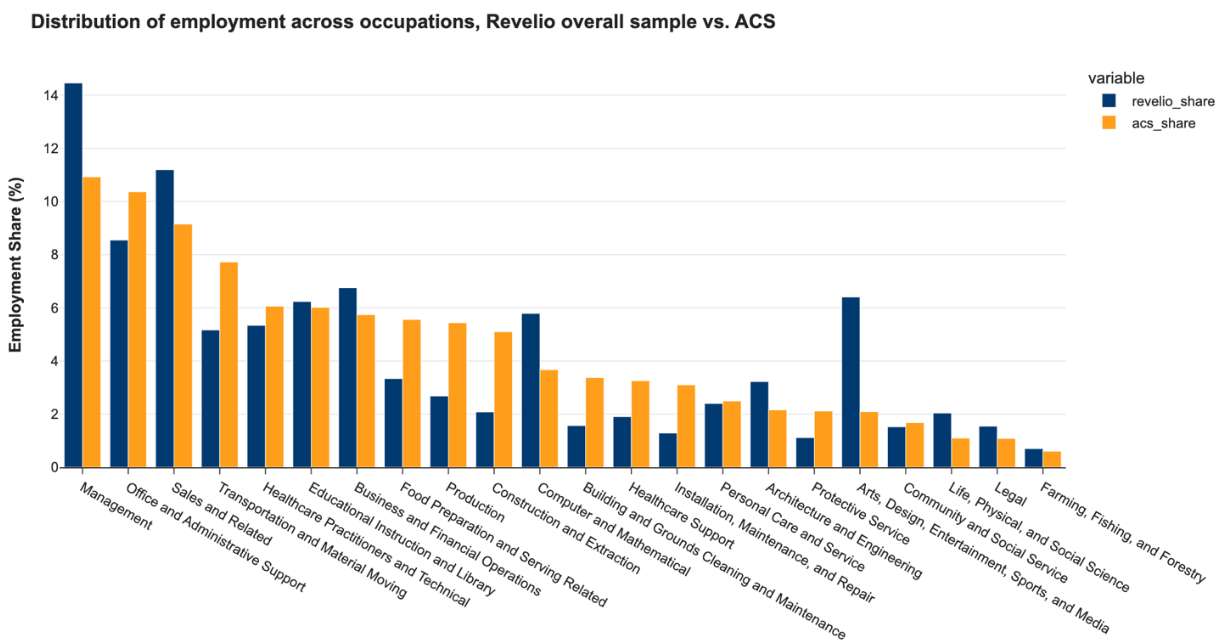


Figure A1.2 Occupations of workers in Revelio sample vs American Community Survey



Appendix A2: NDC standardization and classification

Our initial dataset contains approximately 8 million unique raw non-degree credential (NDC) entries extracted from resume data. These entries ranging from formally recognized credentials (e.g., "Certified Public Accountant") to non-credential entries (e.g., "painting," "subject matter expert"). To ensure data quality and enable systematic analysis, we implement a two-step standardization procedure: (1) classification of genuine NDCs versus non-NDCs, and (2) mapping of validated credentials to the Credential Engine standardized taxonomy.

A2.1 Step 1: Genuine NDC classification

Data preparation

Raw NDC entries undergo initial text preprocessing to standardize their format. Preprocessing includes conversion to lowercase, removal of extraneous characters (quotation marks, parentheses, periods, and non-alphanumeric symbols except numbers and plus signs), normalization of whitespace, and removal of duplicate words within credential strings. We simultaneously expand a comprehensive list of credential and organizational abbreviations (e.g., CNA → Certified Nursing Assistant) and standardize variable terminology (e.g., "licence" to "license," "cert" to "certificate").

After preprocessing, we classify all 8 million unique raw credential entries into two categories: Likely NDCs and non-NDCs. Examples of non-credentials removed from further analysis include:

- **Junk or irrelevant entries**: "painting," "life member," "participation in the international volunteer day," "unpaid leave"
- **Job titles or positions**: "aesthetician," "ski instructor," "superintendent of schools," "federal boarding officer"
- **Organization names or affiliations**: "the oxford consortium for human rights," "explorers club member," "fellow american board of forensic toxicology"
- **Ambiguous course or training titles:** "poverty 101," "performance and reward management," "leading strategic growth"
- **Self-assessments**: "subject matter expert"

To conduct this classification, we employ a pre-trained, instruction-tuned sentence transformer model (hkunlp/instructor-base; Su et al. 2023) combined with human-in-the-loop iterative refinement. This approach was selected over alternatives (e.g., TF-IDF embeddings) for three key advantages: (1) the instruction-tuned architecture enables task-specific guidance through natural language prompts, (2) superior performance on informal, noisy text relative to generic embeddings, and (3) ability to distinguish subtle patterns such as "AWS Certified" (credential) versus "Amazon Certified Organic" (non-credential).

Model training procedure

We generate dense vector embeddings for all preprocessed entries using the instruction: "Represent the informal or noisy text for classification as a credential or not a credential." These embeddings guide the model to emphasize semantic features relevant for credential identification.

A random forest classifier is trained iteratively on these embeddings. Initial training begins with 200 hand-labeled observations plus 50 additional observations with associated URLs (assumed to be valid credentials). The training data is split into training (60%), validation (20%), and test (20%) subsets.

We refine the classifier through iterative human-in-the-loop review across multiple rounds. In each iteration, we: (1) generate predictions on a randomly sampled subset of 10,000 entries, (2) curate equal-sized samples of predicted "credential" and "not a credential" entries for manual review, (3) add manually reviewed samples to the training dataset, and (4) retrain the classifier with the augmented dataset. We continue iterations until validation set performance reaches 80% accuracy—a reasonable target given that inter-rater agreement among human reviewers likely approximates this threshold due to ambiguous cases.

A2.1 Step 2: Mapping genuine NDCs to standardized taxonomy

Matching procedure

Validated NDCs are matched to the Credential Engine (CE) taxonomy—the most comprehensive U.S. credential registry, at time of analysis containing approximately 100,000 verified entries with standardized type classifications and metadata including issuer, credential description, and associated industries and occupations.

