Do US Retraining Programs Protect Against Technological Automation?

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Abstract

This paper evaluates whether the U.S. Workforce Innovation and Opportunity Act (WIOA) transitions workers away from occupations susceptible to routine-task automation. Analyzing over 23 million WIOA participation records (2017-2023), we introduce the "Retrainability Index," a composite metric measuring program outcomes through post-intervention wage recovery and shifts in Routine Task Intensity (RTI). Our findings suggest that while WIOA participation is associated with wage gains for some workers, this is rarely coupled with resilience to automation. When successful, WIOA acts primarily as a wage "catch-up" mechanism for the lowest earners—likely reflecting mean reversion—rather than a driver of genuine upskilling. Lower-wage states (e.g., Mississippi, Alabama) achieve higher transition rates than high-wage states (e.g., Massachusetts, California), suggesting a potential "ceiling effect." Programmatically, registered apprenticeships are associated with the most positive outcomes, particularly when compared to lighter-touch services. Finally, we note a significant "age penalty," with WIOA success rates steadily declining from 0.57 for early-career workers to 0.41 by age 60. We argue that the United States' public active labor market programming can support baseline wage recovery for vulnerable populations, but is currently ill-equipped to support the large-scale, cross-industry labor transitions that may be required due to AI.

1 Introduction

This paper evaluates whether the United States' primary active labor market program (ALMP) successfully insulates workers from technology-enabled labor automation. By analyzing over 23 million participation records from the U.S. Workforce Innovation and Opportunity Act (WIOA) between 2017 and 2023, we introduce the "Retrainability Index," a novel composite metric measuring program success through post-intervention wage recovery and shifts in Routine Task Intensity (RTI). Our central takeaway is that while WIOA programming —particularly retraining—is associated with wage recovery for vulnerable workers, it rarely supports broader resilience to automation. Rather than driving genuine upskilling into technology-complemented sectors, the U.S. public workforce system currently functions primarily as an economic floor, facilitating rapid wage "catch-up" for the lowest earners. Consequently, it appears poorly suited for scenarios in which large-scale labor automation—such as the forthcoming artificial intelligence (AI) shock—requires managing complex, cross-industry transitions.

The mismatch between public exhortations for retraining and the poor evidence of its efficacy remains striking. While active labor market programming is ubiquitous in policy proposals addressing technological change, the literature on government-funded ALMPs is generally patchy, marked by disappointing

*The views expressed here do not necessarily reflect the views of the University of Oxford, Google DeepMind, or the Forecasting Research Institute.

randomized control trials and difficult-to-interpret observational data [Card et al., 2018, Heckman et al., 1999]. As scholarship by Barnow and Smith [2015] suggests, the US may have a particularly poor record of ALMP and retraining among rich countries. This paper develops a more nuanced picture of these programs by examining the outcomes of participants in WIOA, the primary public funder of retraining across the US [Andersson et al., 2024]. We distinguish between WIOA's light-touch job search assistance and heavier-touch formal retraining to understand how well these interventions insulate workers from automation, and how these outcomes are shaped by local labor market dynamics.

The contributions of this paper are twofold. First, we produce a novel index of retraining outcomes—the Retrainability Index—which operationalizes automation exposure through routine task intensity (RTI), an effective proxy for exposure to routine-task-replacing computerization. Second, we provide a highly granular analysis of the individual, programmatic, and environmental factors that predict success in the US public ALMP system. Specifically, we show that 45 percent of all WIOA program participants return to their prior industry of work. When positive outcomes occur, they are primarily driven by improved wages rather than lower levels of routine task intensity. We also identify a significant "age penalty" in ALMP success, while finding that apprenticeship programs and employer-led models produce the most successful outcomes.

The goal of our work is to help researchers and policymakers better understand US ALMP readiness to support workforce technological adjustment. If AI is likely to kindle a significant labor market shock, we will need better evidence on the factors that make workforce transition programs successful. This paper advances this literature by identifying the structural, programmatic, and geographic conditions that facilitate—and hinder—successful transitions in the existing American workforce system.

2 A Brief History of US Active Labor Market Programs

Over the last 80 years, US public active labor market programs (ALMPs) have steadily evolved from centralized, New Deal-style interventions—beginning with the 1933 Wagner-Peyser Act [Barnow and Smith, 2015, O'Leary and Eberts, 2008]—to decentralized efforts targeting local private sector employers. While earlier programs heavily targeted basic skills and poverty reduction [Barnow and Smith, 2015], the 1998 Workforce Investment Act (WIA) significantly widened participation and introduced "Individual Training Accounts" (ITAs) so individuals could choose the skills and sectors to invest their time in [Barnow and Smith, 2015, Heinrich et al., 2008]. In 2014, the Workforce Innovation and Opportunity Act (WIOA) streamlined this system, providing most US federally-funded active labor market programming today [Barnow and Smith, 2015, Hyman et al., 2025].

Every year, approximately 500,000 participants take part in the WIOA's 'Adult' and 'Dislocated Worker' streams. Most 'Adult' participants are near the poverty line [Social Policy Research Associates, 2022], while 'Dislocated Worker' participants are typically older workers who have lost stable employment. Of these participants, around 200,000 receive training vouchers at a cost of $500 million—a relatively low figure compared to the $25 billion spent annually on Pell Grants [Deming, 2023]. Because local providers bid for federal funding based on regional employer needs and political considerations, the skills imparted and methods of instruction vary considerably across US states, resulting in a programmatic patchwork [Barnow and Smith, 2015]. For instance, according to data from 2023-24, less than 10% of WIOA training involved *paid* on-the-job training, and just 2% involved apprenticeships [ETA, 2024].

Evaluating ALMPs is methodologically challenging. Researchers tracking post-exit employment and earnings [Barnow and Smith, 2015] generally struggle to show statistically significant benefits. A primary challenge is *non-random selection*; participants are not representative of the wider displaced population, making it difficult to isolate the impact of program participation from a willingness to take part [Heckman et al., 1999, LaLonde, 1986]. While quasi-experiments attempt to construct counterfactuals [Card et al., 2018, Rothstein et al., 2022], unobservable characteristics and the huge variance in state

programming make reliable causal claims difficult [Barnow and Smith, 2015]. The existing evidence provides cause for skepticism. Historical randomized controlled trials found no statistically significant improvements in employment or earnings, and recent 10-year evaluations suggest WIOA's retraining streams did not improve outcomes [Barnow and Smith, 2015]. While 70% of recent WIOA participants were employed within a year of exit [ETA, 2024], these outcomes lack control groups. Furthermore, Deming [2023] suggests approximately 40% of participants are driven into low-wage, high-demand support roles (e.g., nursing assistants) that offer little career growth and remain highly vulnerable to automation.