Each validated credential embedding is paired with the task-specific instruction: "Represent the informal or noisy credential for matching to a standardized list." CE credential embeddings use the complementary instruction: "Represent the formal and standardized credential for matching to a noisy list." These instruction pairs optimize embeddings for the matching task by guiding the model to emphasize relevant semantic features on each side of the matching process.

For each credential, we compute cosine similarity scores between its embedding and embeddings of all CE credentials, identifying the three CE credentials with highest similarity scores. We retain both matched credential names and their similarity scores to support downstream thresholding decisions.

Quality evaluation

We evaluate matching quality by examining the relationship between cosine similarity scores and type consistency across top matches. Our analysis confirms that higher similarity scores strongly predict type consistency across matched credentials:

- Broad category consistency (the NDC types evaluated in this paper's analysis) (e.g., Certificate vs. Degree) exhibits the strongest alignment, even among lower-similarity matches
- Specific category consistency shows greater heterogeneity, though manual inspection confirms that many apparent mismatches represent near-correct matches where secondary alternatives remain plausible

Most common mismatches reflect semantic similarity within credential types (e.g., "Certificate" vs. "Certification"), and inspection of mismatched cases frequently confirms that the highest-ranked match is correct while secondary matches represent reasonable alternatives. This evaluation supports confidence in our matching approach.

Filtering and final sample

We exclude matches with cosine similarity below the 20th percentile to ensure match quality. This conservative threshold yields our final matched sample of 54.3 million NDC observations corresponding to 30,450 unique standardized NDCs held by 16.5 million workers (10.5% of the full resume dataset).

Appendix A3: Constructing credential-job relevance measures

Credential clustering procedure

To construct the measures of credential relevance to a particular occupation, we first pursue a clustering procedure to group similar credentials into credential families. The Credential Engine taxonomy to which we match raw credentials in resumes identifies specific credentials offered across institutions. This means similar credentials are sometimes treated as distinct in the data. For example, nine different 200-hour yoga training certificates from various studios appear separately in the Credential Engine taxonomy. However, when assessing their relevance to a yoga instructor—or any job—we want to consider them collectively, not individually.

The cluster procedure is organized in four stages:

1. **Prepare credential names for clustering:** The clustering is performed based on credential name and additional metadata provided by Credential Engine on each credential's related industries (NAICS), occupations (SOC) and instructional programs (CIP). This metadata is appended to the credential name to provide additional information for clustering.
2. **Transform credential names into text embeddings:** Enhanced credential names are cleaned using standard text cleaning procedures (lowercase, remove punctuation, remove duplicate words), in addition to expanding common acronyms into their full titles (such as CNA and TOEFL), and removing vague but

common terms in credential names (such as ‘achievement’ and ‘applied’). These cleaned names are then vectorized into text embeddings using an instructor-tuned large language model from the HuggingFace library (hkunlp/instructor-large). This method is preferred over other embeddings such as tf-idf for its ability to capture semantic meaning and recognize synonyms in credential naming schemes.

3. **Implement DBSCAN clustering algorithm on text embeddings:** Clustering is performed separately for each credential type using DBSCAN, ensuring each cluster contains only one type. The DBSCAN algorithm works by identifying high-density areas of projected embeddings. It is preferred over other clustering methods such as k-means for its ability to identify irregularly shaped clusters and clusters of heterogeneous size. This method classifies approximately 50% of credentials into 2,356 clusters, with the other 50% of credentials falling outside a high-density region and thus unassigned to a cluster.

Table A3.1 lists several sample clusters. Table A3.2 gives a sample of RCJs for NDCs in three occupations. Figure A3.1 shows the regression sample’s distribution of job-credential relevance scores, and Figure A3.2 shows counts of individuals holding NDCs by their job-relevance.

Table A3.1 Sample of credential clusters

Cluster	Credentials
Certificate Cluster 319	Bartending Class and Internship (Famous Bartending School ETP)
	Bartending Essentials Certificate (International Bartending School - PCS ETP)
	Bartending/Mixology Certificate (International Bartending School - PCS ETP)
	Catering Management (Mercer County Community College - Credit Programs ETP)
Certificate Cluster 1292	Certificate of Completion in Medical Interpretation (Los Angeles City College)
	Healthcare Interpreter (Highline College)
	Medical Interpreter Spanish (Everett Community College)
	Medical Transcription Editor (Seattle Central College)
	Spanish Medical Interpreter (Walla Walla Community College)

License Cluster 72	Licensed Marriage and Family Therapist Associate (LMFTA) (Indiana BHHS)
	Licensed Marriage and Family Therapist (LMFT) (Indiana BHHS)
	Marriage and Family Therapist Educational Limited License (LARA)
	Marriage and Family Therapist (Indiana BHHS)
	Marriage & Family Associate (Indiana BHHS)

Table A3.2 Sample of job-credential relevance scores for Software Developers, Nurses, and Management Analysts.

Software Developer

Credential	RCA
Javascript Certification	10.66
Python Programming Fundamentals Certification	4.89
Excel Introduction Certification	1.26
Intermediate Spanish Language Skills Micro Credential	1.22
Project Management Certification	0.95
Certificate In Leadership	0.61
Servsafe Food Handler Certification	0.08
Certified Nursing Assistant Certification	0.03
Bls Basic Life Support For Healthcare Providers Certificate	0.03
Registered Nurse RN Certificate	0.02

Nurse

Credential	RCA
Registered Nurse RN Certificate	26.06
Bls Basic Life Support For Healthcare Providers Certificate	14.47
Certified Nursing Assistant Certification	9.97
Servsafe Food Handler Certification	0.79
Intermediate Spanish Language Skills Micro Credential	0.42
Certificate In Leadership	0.37
Project Management Certification	0.14
Excel Introduction Certification	0.14
Javascript Certification	0.05
Python Programming Fundamentals Certification	0.04

Management Analyst

Credential	RCA
Project Management Certification	3.82
Excel Introduction Certification	1.58
Python Programming Fundamentals Certification	1.17
Certificate In Leadership	1.01
Intermediate Spanish Language Skills Micro Credential	0.56
Javascript Certification	0.48
Registered Nurse RN Certificate	0.12
Servsafe Food Handler Certification	0.12
Certified Nursing Assistant Certification	0.11
Bls Basic Life Support For Healthcare Providers Certificate	0.06

Figure A3.1 Job-credential relevance scores

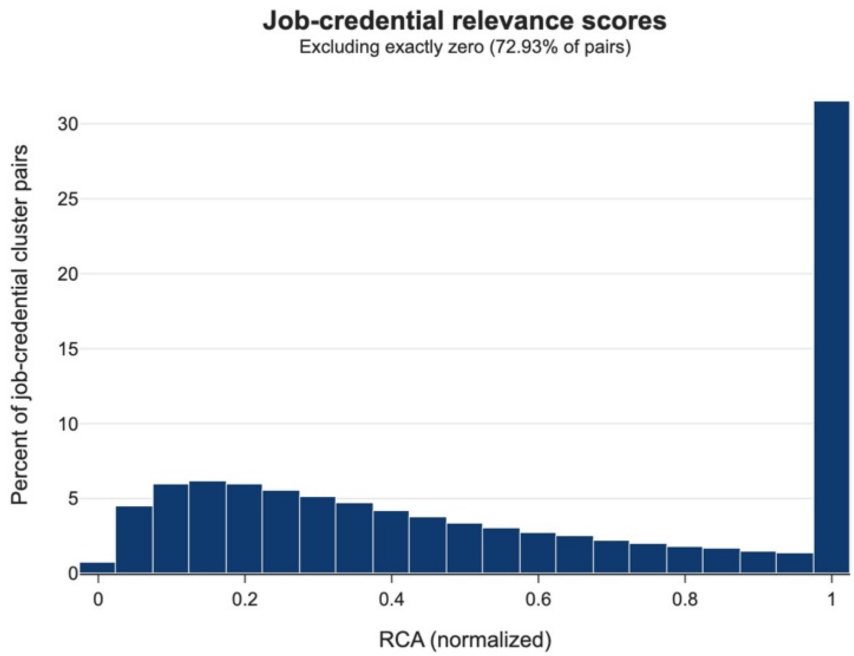
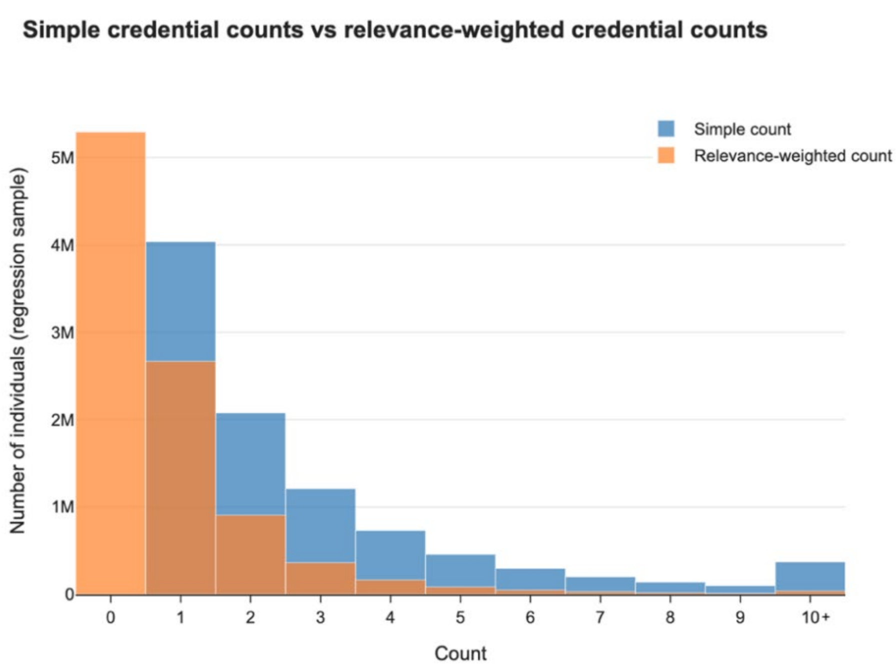


Figure A3.2 Simple vs relevance-weighted credential counts of individuals in the regression sample



Appendix B: Robustness

Appendix B1: Alternative earnings measure

Table B1 presents results using Bureau of Labor Statistics Occupational Employment and Wage Statistics (OEWS) median wages by occupation instead of Revelio's estimated individual wages.

Table B1 Base specification with OEWS wages

Dependent Variable:	Log Median Wage
First relevant credential	0.0279***
	(0.0045)
Additional relevant credentials	0.0225***
	(0.0015)
First irrelevant credential	-0.0029
	(0.0032)
Additional irrelevant credentials	-0.0083***
	(0.0013)
Sex (Male)	0.1054***
	(0.0077)
Education (BA or more)	0.2063***
	(0.0132)
Experience	0.0011***
	(7.82×10^{-5})
Experience SQ	-1.17×10^{-6}
	(1×10^{-6})
Fixed-effects	
Ethnicity	Yes
State	Yes
NAICS industry	Yes
Fit statistics	
Observations	37,586,802
R^2	0.15813
Within R^2	0.06668

Results using OEWS wages are broadly consistent with our main findings.

Appendix B2: Sample weighting

Table B2 replicates our main results using post-stratification weights to address the non-representative nature of our resume sample. The weights align our sample with the national distribution of employment across state-occupation cells from the American Community Survey.

Table B2 Base specification with weighted observations

Dependent Variable:	Log Salary
First relevant credential	0.0488***
	(0.0072)
Additional relevant credentials	0.0116***
	(0.0029)
First irrelevant credential	0.0287***
	(0.0059)
Additional Irrelevant credentials	-0.0085***
	(0.0012)
Sex (Male)	0.1072***
	(0.0119)
Education (BA or more)	0.3198***
	(0.0192)
Experience	0.0026***
	(0.0002)
Experience SQ	$-2.89 \times 10^{-6***}$
	(1.02×10^{-6})
Fixed-effects	
Ethnicity	Yes
State	Yes
NAICS Industry	Yes
Fit statistics	
Observations	37,730,478
R^2	0.27684
Within R^2	0.14584

The weighted results remain similar to our main findings, which suggests our main results are not driven by sample composition biases along observable dimensions.