This patchwork evidence begs the question: why do ALMPs fail to support labor transitions during economic shifts? The challenges are threefold. First, *participant barriers*: prohibitive costs, lack of childcare, and short-run opportunity costs limit participation [Hendra et al., 2016]. Older workers displaced by digitalization may be reluctant to retrain entirely [Maestas et al., 2016, Neumark and Song, 2013], and participants can be bewildered by a voucher system offering over 75,000 programs without comparable performance data [Deming, 2023]. Second, *provider challenges*: local provider quality varies widely, and public programs struggle to supply easily transferable skills [Autor, 2010] while anticipating future demands [Acemoglu and Autor, 2011]. Finally, *structural challenges*: there may simply not be enough secure, skilled jobs to retrain into, as past technologies have often hollowed out these very occupations [Autor, 2015, Acemoglu and Autor, 2011, Acemoglu and Restrepo, 2019].

Dataset and Index Construction

To construct the *Retrainability Index*, we utilize WIOA Participant Individual Record Layout (PIRL) files submitted by state workforce agencies to the Employment and Training Administration (ETA) of the U.S. Department of Labor [ETA, 2024]. The PIRL serves as the primary administrative reporting system for WIOA Titles I and III, providing granular data on demographic characteristics, program participation, services received, and post-exit labor market outcomes. As noted by Barnow and Smith [2015], administrative databases like the PIRL offer substantial advantages over survey data for evaluating training interventions, particularly regarding the accuracy of service receipt timing and earnings histories.

We compile all available PIRL files from Program Year (PY) 2017, Quarter 4 through PY 2023, Quarter 4, treating each distinct period of participation as a unique observational unit. To ensure the analysis focuses on substantive interventions, we restrict the sample by removing all observations classified as *Reportable Individuals* (who receive only self-services or information-only services). Additionally, we exclude records lacking an observed program exit date, yielding a final dataset of approximately 23 million unique and completed participation periods. While our reliance on a four-quarter post-exit window captures immediate re-employment dynamics, it inherently misses longer-term wage trajectories. As noted by Jacobson et al. [1993], displaced workers entering new industries often face initial wage penalties before experiencing gradual, long-term earnings growth, meaning our short-term index may underestimate the ultimate value of certain retraining transitions.

Furthermore, while requiring an observed program end date and post-program earnings is essential for calculating the index, this restriction inherently conditions on a successful labor market re-attachment. It drops individuals who abandon the program, remain persistently enrolled, or exit into unemployment—plausibly the worst outcomes. Consequently, this selection mechanism biases our index results upward, meaning the aggregate incidence of success detailed in this paper likely inflates the true share of WIOA participants experiencing positive outcomes. Furthermore, this survivorship bias interacts directly with our core findings: the robust "catch-up" effect among low earners may partially reflect selection and mean reversion, and the significant "age penalty" we observe is likely understated.

[Drafting Note regarding Future Revisions: To address these non-random selection and survivorship biases, future iterations of this analysis will incorporate Inverse Probability Weighting (IPW)

to balance the observable characteristics of the computable sub-sample against the broader WIOA population.]

Each participation period includes occupation codes capturing employment in the three quarters prior to and four quarters following participation. To address data inconsistencies, we prioritize the occupation code recorded temporally closest to the participation window. To enrich this data, we merge the 2018 Standard Occupational Classification (SOC) structure to assign detailed occupational attributes.[1] Furthermore, we extract the nearest North American Industry Classification System (NAICS) code for pre- and post-program employment, collapsing these to the 3-digit subsector level to harmonize industrial classifications.[2]

[Drafting Note for Future Revisions: We intend to update the index weighting mechanics to prioritize occupation-level RTI over subsector-level proxies for the subset of records where granular occupation codes are available, addressing the high intra-industry variance of routine task intensity.]

To capture local labor market heterogeneity, each participation period is assigned to a *Local Workforce Development Board* (WDB), the primary sub-state governance unit coordinating WIOA service delivery [Barnow and Smith, 2015]. After harmonizing annual WDB designations (PY 2016–2023) and prioritizing primary codes where multiple exist, we attach jurisdiction-level demographic and economic indicators—including population, median household income, median age, and population density—aggregated to the board level while preserving program-year identifiers.

Index Construction

Our index is constructed as a composite of changes in wages and routine task intensity (RTI) prior to and following program participation. We use quarterly wages reported prior to program entry and following program exit, which are converted to constant 2010 dollars using the annual Consumer Price Index (CPI) to ensure comparability across program years [Barnow and Smith, 2015]. We compute mean quarterly wages pre- and post-program, ignoring missing wage quarters, and construct the difference in these means. We then merge occupation-level RTI measures [Acemoglu and Autor, 2011], aggregated to the industry subsector level using employment-share weights, to characterize the routine task environment of participants' pre- and post-program employment.[3] We define these subcomponents in additional detail in Appendix A.1.

[Drafting Note for Future Revisions: Future iterations of this analysis will shift from calculating raw dollar wage differences to utilizing log wage changes. This will better capture percentage gains and mitigate level-effect distortions, particularly for the low-wage cohorts driving the observed catch-up effects.]

We argue that RTI is the correct proxy for the particular form of automation that American workers were exposed to in the period we study (up to 2023) [Acemoglu and Autor, 2011, Frey and Osborne, 2017]. While RTI effectively captures computerization-driven automation, it does not capture exposure to artificial intelligence (AI). A worker transitioning into less routine work might score as a "success" in our Index while simultaneously increasing their AI exposure. In this regard, our methods differ from Hyman et al. [2025], who find wage penalties for WIOA participants explicitly targeting AI-intensive roles. Despite this, AI-exposure remains an inappropriate variable for our analysis for three reasons: (1) AI exposure often corresponds to *complementarity* rather than displacement; (2) AI exposure is concentrated in highly paid sectors where WIOA rarely places vulnerable workers; and (3) the AI-labor

[1] Specifically, we use the 2018 SOC Structure file, available for download at `https://www.bls.gov/soc/2018/`.

[2] We use the Bureau of Labor Statistics *National Employment Matrix* to identify occupation–industry employment by SOC and NAICS codes, available at `https://www.bls.gov/emp/data/occupational-data.htm`.

[3] The task measures are available in the replication files provided by the authors and can be downloaded directly as `onet-soc.dta` from https://economics.mit.edu/people/faculty/daron-acemoglu/data-archive [Acemoglu and Autor, 2011].

shock was either nascent or nonexistent prior to 2023. Consequently, RTI provides the most grounded metric to discern how WIOA helped workers adapt to prior technological shocks.

Currently, our index normalizes components asymmetrically, anchoring "no change" at 0.5. A participant exiting into an industry with identical RTI and wages receives exactly 0.5, while departures move proportionally toward 1.0 (best outcome) or 0.0 (worst outcome). Concretely, $\text{Index}_n > 0.5$ indicates labor market improvement, $\text{Index}_n = 0.5$ indicates stasis, and $\text{Index}_n < 0.5$ indicates deterioration.