Appendix B3: Occupation controls

Table B3 examines robustness to inclusion of occupation fixed effects, which identify credential effects from within occupational categories and controls for occupational sorting.

Table B3-1 Base specification with occupation fixed effects

Dependent Variable:	Log Salary
First relevant credential	0.0186***
	(0.0059)
Additional relevant credentials	-0.0005
	(0.0011)
First irrelevant credential	0.0130***
	(0.0049)
Additional irrelevant credentials	-0.0061***
	(0.0010)
Sex (Male)	0.1056***
	(0.0067)
Education (BA or more)	0.2275***
	(0.0105)
Experience	0.0020***
	(9.58×10^{-5})
Experience SQ	-2.25×10^{-6}**
	(1.01×10^{-6})
Fixed-effects	
Ethnicity	Yes
State	Yes
NAICS industry	Yes
Occupation	Yes
Fit statistics	
Observations	37,730,478
R^2	0.37783
Within R^2	0.08417

Within occupations, we find no returns to additional relevant NDCs. However, as discussed in Section 5, the broad result masks substantial heterogeneity. Consistent with the core patterns documented in the other specifications, Table B3-2 shows that additional job-relevant NDCs yield positive returns for early-career and non-college workers, even after controlling for occupation. In contrast, and consistent with estimates in other specifications, accumulation of job-irrelevant NDCs does not yield positive returns for these groups. The persistence of significant effects suggests NDCs provide value within jobs, beyond occupational sorting.

Table B3-2 Heterogeneous effects by education and experience with occupation fixed effects

Dependent Variable:	Log Salary	
Model:	(1)	(2)
First relevant credential	0.0353***	0.0329***
	(0.0069)	(0.0055)
Additional relevant credential	0.0080***	0.0011
	(0.0015)	(0.0023)
First irrelevant credential	0.0218***	0.0328***
	(0.0059)	(0.0028)
Additional irrelevant credential	-0.0054***	0.0010
	(0.0013)	(0.0012)
First relevant credential X BA or more		-0.0352***
		(0.0068)
Additional relevant credential X BA or more		-0.0017
		(0.0020)
First irrelevant credential X BA or more		-0.0218***
		(0.0042)
Additional irrelevant credential X BA or more		-0.0077***
		(0.0011)
First relevant credential X experienced	-0.0216***	
	(0.0083)	
Additional relevant credential X experienced	-0.0122***	
	(0.0017)	
First irrelevant credential X experienced	-0.0098***	
	(0.0036)	
Additional irrelevant credential X experienced	-0.0004	
	(0.0010)	

Note: Table compares combined wage effects of workers by experience level of formal education. Controls include gender and ethnicity as well as industry, location, occupation, and ethnicity fixed effects

Appendix B4: Selection correction

Table B4 presents results using inverse probability weighting (IPW) to address potential selection into credential attainment.

To address potential selection bias in credential acquisition, we employ inverse probability weighting (IPW) following the methodology of Robins et al. (2000) and Haneuse et al. (2009). Selection bias may arise if workers who choose to acquire credentials differ systematically from those who do not in ways that also affect wages but are unobserved in our data.

Table B4 Base specification with IPW

Dependent Variable:	Log Salary
First relevant credential	0.0381***
	(0.0076)
Additional relevant credentials	0.0012***
	(0.0002)
First irrelevant credential	0.0178***
	(0.0058)
Additional irrelevant credentials	-0.0082***
	(0.0012)
Sex (Male)	0.1371***
	(0.0109)
Education (BA or more)	0.3497***
	(0.0141)
Experience	0.0024***
	(0.0001)
Experience SQ	-2.78×10^{-6}**
	(1.02×10^{-6})
Fixed-effects	
Ethnicity	Yes
State	Yes
NAICS industry	Yes
Fit statistics	
Observations	37,730,478
R^2	0.26061
Within R^2	0.12534

The IPW approach creates a "pseudo-population" by weighting observations based on their inverse probability of selection into credential attainment. We estimate propensity scores for credential acquisition using a logistic regression model that includes all observed covariates (education, experience, demographic characteristics, occupation, industry, and geographic indicators). Each individual receives a weight equal to 1/P(credential|X) for credentialed workers and 1/P(no credential|X) for non-credentialed workers.

This reweighting adjusts the sample composition to reflect what would be observed if credential acquisition were independent of the selection factors, effectively addressing selection bias under the assumption that selection is based solely on observable characteristics (selection on observables). While this approach cannot eliminate bias from unobserved confounders, it provides a valuable robustness check for our main findings by correcting for selection on all measured individual and job characteristics.

IPW results show very similar results to those of the base specification in terms of sign and magnitude of all key variables.

Appendix B5: Alternative functional form

Table B5 Test for nonlinear returns

Dependent Variable:	Log Salary
First relevant credential	0.0382***
	(0.0078)
Additional relevant credentials	0.0096***
	(0.0028)
First irrelevant credential	0.0183***
	(0.0059)
Additional Irrelevant credentials	-0.0102***
	(0.0018)
Number of credentials SQ	5.45×10^{-5}
	(5.88×10^{-5})
Sex (Male)	0.1360***
	(0.0106)
Education (BA or more)	0.3518***
	(0.0142)
Experience	0.0024***
	(0.0001)
Experience SQ	-2.79×10^{-6}**
	(1.02×10^{-6})
Fixed-effects	
Ethnicity	Yes
State	Yes
NAICS Industry	Yes
Fit statistics	
Observations	37,730,478
R^2	0.26505
Within R^2	0.12798

We find no evidence for nonlinear returns to NDCs by including a term in our main specification for the square of the number of NDCs held by an individual.

Appendix B6: Missing observations

Our regression sample (37.7 million observations) is created by filtering the overall sample (156.5 million observations) to exclude observations with missing state, occupation, salary, NAICS2, sex, ethnicity, education, and experience. Dropping observations with missing education and experience are particularly restrictive: 99.5 million out of 156.5 million record no education information, and 84.1 million record no experience (only have one position on their resume, with no start or end dates).