To arrive at these scores, we winsorize each raw subcomponent at the 1st and 99th percentiles. The composite score uses a weighted linear combination: wage change receives 50% weight, while routine cognitive and routine manual task shifts receive 25% each. Because the index is defined at the individual participation period, it can be flexibly aggregated to any geographic or demographic unit without loss of consistency [OECD, 2008]. The index is computed strictly for the subset of participants with observed pre- and post-participation wage and industry data (reported as '% w/ Index' in our results). We provide a complete formal specification in Appendix A.2.

[Drafting Note for Future Revisions: We plan to simplify the normalization procedure to a standard [0,1] scale without the engineered 0.5 anchor. Furthermore, acknowledging the high intra-industry variance of RTI, we will reconsider the 50% RTI weighting and shift to occupation-level RTI wherever data permits.]

3 Data Summary and Descriptive Analysis

We begin by analyzing the distribution of the Retrainability Index across a random subset (10%) of the full sample participation periods and across key aggregation levels. Table 1 presents the summary statistics for the index and its primary components.

Table 1: Summary Statistics for the Retrainability Index and Key Aggregations

Aggregation	Count	Mean	Std Dev	Min	25%	50% (Median)	75%	Max
Participation Period (Index_n)	1,138,736	0.51	0.09	0	0.46	0.50	0.55	1
Local Workforce Board (WDB)	642	0.51	0.10	0	0.47	0.50	0.54	1
Employment Status at Entry	4	0.51	0.04	0.48	0.49	0.49	0.49	0.57
Program Year	8	0.50	0.05	0.43	0.48	0.50	0.50	0.59
Pre-Program Occupation	1,254	0.47	0.20	0	0.41	0.48	0.54	1
Received Training Indicator	2	0.57	0.11	0.49	0.49	0.64	0.64	0.64
Funding Stream	5	0.53	0.07	0.46	0.48	0.49	0.58	0.64
Training Service Type	14	0.61	0.09	0.45	0.49	0.63	0.68	0.75
Participant Age	87	0.47	0.09	0.26	0.39	0.48	0.52	0.75
State	52	0.50	0.04	0.35	0.48	0.50	0.52	0.64
Race / Ethnicity	8	0.50	0.02	0.47	0.50	0.51	0.51	0.54
Low Income Status	2	0.52	0.04	0.49	0.49	0.54	0.54	0.54
Highest Educational Level	10	0.51	0.07	0.43	0.49	0.50	0.51	0.69
Routine Cognitive Intensity (Pre-Program)	693	0.48	0.14	0	0.42	0.48	0.53	1
Routine Manual Intensity (Pre-Program)	693	0.48	0.14	0	0.42	0.48	0.53	1
Sex	3	0.51	0.01	0.50	0.50	0.50	0.52	0.52

At the individual level, the index follows an approximately Laplace distribution centered at the normalized anchor of 0.50 (Median = 0.50, Mean = 0.51). The distribution exhibits a standard deviation of 0.09. The composite variance is primarily driven by wage changes, which show a wider dispersion. In contrast, the RTI components are highly peaked at 0.5, indicating that a significant portion of participants remain in industries with similar technological profiles to those they left. Approximately 45% of participants remain in the same industry subsector after program participation.

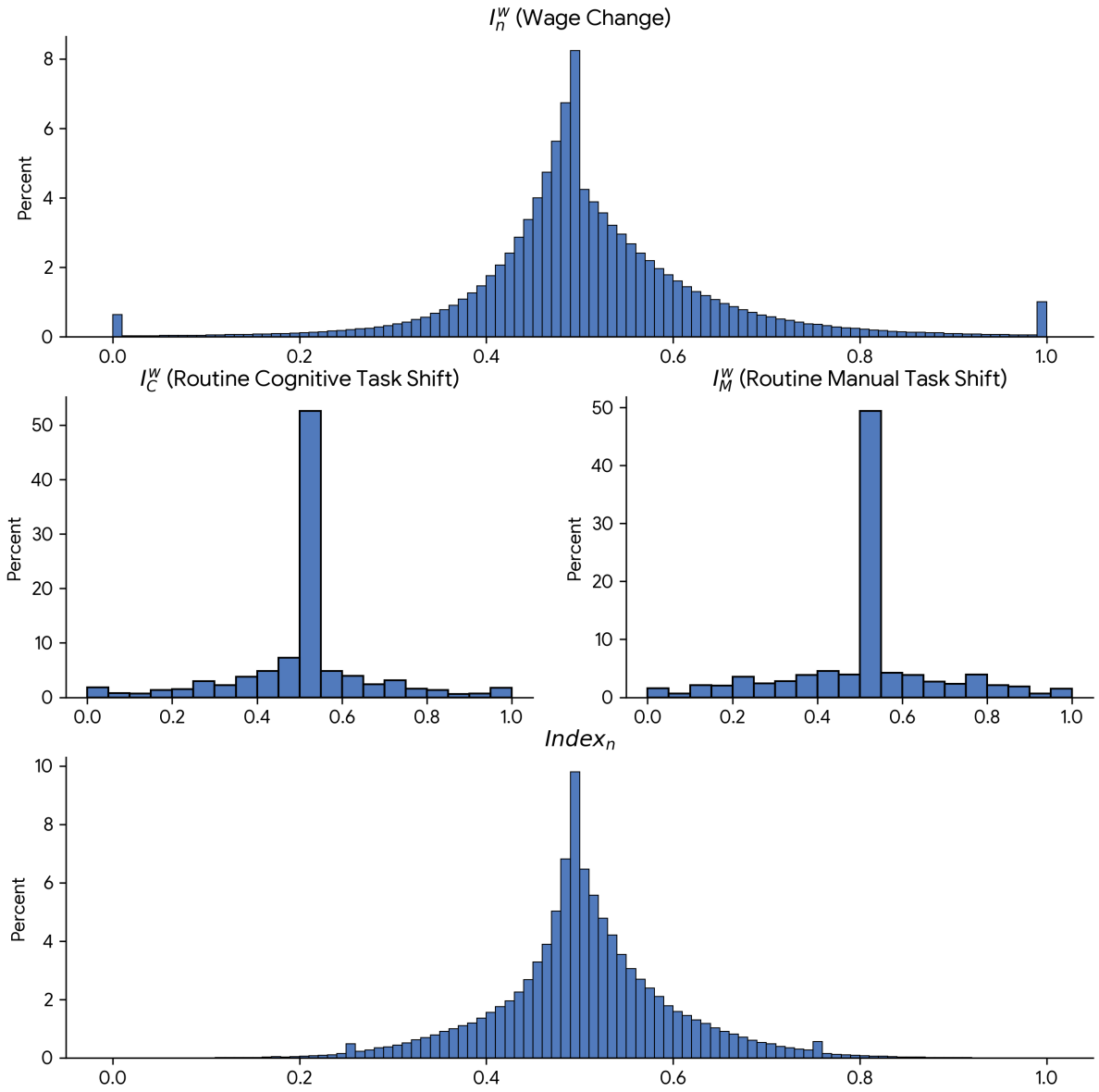


Figure 1: Component and composite index distributions illustrating how wage gains and routine task intensity shift measures combine into the overall index. Note the higher variance in wage outcomes relative to the peaked distribution of RTI changes.