We create an expanded regression sample that drops observations with missing values for all of the variables above except education and experience. This resulting expanded regression sample has 95.5 million observations.

Removing so many observations due to missing observations raises a concern of introducing additional bias if the data are not missing at random. To test robustness of our results, we estimate a regression specification that includes occupation controls and excludes controls for education and experience so we can include these additional observations in the regression. We compare results to a base specification that includes occupation controls (Appendix B3) to recapture variation explained by level of formal education.

Model 2 shows results from the main specification sample without controls for education and experience. Model 1 shows estimates of the same specification on the expanded sample.

Table B6 Test for robustness to missing data

Dependent Variable:	Log Salary	
Model:	(1)	(2)
First relevant credential	0.0625***	0.0404***
	(0.0107)	(0.0064)
Additional relevant credentials	0.0063***	0.0054***
	(0.0020)	(0.0015)
First irrelevant credential	0.0529***	0.0304***
	(0.0097)	(0.0055)
Additional irrelevant credentials	-0.0034**	-0.0046***
	(0.0014)	(0.0012)
Sex (Male)	0.1305***	0.1173***
	(0.0072)	(0.0075)
Fixed-effects		
Ethnicity	Yes	Yes
State	Yes	Yes
NAICS Industry	Yes	Yes
Occupation	Yes	Yes
Fit statistics		
Observations	95,487,601	37,730,478
R^2	0.38616	0.32886
Within R^2	0.01592	0.01209

Appendix C: Sample statistics

Appendix C1: Credential type prevalence

Table C.1 Most common credentials in the resume data

Type	Credential	Count
Badge	foundations of statistics badge	31,406
	empathy skill credential open badge	26,033
	neural networks and applications open badge	16,223
	data visualization and storytelling open badge	10,187
	introduction to statistics badge	5,698
Certificate	bls basic life support for healthcare providers certificate	293,010
	taxation certificate	261,161
	registered nurse rn certificate	245,879
	google adwords certificate	235,232
	google data analytics certificate	226,985
Certification	standardized work certification	380,291
	project management professional pmp certification	329,841
	advanced cardiac life support certification acls cardiovascular reference	269,881
	comptia security+ certification	262,869
	bls basic life support provider certification reference	223,691
License	prelicensing life and health insurance training license	76,614
	architect license	52,468
	real estate license	50,547
	pharmacist license	45,284
	professional counselor license	44,215
Microcredential	communication standards micro credential	137,157
	micro credential in diversity and inclusion	111,327
	micro credential in teamwork skills	92,871
	critical thinking skill credential micro	79,179
	creating text sets for deeper learning micro credential	67,769

Note: *this table and the summary statistics charts below include only the "good" matches to CE (80% of the 54.3 million credentials, approximately 43.5 million).*

Of all five credential types, certificates and certifications are the most common, comprising over 90% of all credentials in the sample and held by 5-7% of all individuals. Badges are emerging but still the lowest frequency, comprising only 0.41% of all credentials and held by less than 0.1% of all individuals (Figures C.1 and C.2).

Figure C.1 Credential prevalence in the overall sample

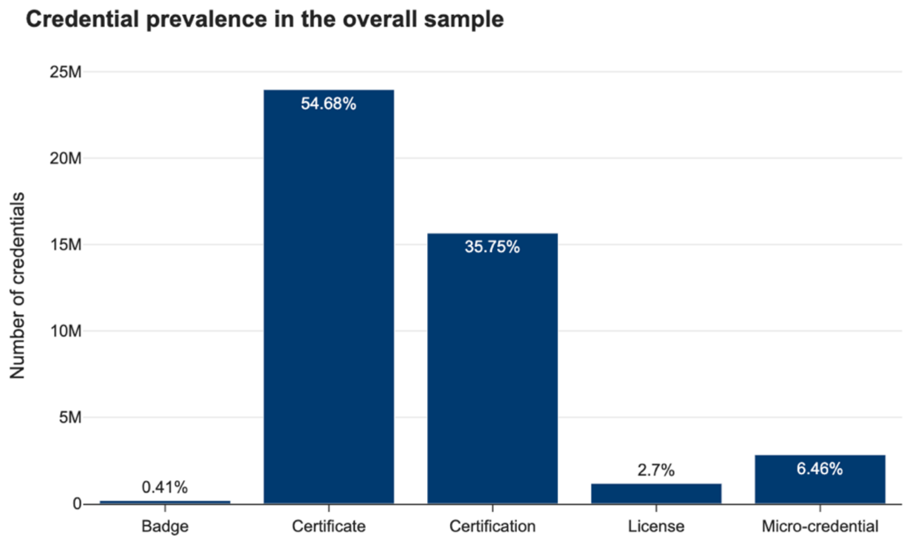
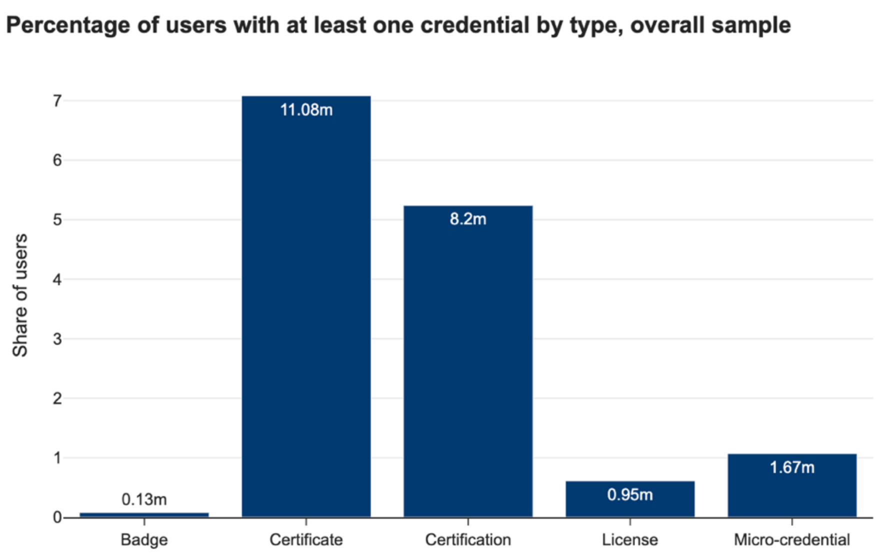


Figure C.2 Percentage of individuals with at least one credential by type



Appendix C2: Regression sample statistics

Table C.2 Regression sample statistics by education level.