When aggregated to program and participant demographic characteristics, the index score demonstrates stability with mean scores falling between 0.47 and 0.61 as shown in Table 1. Across 52 state-level entities (including territories), the index score ranges from 0.35 to 0.64 with a standard deviation of 0.04. Local Workforce Development Boards ($N = 642$) show higher variation (Range: 0–1), reflecting local economic heterogeneity, yet the interquartile range remains narrow (0.47–0.54). Training services and industry subsectors show similarly high stability (see Figure 2). The 14 distinct training service types exhibit the highest average index score, with a mean of 0.61. Substantively, this suggests that participants in formal retraining interventions tend to experience better outcomes when compared with the baseline, and non-training WIOA programs.

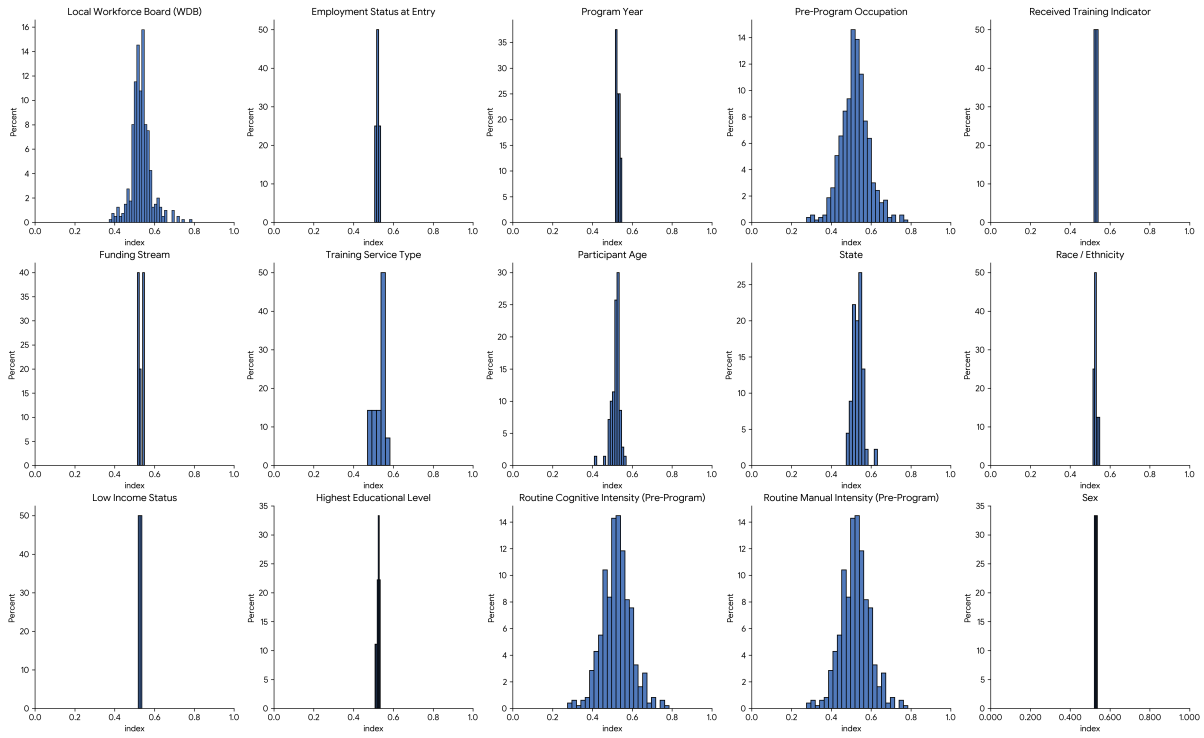


Figure 2: Composite index distributions aggregated by key aggregation levels. Training services (top right) show a distinct rightward shift, indicating higher index scores compared to other groupings.

Across all WIOA participation, the median age is 30. Notably, the majority (69.0%) were unemployed at the time of program entry. As illustrated in Figure 3, the proportion of unemployed participants generally increases with age. While roughly 65% of participants aged 20 are unemployed, this figure rises to nearly 85% for those approaching retirement age. This suggests that older workers engaging with the system are doing so from a position of significantly deeper labor market detachment compared to their younger counterparts, who are more likely to be employed or not in the labor force at entry. This also clarifies WIOA's practical function in American economic policy: it serves chiefly as a kind of 'second-chance' intervention aimed at re-introducing participants to stable employment, rather than a means of supporting upskilling.



Figure 3: Employment status at participation by age for participants who received formal training. Unemployment (gray area) dominates across all age groups but expands significantly as age increases, indicating deeper labor market detachment among older trainees.

WIOA participants are also racially diverse, comprised of White (37.1%), Black (29.3%), and Hispanic (20.5%) participants. Gender representation is nearly balanced (50.1% Female, 49.2% Male).

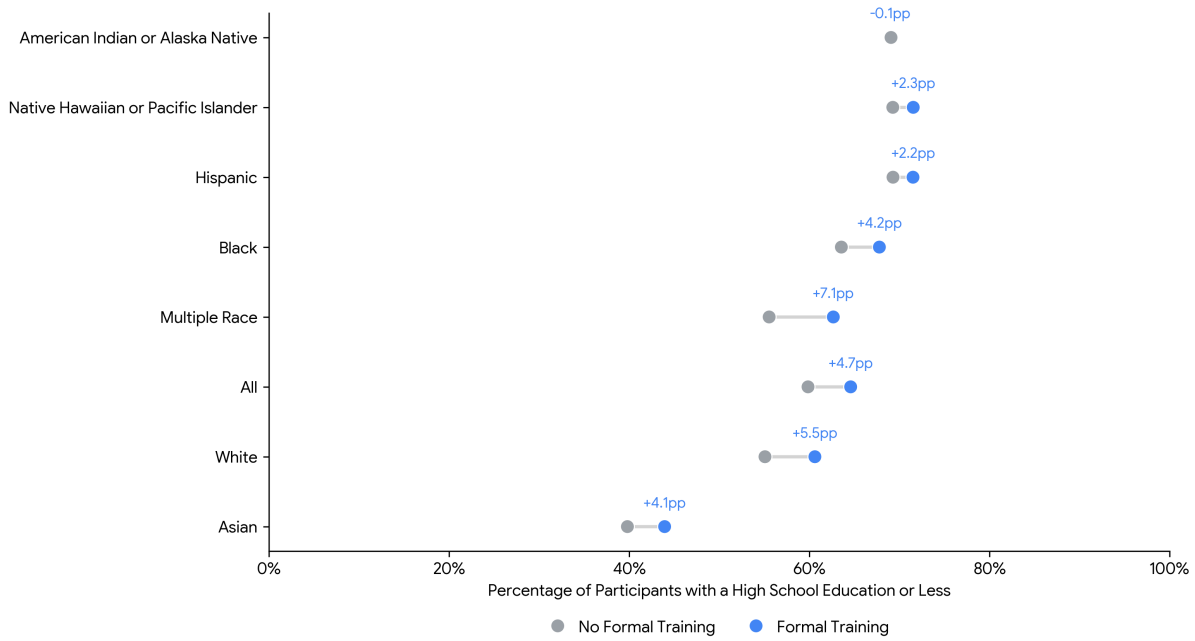


Figure 4: Comparison of educational attainment between training and non-training cohorts. Training recipients are more likely to have a high school education or less, indicating successful targeting of lower-skilled workers.