	Mean	Median	St. Dev.	Min	Max
College Graduates					
Salary	107,387	87,253	72,615	0.00	3,000,000
Sex (Male)	0.51	1.00	0.50	0.00	1.00
Experience (Years)	13.03	10.58	10.41	0.00	80.00
Has credential	0.26	0.00	0.44	0.00	1.00
Number of credentials	0.74	0.00	1.93	0.00	26.00
Number of relevance-weighted credentials	0.26	0.00	0.82	0.00	26.00
Non-College Workers					
Salary	64,044	51,771	42,475	0.02	1,600,000
Sex (Male)	0.49	0.00	0.50	0.00	1.00
Experience (Years)	11.03	8.17	10.15	0.00	80.00
Has credential	0.20	0.00	0.40	0.00	1.00
Number of credentials	0.52	0.00	1.64	0.00	26.00
Number of relevance-weighted credentials	0.19	0.00	0.70	0.00	25.00

Appendix D: Instrumental variable approach

A concern with the main approach is selection bias in credential completion, which can lead to overstated effects of credential attainment on wages. Workers who choose to complete a credential may be inherently different from those who do not (e.g., unobserved characteristics such as career motivation or ability), and these characteristics may drive the observed differences in wages.

This issue is plausible and described in other studies that examine the impact of education and training decisions on labor market outcomes (Card, 1995; Neumark & Joyce, 2000; Liu, 2016; Cuartas, 2022; Lang, 2022). These studies address this concern by implementing an instrumental variable approach that exploits exogenous variation in some characteristic that may likely affect education and training decisions but not outcomes directly (such as the distance from an education center or policy changes that affect the cost of education). Similar instruments are not possible with our data, because many credentialling programs are administered remotely online and no clear policy changes have been enacted that satisfy these conditions.

Instead, we construct an instrumental variable following the approach of Baird, Bozick, and Zaber (2022) that suggest a person's credential attainment is influenced by the credential attainment of local peers, irrespective of their career motivation or other unobserved characteristics that may also influence wages. For each worker in our analysis, this "local peer influence" instrument is calculated as the leave-one-out proportion of the worker's peer group that hold a credential. Peer groups are defined as all workers in the same geographic region with the same sex, ethnicity, education level and experience level.[23] Similar to Baird, Bozick, and Zaber, we also incorporate controls for the log mean salary of the peer group excluding the worker in question.

This instrumental variable approach still suggests a positive effect of credential attainment on wages, but results are not statistically significant (Table D1 and D2). While we cannot conclude a causal relationship between credential attainment and economic outcomes through this approach, these results do not contradict our main findings.

[23] Education level is defined as the highest degree obtained, and experience level is a band of +/- 5 years of experience based on all positions on the worker's resume. Geographic region includes either specific metropolitan areas (CBSAs) or the nonmetropolitan area for each state. When the resulting peer group is less than 30 observations, we use an alternative, broader peer group that is defined using geographic region and education level only.

Table D1 Instrumental variable specification, Stage 1

Dependent Variable:	Has Credential (0/1)
Cohort leave-one-out proportion with credential (IV)	0.9394***
	(0.0627)
Sex (Male)	0.0057
	(0.0068)
BA or more	0.0015
	(0.0042)
Experience	0.0002***
	(4.15×10^{-5})
Experience SQ	-2.34×10^{-7}***
	(4.57×10^{-8})
IV cohort log mean salary (leave-one-out)	-0.0169
	(0.0182)
Fixed-effects	
Ethnicity	Yes
State	Yes
NAICS Industry	Yes
Observations	37,730,478
R^2	0.02333
Within R^2	0.0141

Clustered standard-errors by metro area & NAICS industry in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table D2 Instrumental variable specification, Stage 2

Dependent Variable:	Log Salary
Has credential (IV)	0.1008
	(0.1151)
Sex (Male)	-0.0253***
	(0.0060)
BA or more	-0.0167
	(0.0107)
Experience	0.0003*
	(9.39×10^{-5})
Experience SQ	-3.72×10^{-7}**
	(1.13×10^{-7})
IV cohort log mean salary (leave-one-out)	0.8909***
	(0.0290)
Fixed-effects	
Ethnicity	Yes
State	Yes
NAICS Industry	Yes
Fit statistics	
Observations	37,730,478
R^2	0.30606
Within R^2	0.17665

Clustered standard-errors by metro area & NAICS industry in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix E: Additional regression results

Appendix E1: Standard reporting

Dependent Variable:	Log Salary
Has credential	0.0272***
	(0.0065)
Number of credentials	-0.0094***
	(0.0012)
Number of relevance-weighted credentials	0.0198***
	(0.0031)
Sex (Male)	0.1360***
	(0.0106)
Education (BA or more)	0.3518***
	(0.0142)
Experience	0.0024***
	(0.0001)
Experience SQ	$-2.79 \times 10^{-6***}$
	(1.89×10^{-7})
Fixed-effects	
Ethnicity	Yes
State	Yes
NAICS Industry	Yes
Observations	37,730,478
R^2	0.2651
Within R^2	0.1280

Clustered standard errors by state & NAICS industry in parentheses
*Note: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	Log Salary
Has badge	0.0474***
	(0.0116)
Has certificate	0.0245***
	(0.0042)
Has certification	0.0184
	(0.0110)
Has micro-credential	0.0107
	(0.0056)
Number of badges	0.0052
	(0.0078)
Number of certificates	-0.0105***
	(0.0013)
Number of certifications	-0.0094**
	(0.0027)
Number of micro-credentials	-0.0196***
	(0.0051)
Number of relevance-weighted badges	-0.0356*
	(0.0141)
Number of relevance-weighted certificates	-0.0057
	(0.0038)
Number of relevance-weighted certifications	0.0317***
	(0.0047)
Number of relevance-weighted micro-credentials	0.0540**
	(0.0163)
Sex (Male)	0.1352***
	(0.0105)
BA or more	0.3519***
	(0.0142)
Experience	0.0024***
	(0.0001)
Experience SQ	-2.79×10^{-6}***
	(1.9×10^{-7})
Fixed-effects	
Ethnicity	Yes
State	Yes
NAICS Industry	Yes
Observations	37,730,478
R^2	0.2654
Within R^2	0.1284

Clustered standard errors by state & NAICS industry in parentheses
*Note: *** 0.01, ** 0.05, * 0.1, · 0.1*

Appendix E2: Results by credential type and worker characteristic

Dependent Variable:	Log Salary	
	(1)	(2)
First relevant badge	0.04223**	0.02054*
	(0.01869)	(0.01242)
Additional relevant badges	0.00646	-0.02954**
	(0.00851)	(0.01214)
First irrelevant badge	0.05455***	0.05772***
	(0.01091)	(0.01898)
Additional irrelevant badges	0.01880*	0.00760
	(0.01060)	(0.00830)
First relevant certificate	0.03121***	0.03428***
	(0.00543)	(0.00652)
Additional relevant certificates	-0.01879***	0.00061
	(0.00343)	(0.00403)
First irrelevant certificate	0.05089***	0.02298***
	(0.00311)	(0.00575)
Additional irrelevant certificates	0.00090	-0.01070***
	(0.00160)	(0.00170)
First relevant certification	0.07064***	0.05222***
	(0.01384)	(0.01467)
Additional relevant certifications	0.03489***	0.03203***
	(0.00335)	(0.00296)
First irrelevant certification	0.02919***	0.01323
	(0.00788)	(0.00936)
Additional irrelevant certifications	-0.00660*	-0.00700*
	(0.00360)	(0.00400)
First relevant micro-credential	0.03316***	0.04683***
	(0.00936)	(0.01800)
Additional relevant micro-credentials	-0.00467	0.04013***
	(0.00638)	(0.01430)
First irrelevant micro-credential	0.02365***	-0.01215
	(0.00556)	(0.00910)
Additional irrelevant micro-credentials	-0.01420***	-0.01880***
	(0.00300)	(0.00700)
First relevant badge × BA or more	-0.02577*	—
	(0.01426)	
Additional relevant badges × BA or more	-0.03974***	—
	(0.00878)	
First irrelevant badge × BA or more	-0.00037	—
	(0.01224)	
Additional irrelevant badges × BA or more	-0.01430	—
	(0.01380)	
First relevant certificate × BA or more	-0.02524***	—
	(0.00687)	
Additional relevant certificates × BA or more	0.00284	—
	(0.00502)	
First irrelevant certificate × BA or more	-0.04044***	—
	(0.00390)	
Additional irrelevant certificates × BA or more	-0.01230***	—
	(0.00190)	
First relevant certification × BA or more	-0.03315***	—
	(0.01131)	
Additional relevant certifications × BA or more	-0.01375***	—
	(0.00302)	
First irrelevant certification × BA or more	-0.02251***	—
	(0.00788)	
Additional irrelevant certifications × BA or more	-0.00310	—
	[illegible]	

First relevant certification × BA or more	-0.03315***	—
	(0.01131)	
Additional relevant certifications × BA or more	-0.01375***	—
	(0.00302)	
First irrelevant certification × BA or more	-0.02251***	—
	(0.00788)	
Additional irrelevant certifications × BA or more	-0.00310	—
	(0.00270)	
First relevant micro-credential × BA or more	0.01429	—
	(0.01343)	
Additional relevant micro-credentials × BA or more	0.04217***	—
	(0.01084)	
First irrelevant micro-credential × BA or more	-0.03420***	—
	(0.00355)	
Additional irrelevant micro-credentials × BA or more	-0.00630	—
	(0.00420)	
First relevant badge × Experienced	—	0.00265
		(0.00940)
Additional relevant badges × Experienced	—	0.00449
		(0.01109)
First irrelevant badge × Experienced	—	-0.00725
		(0.01720)
Additional irrelevant badges × Experienced	—	-0.00540
		(0.00440)
First relevant certificate × Experienced	—	-0.03426***
		(0.00522)
Additional relevant certificates × Experienced	—	-0.02307***
		(0.00352)
First irrelevant certificate × Experienced	—	-0.01168***
		(0.00452)
Additional irrelevant certificates × Experienced	—	-0.00050
		(0.00110)
First relevant certification × Experienced	—	-0.01614**
		(0.00672)
Additional relevant certifications × Experienced	—	-0.01489***
		(0.00141)
First irrelevant certification × Experienced	—	-0.00227
		(0.00359)
Additional irrelevant certifications × Experienced	—	-0.00100
		(0.00310)
First relevant micro-credential × Experienced	—	-0.00245
		(0.00569)
Additional relevant micro-credentials × Experienced	—	-0.01359***
		(0.00509)
First irrelevant micro-credential × Experienced	—	0.01187*
		(0.00609)
Additional irrelevant micro-credentials × Experienced	—	0.00070
		(0.00360)
Sex (Male)	0.1350***	0.1371***
	(0.0105)	(0.0106)
BA or more	0.3626***	0.3648***
	(0.0149)	(0.0142)
Experience	0.0024***	
	(0.0001)	
Experience SQ	$-2.79 \times 10^{-6***}$	
	(1.89×10^{-7})	
Experienced (High / Low)		0.2640***
		(0.0151)

References

Bitar, J., Perez, S., Reese, S., & Elliott, M. (2024). Understanding the Full Cost of Short-Term Credentials. The Education Trust. https://edtrust.org/rti/understanding-the-full-cost-of-short-term-credentials/

Brand, J. E., & Xie, Y. (2010). "Who Benefits Most from College? Evidence for Negative Selection in Heterogeneous Economic Returns to Higher Education." *American Sociological Review*, 75(2), 273-302.