Descriptive Profile of the Formal Training Cohort To contextualize the *Retrainability Index* results, we now look at the descriptive characteristics of the population group that received formal training services, which are primarily funded through the WIOA Adult program (66.5%) and Dislocated Worker program (30.1%). This cohort consists of $N = 1,080,849$ unique participation periods, representing approximately 4.5% of the total sample in our analysis. As illustrated in Figure 5, the rate of training received has remained consistently low across program years, fluctuating between 3.4% and 6.1% with a yearly mean of 4.8%.

In other words, the vast majority of people that participate in the US WIOA system do not receive formal training services. The training that is provided is heavily skewed toward hard skills acquisition, with 'Occupational Skills Training' appearing as the dominant training service type, accounting for 59.3% of all records, followed by 'Skill Upgrading' (15.7%) and 'On-the-Job Training' (11.4%). In reality, however, the majority of WIOA participants receive lighter touch active-labor market support, such as job matching and career counseling.

As we previously suggested, Americans that receive formal retraining are *self-selecting*. Individuals who enter WIOA-funded training programs generally differ considerably from the general pool of non-training WIOA participants in both observable and unobservable ways (e.g., motivation, career intent, or eligibility for specific funding streams). As a consequence, we cannot make causal determinations about formal training impacts on retraining outcomes using this observational dataset.

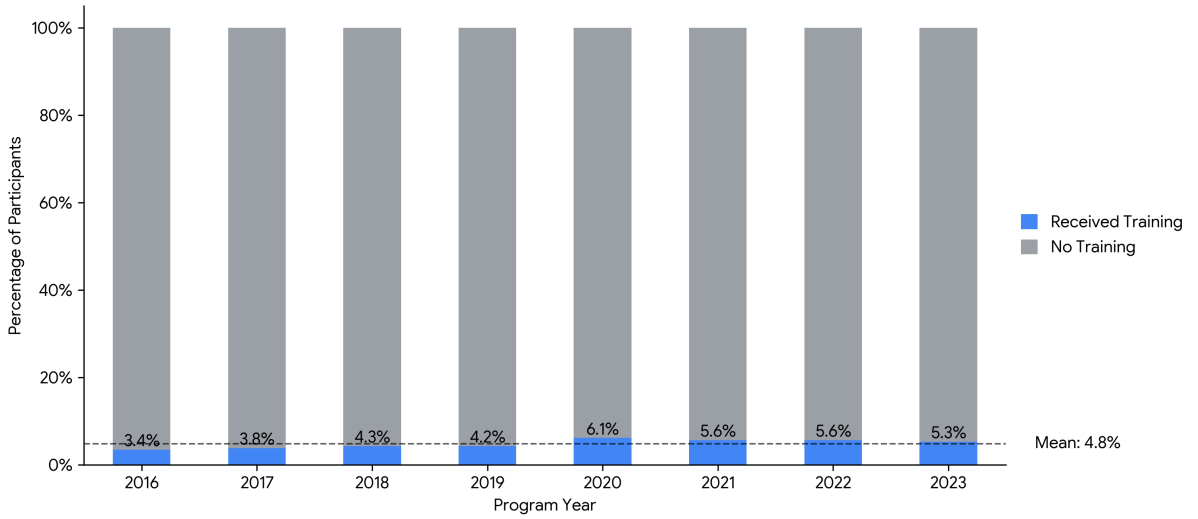


Figure 5: Percentage of WIOA participants receiving training services by program year (2016–2023). The consistently low training rate ($< 6.1\%$) highlights that deep upskilling interventions are concentrated on a small minority of the WIOA population.

Surprisingly, people who participate in formal training have lower levels of educational attainment than those that do not receive formal training. This finding could be explained under the logic that people with less education have more to gain from additional formal training, including classroom time. However, we equally might have assumed that prior-education at least partly predicts a person's likelihood of benefiting from further formal training. Instead, what we see is that formal trainers are more diverse, economically vulnerable, mid-career, and have lower educational baselines when compared with non-formal trainers. In Figure 4, we show that a larger proportion of WIOA participants who received training have a high school education or less compared to those who did not receive training. The rate of *lower* educational attainment is 4.7 percentage points higher among the training cohort than the non-training cohort. This trend holds across almost all demographic groups, with the widest gaps observed for White

(+5.5pp) and Multiple Race (+7.1pp) participants.

Among training recipients, we see evidence of potential upskilling. Prior to training, the most common origin subsectors were *Administrative and Support Services* (16.9%) and *Food Services and Drinking Places* (9.0%)—sectors often characterized by highly routine task profiles. Post-training, the share of employment in Food Services drops by more than half to 4.3%. Conversely, we observe substantial inflows into the healthcare and logistics sectors: *Hospitals* (8.2%), *Nursing and Residential Care* (7.6%), and *Truck Transportation* (6.7%) emerge as top destinations.

This potential upskilling dynamic is further mirrored in occupational data. The most common pre-program occupations—*Customer Service Representatives*, *Cashiers*, and *Laborers*—are largely generalist roles with high exposure to digitalization. Following program exit, the distribution shifts decisively toward licensed and credentialed technical roles. *Heavy and Tractor-Trailer Truck Drivers* becomes the single largest occupational category (6.7%), followed by a cluster of specialized healthcare roles: *Licensed Practical/Vocational Nurses* (2.4%), *Registered Nurses* (2.3%), and *Medical Assistants* (1.2%).

4 Findings

We now examine the individual and environmental factors that predict successful ALMP outcomes through the WIOA program. Our analysis indicates that success in the U.S. workforce development system is strongly associated with structural program factors and local labor market conditions, rather than participant demographics. We note the possibility of a ceiling effect, whereby WIOA participants in more affluent regions or industries benefit *less* than participants in more vulnerable circumstances.

First, we examine how the individual-level index varies with different measures of wages and routine task intensity before and after program participation. By estimating separate bivariate relationships for each variable, the analysis isolates the simple marginal association between each factor and our index. We note in Table 2 that, while statistically significant relationships exist, the explanatory power of any single variable is low. The strongest predictor among the bivariate set is the *pre-program routine manual intensity* of the subsector ($R^2 = 0.09$), suggesting that workers starting in highly manual industries have slightly more "room for improvement" in the index.

Table 2: Bivariate Regression Results: Individual Factors vs. Retrainability Index

Predictor	**Regression Equation**	R^2
Routine manual intensity (subsector, pre)	$\text{Index}_n = 0.057\, R_n^{M_x} + 0.50$	0.09
Mean wage (pre)	$\text{Index}_n = -4 \times 10^{-6}\, w_n^{\text{pre}} + 0.54$	0.08
Routine manual intensity (pre)	$\text{Index}_n = 0.0095\, R_n^{M_x} + 0.50$	0.0096
Routine cognitive intensity (subsector, pre)	$\text{Index}_n = 0.056\, R_n^{C_x} + 0.51$	0.035
Routine cognitive intensity (pre)	$\text{Index}_n = 0.0051\, R_n^{C_x} + 0.50$	0.0023

To assess the combined predictive power of observable characteristics, we employ a gradient-boosted decision tree model (XGBoost) to predict whether participation resulted in a positive outcome (defined as $\text{Index}_n > 0.5$). We prefer gradient boosting over standard logistic regression because tree-based models naturally capture nonlinear relationships and higher-order interactions between features without requiring manual specification of interaction terms. The model uses pre-program demographic, socioeconomic, and training inputs as features.[4] The model is tuned via randomized hyperparameter search and evaluated on a held-out test set. We emphasize again that this exercise is predictive rather than causal and do not claim that any feature identified as important by the model has a causal effect on retraining

[4]We exclude post-program attributes (e.g., post-training occupation, post-exit wages) from the feature set to prevent data leakage, as these components are used to calculate the target Index itself.

outcomes. Rather, our aim is to characterize which observable characteristics carry the most information about whether a participant experiences a positive transition, recognizing that many of these features are likely proxies for deeper, unobserved factors.

Table 3 summarizes the classification metrics. The model achieves an overall accuracy of 61% and an ROC-AUC of 0.6034. These results indicate that positive 'retrainability' outcomes are difficult to predict based solely on administrative data variables. This suggests that success in retraining—defined as wage gains and RTI shifts—is likely driven by *unobserved heterogeneity* such as individual motivation, specific provider quality, or idiosyncratic employer matches rather than broad demographic or regional profiles.

Table 3: XGBoost Classification Performance Metrics (Test Set)

Class	**Precision**	**Recall**	**F1-Score**	**Support**
$\text{Index}_n \leq 0.5$	0.61	0.60	0.60	364,177
$\text{Index}_n > 0.5$	0.60	0.61	0.61	364,979
Accuracy			0.61	369,963
Macro Avg	0.61	0.61	0.61	729,156
Weighted Avg	0.61	0.61	0.61	729,156

Table 4 presents the hierarchy of feature importance measures, isolating the observable characteristics that are associated with Retrainability Index outcomes. We report *Model Feature Importance* (measured by Gain, which quantifies the improvement in split quality when using each feature), *Permutation Feature Importance* (which measures the decrease in model performance when feature values are randomly shuffled), and *SHAP Feature Importance* (which quantifies each feature's average contribution to predictions across all samples based on Shapley values from cooperative game theory) [Lundberg and Lee, 2017]. We rank each importance metric independently and report the average of these ranks. The analysis indicates that structural program factors possess significantly higher predictive power than demographic characteristics, with average ranks of 6.1 and 12.5 respectively.

Three specific mechanisms explain the predictive hierarchy observed among the remaining variables. First, *Employment Status at Entry* (Importance = 0.11) and *Program Year* (Importance = 0.06) serve as proxies for labor market attachment and macroeconomic conditions, respectively. The high predictive value of employment status suggests path dependence: participants with recent labor market attachment likely possess retained human capital (e.g., soft skills) that reduces search friction, independent of the training curriculum. Similarly, the significance of the program year indicates that individual outcomes are conditioned by aggregate labor demand shocks; the index captures cyclicality where tight labor markets mechanically boost transition probabilities.

Second, the analysis highlights a "proxy effect" regarding local economic geography. The *Local Workforce Board (WDB)* identifier (Importance = 0.08) significantly exceeds the predictive contribution of specific regional covariates, such as unemployment rates or median income (≈ 0.01). Econometrically, the WDB identifier acts as a fixed effect that absorbs the variance of these specific economic indicators while simultaneously capturing unobserved local heterogeneity, such as the quality of administrative leadership, localized employer networks, and regional industry clusters, that generic macroeconomic statistics fail to measure. This is in line with prior literature emphasizing the important role of local dynamics in shaping ALMP efficacy [Barnow and Smith, 2015].

Third, *Pre-Program Occupation* (Importance = 0.08) serves as a sufficient statistic for both human capital and the baseline for potential marginal gains. Its predictive dominance over *Highest Educational Level* (0.01) implies that in the U.S. labor market, occupational classification effectively proxies for the credentialing required to hold a position, rendering education statistically redundant in the tree structure.

Furthermore, this variable captures convergence dynamics: workers originating from low-wage, high-routine sectors (e.g., Food Services) have a lower baseline, allowing for larger marginal increases in the index (Δ) compared to workers displaced from high-skill sectors who face diminishing marginal returns to short-term retraining.

Finally, the low feature importance of demographic variables—*Sex* (0.01), *Race/Ethnicity* (0.02), and *Age* (0.04)—is a structural consequence of the Index's design rather than an indication of demographic neutrality in the labor market. Because the Retrainability Index measures the *first difference* (change in wages and task intensity) rather than absolute levels, it effectively differences-out time-invariant individual characteristics that determine wage levels. This confirms that the index isolates the value-added component of the transition, controlling for the structural intercepts typically associated with demographic advantages.

Table 4: Feature Importance for Predicting Positive Index Outcomes

Feature	Model (Gain) Importance	Permutation Importance	SHAP Importance	Avg Rank
Program Participation & Structure				
Local Workforce Board (WDB)	0.09 (3)	0.01 (3)	0.1 (2)	2
Employment Status at Entry	0.12 (2)	0.01 (4)	0.06 (5)	4
Program Year	0.05 (5)	0.01 (2)	0.08 (4)	4
Pre-Program Occupation	0.07 (4)	0.01 (5)	0.1 (3)	5
Received Training Indicator	0.27 (1)	0.0 (9)	0.02 (10)	7
Funding Stream	0.04 (8)	0.0 (7)	0.02 (8)	8
Training Service Type	0.03 (10)	0.0 (12)	0.01 (17)	13
Regional Economic Indicators (Workforce Board Level)				
WDB Unemployment Rate	0.02 (13)	0.0 (11)	0.01 (11)	11
WDB High Household Debt-to-Income Ratio	0.02 (16)	0.0 (14)	0.01 (12)	14
WDB Median Age	0.02 (15)	0.0 (18)	0.01 (14)	15
WDB Population (per sq km)	0.02 (14)	0.0 (17)	0.0 (19)	17
WDB Diversity Index	0.02 (17)	0.0 (16)	0.0 (21)	18
WDB Population	0.01 (21)	0.0 (19)	0.01 (16)	19
WDB Mean Commuting Time (Min)	0.01 (19)	0.0 (22)	0.0 (18)	20
WDB Median Income Level	0.01 (20)	0.0 (21)	0.0 (23)	21
WDB Metro Status	0.01 (23)	-0.0 (24)	0.0 (24)	24
Demographics & Individual Characteristics				
Participant Age	0.04 (6)	0.02 (1)	0.11 (1)	2
State	0.04 (7)	0.0 (6)	0.04 (6)	6
Race / Ethnicity	0.02 (11)	0.0 (8)	0.03 (7)	9
Low Income Status	0.03 (9)	0.0 (10)	0.02 (9)	10
Highest Educational Level	0.02 (12)	0.0 (13)	0.01 (13)	12
Routine Manual Intensity (Pre-Program)	0.02 (18)	0.0 (15)	0.01 (15)	16
Routine Cognitive Intensity (Pre-Program)	0.01 (22)	-0.0 (23)	0.0 (20)	22
Sex	0.01 (24)	0.0 (20)	0.0 (22)	23