Bovenberg, A. L., & Jacobs, B. (2005). Redistribution and education subsidies are Siamese twins. Journal of Public Economics, 89(11-12), 2005-2035.

Card, D. (1993). *Using geographic variation in college proximity to estimate the return to schooling* (NBER Working Paper No. 4483). National Bureau of Economic Research. https://www.nber.org/papers/w4483

Caplan, B. (2018). The case against education: Why the education system is a waste of time and money. Princeton University Press.

Christensen, G., Steinmetz, A., Alcorn, B., Bennett, A., Woods, D., & Emanuel, E. J. (2013). The MOOC phenomenon: Who takes massive open online courses and why? (SSRN Working Paper No. 2350964). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2350964

Cuartas, J. (2022). The effect of maternal education on parenting and early childhood development: An instrumental variables approach. *Journal of Family Psychology, 36*(2), 280–290. https://psycnet.apa.org/buy/2021-53190-001

Cunningham, E. (2019). "Professional certifications and occupational licenses: evidence from the Current Population Survey," Monthly Labor Review, U.S. Bureau of Labor Statistics, https://doi.org/10.21916/mlr.2019.15

Credential Engine. 2025. Counting Credentials 2025. Washington, DC: Credential Engine. https://credentialengine.org/all-resources/2025-counting-credentials/

Cronen, S., McQuiggan, M., & Isenberg, E. (2017). Adult Training and Education: Results from the National Household Education Surveys Program of 2016 (NCES 2017-103rev). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC. https://nces.ed.gov/pubs2017/2017103rev.pdf

Dale, S. B., & Krueger, A. B. (2002). "Estimating the Payoff to Attending a More Selective College: An Application of Selection on Observables and Unobservables." *The Quarterly Journal of Economics*, 117(4), 1491-1527.

Deming, D. J., & Silliman, M. I. (2024). Skills and human capital in the labor market (NBER Working Paper No. 32908). National Bureau of Economic Research. https://www.nber.org/papers/w32908

Dorn, D., Schoner, F., Seebacher, M., Simon, L., & Woessmann, L. (2024). Multidimensional skills on LinkedIn profiles: Measuring human capital and the gender skill gap (arXiv:2409.18638). arXiv. https://doi.org/10.48550/arXiv.2409.18638

Escobari, M., Seyal, I., & Meaney, M. (2019). Realism About Reskilling: Upgrading the Career Prospects of America's Low-Wage Workers. Brookings Institution. https://www.brookings.edu/wp-content/uploads/2019/11/Realism-About-Reskilling-Final-Report.pdf

Ecton et al., "Money for Less Time? Examining the Relative and Heterogenous Financial Returns to Non-Degree Credentials and Degree Programs" (EdWorkingPaper 24-1046 / later versions).

Frank et al. (2024) https://www.researchgate.net/publication/377347893_Network_constraints_on_worker_mobility

Hampole et al. (2025) https://www.nber.org/system/files/working_papers/w33509/w33509.pdf

HolonIQ. (2024). The future of post-secondary education in the US. HolonIQ. https://www.holoniq.com/notes/the-future-of-post-secondary-education-in-the-us

Horrigan, J. B. (2016, March 22). Lifelong learning and technology. Pew Research Center. https://www.pewresearch.org/internet/2016/03/22/lifelong-learning-and-technology/

Hout, M. (2012). Social and economic returns to college education in the United States. Annual Review of Sociology, 38, 379-400.

Kleiner, Morris M., and Alan B. Krueger. 2013. "Analyzing the Extent and Influence of Occupational Licensing on the Labor Market." Journal of Labor Economics 31 (S1): S173–S202.

Lang, J. (2022). Employment effects of language training for unemployed immigrants. *Journal of Population Economics, 35*, 719-754. https://doi.org/10.1007/s00148-021-00832-7

Li et al. (2020): https://pubsonline.informs.org/doi/abs/10.1287/mnsc.2021.4199

Liu, V. Y. T. (2016). *Do students benefit from going backward? The academic and labor market consequences of four- to two-year college transfer* (CAPSEE Working Paper). Community College Research Center, Teachers College, Columbia University.

Neumark, D., & Joyce, M. (2000). *Evaluating school-to-work programs using the new NLSY* (NBER Working Paper No. 7719). National Bureau of Economic Research. https://www.nber.org/papers/w7719

Neugebauer, M., Heisig, J. P., & Bol, T. (2025). What does successful university graduation signal to employers? A factorial survey experiment on sheepskin effects. *European Sociological Review*, Advance online publication. https://doi.org/10.1093/esr/jcaf028

Nguyen and Sila (2025) https://academic.oup.com/rcfs/advance-article/doi/10.1093/rcfs/cfaf008/8160023

Nunn, Ryan. 2018. "How Occupational Licensing Matters for Wages and Careers." The Hamilton Project, Brookings Institution.

Sigelman, M., Schneider, M., Rao, S., Spitze, S., & Wasden, D. (2025). Holding New Credentials Accountable for Outcomes: We Need Evidence-Based Funding Models. American Enterprise Institute & The Burning Glass Institute.

Spence, M. (1973). Job market signaling. The Quarterly Journal of Economics, 87(3), 355–374.

Su et al (2023): Su, Hongjin, Weijia Shi, Jungo Kasai, Yizhong Wang, Yushi Hu, Mari Ostendorf, Wen-tau Yih, Noah A. Smith, Luke Zettlemoyer, and Tao Yu. 2022. “One Embedder, Any Task: Instruction-Finetuned Text Embeddings.” arXiv:2212.09741. (Model: HKU NLP. 2022. INSTRUCTOR-large. Hugging Face model. Accessed 2024)

Stoller, B. (2024, September 2). Workers and companies face irrelevance without immediate reskilling. The Express Blog. https://expresspros.blog/inside-express/workers-and-companies-face-irrelevance-without-immediate-reskilling/

Tambe (2025) https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3776492

World Economic Forum. (2025). Future of jobs report 2025. https://www.weforum.org/reports/the-future-of-jobs-report-2025/

BROOKINGS

1775 Massachusetts Ave NW,
Washington, DC 20036
(202) 797-6000
www.brookings.edu