To improve the granularity of this analysis, in *Program Participation & Structure* (Table 5) we narrow the analysis to focus on a more narrow set of participation conditions. We find evidence for the importance of local administration and labor market attachment. The *Local Workforce Board (WDB)* identifier is a dominant predictor (Avg Rank 1), exceeding the predictive contribution of specific economic covariates. Econometrically, the WDB identifier likely acts as a proxy for unobserved local heterogeneity, such as the quality of administrative leadership and localized employer networks, that generic statistics fail to measure [Barnow and Smith, 2015]. Additionally, *Employment Status at Entry* (Avg Rank 4) suggests strong path dependence: participants with recent labor market attachment likely possess retained human capital that reduces search friction, independent of the training curriculum.

Table 5: Feature Importance for Predicting Positive Index Outcomes: Program Participation & Structure

Feature	Model Importance	Permutation Importance	SHAP Importance	Avg Rank
Local Workforce Board (WDB)	0.18 (3)	0.02 (1)	0.11 (2)	1
Pre-Program Occupation	0.13 (4)	0.01 (3)	0.78 (1)	2
Employment Status at Entry	0.19 (2)	0.01 (4)	0.08 (4)	4
Program Year	0.09 (5)	0.02 (2)	0.1 (3)	4
Received Training Indicator	0.29 (1)	0.0 (6)	0.02 (6)	5
Funding Stream	0.07 (6)	0.01 (5)	0.02 (5)	6
Training Service Type	0.06 (7)	0.0 (7)	0.01 (7)	7

In our analysis of *Regional Economic Indicators* (Table 6), we find evidence that local labor market economic complexity positively correlates with retraining success. The *WDB Diversity Index* (Avg Rank 1) emerges as the strongest regional predictor among features included in the sample, outperforming unemployment rates and median income. This suggests that workers in economically complex regions—those with a diverse mix of industries—may have more "landing spots" for successful transitions than those in monocultural local economies, in line with both intuition and prior literature.

Table 6: Feature Importance for Predicting Positive Index Outcomes: Regional Economic Indicators (Workforce Board Level)

Feature	Model (Gain) Importance	Permutation Importance	SHAP Importance	Avg Rank
WDB Diversity Index	0.14 (2)	0.26 (1)	0.08 (1)	1
WDB Unemployment Rate	0.04 (8)	0.15 (2)	0.03 (3)	2
WDB Mean Commuting Time (Min)	0.1 (3)	0.1 (6)	0.02 (5)	4
WDB Median Age	0.05 (7)	0.11 (5)	0.04 (2)	4
WDB Population (per sq km)	0.07 (4)	0.14 (4)	0.02 (7)	5
WDB Population	0.04 (9)	0.14 (3)	0.03 (4)	6
WDB Metro Status	0.45 (1)	-0.0 (9)	0.0 (9)	8
WDB High Household Debt-to-Income Ratio	0.05 (6)	0.09 (7)	0.02 (6)	8
WDB Median Income Level	0.06 (5)	0.01 (8)	0.01 (8)	9

In our further analysis of *Demographics* (Table 7) we find evidence for a potential "age penalty." *Participant Age* (Avg Rank 1) is the single most important demographic feature, creating a "time horizon" challenge for retraining policy; older workers face steeper barriers to recouping the investment in new skills [Jacobson et al., 1993]. Conversely, characteristics such as *Sex* (Avg Rank 8) and *Race/Ethnicity* (Avg Rank 7) appear at the bottom of the importance hierarchy. This, again, is likely a structural consequence of the Index's design and our methods for capturing outcome variables.

Table 7: Feature Importance for Predicting Positive Index Outcomes: Demographics & Individual Characteristics

Feature	Model (Gain) Importance	Permutation Importance	SHAP Importance	Avg Rank
Participant Age	0.18 (3)	0.02 (1)	0.12 (1)	1
State	0.2 (2)	0.02 (2)	0.1 (2)	2
Low Income Status	0.22 (1)	0.01 (3)	0.04 (3)	3
Routine Manual Intensity (Pre-Program)	0.1 (4)	0.0 (4)	0.03 (4)	4
Routine Cognitive Intensity (Pre-Program)	0.09 (5)	0.0 (5)	0.02 (7)	5
Highest Educational Level	0.08 (6)	0.0 (6)	0.02 (6)	6
Race / Ethnicity	0.08 (7)	0.0 (7)	0.03 (5)	7
Sex	0.07 (8)	-0.0 (8)	0.01 (8)	8

Figure 6 further contextualizes the high predictive power of *Employment Status at Entry* and its strong relationship to participant age, particularly among participants who received formal training. Among these participants, we observe a distinct negative gradient between age and labor market attachment; while approximately 30% of participants aged 18–24 enter the program while maintaining some form

of employment, this proportion contracts steadily over time. By age 60, the cohort is overwhelmingly characterized by full unemployment ($> 80\%$). This distribution suggests that the *Employment Status* variable effectively absorbs the variance associated with age-related structural exclusion. It implies that for older workers, the primary barrier to ALMP success may not be age itself, but also the high levels of labor market detachment that typically accompanies displacement later in one's career [Jacobson et al., 1993].

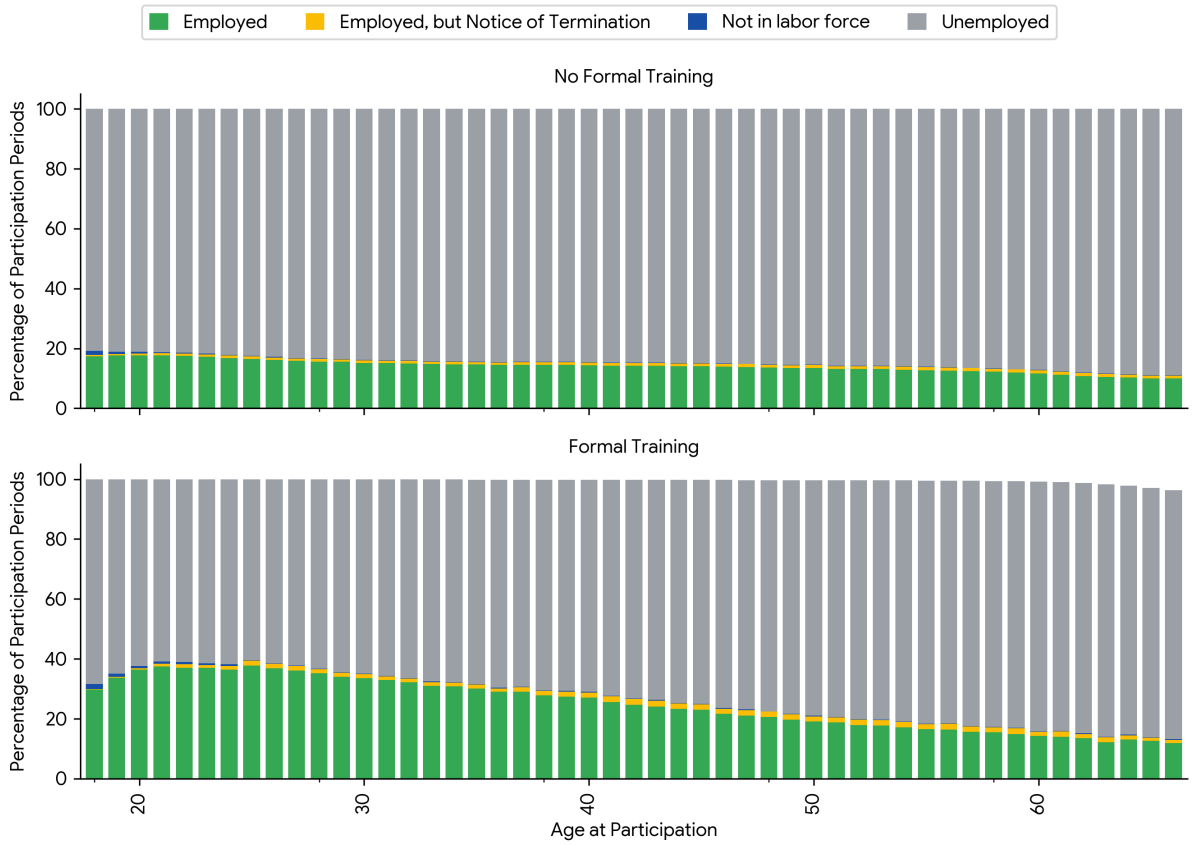


Figure 6: Percentage of participant periods by employment status and age.

A question, then, is what explains positive outcomes in the Index. We can see that for both the formal training and non-formal training cohorts, wages play a dominant role in shaping positive index outcomes.

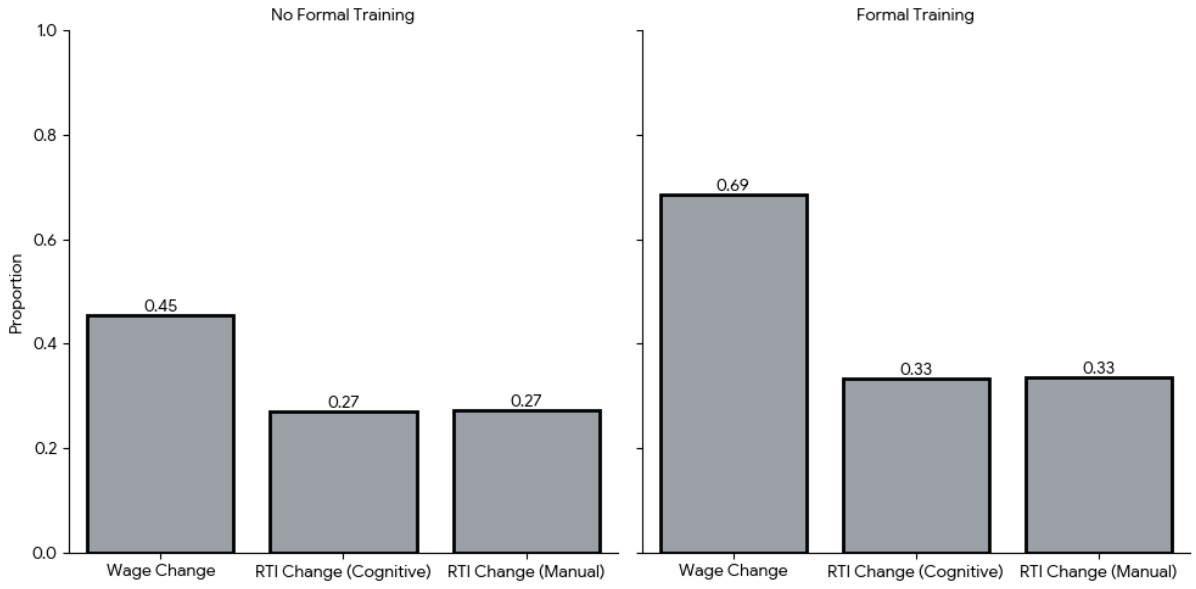
The figure below decomposes the frequency of positive contributions by subcomponent, revealing a divergence in the trajectory of the two groups. For the non-formal-training cohort (those receiving only basic career services), the results indicates that economic standing is unlikely improve, especially in supporting resilience to technological automation. The incidence of positive wage outcomes is only 0.46, implying that the majority (54%) of these participants experienced flat or declining real wages upon re-entry. Furthermore, their RTI change is minimal; only 27% of non-trainers transitioned into roles with lower routine task intensity, suggesting that without formal upskilling, these workers largely churn back into occupations with identical or worse automation vulnerabilities.

Participants who received formal retraining were more likely to have positive outcomes. However, this is primarily driven by positive wage changes at 0.69, indicating that nearly 70% of trainees achieved real earnings growth. Even with formal training, the share of participants who experienced a reduction in the routine nature of their work increased only slightly from 0.27 to 0.33. On its face, this suggests that many formal training participants are simply entering better-paid but equally automation-susceptible

roles.

We approach this conclusion with significant caution, however. Because our current measure of RTI is aggregated at the industry subsector level, it is fundamentally blind to within-industry occupational upgrading. For example, a worker who retrains from a highly routine role (e.g., a cashier) to a less routine role (e.g., a medical assistant) within the same healthcare subsector registers zero RTI improvement in our current index. As detailed in the Appendix, subsector-level changes explain only a small fraction of the variation in actual occupation-level task changes. Consequently, workers who successfully transition into a less routine occupation within a broader industry that remains highly routine on average are artificially penalized by this metric.

[Drafting Note for Future Revisions: We recognize that RTI is fundamentally an occupation-level construct. To address the limitations of the industry-level proxy, future iterations of this paper will utilize the subset of records (approx. 1.2%) where explicit pre- and post-program occupation codes are available. To correct for the non-random missingness of these codes, we will employ Inverse Probability Weighting (IPW) to balance this sub-sample's observable characteristics against the broader 23-million WIOA participant pool. We will also revise the Retrainability Index's normalization structure, transitioning to log wage changes and critically re-evaluating the 50% weight currently assigned to the RTI proxy.]



The divergence in outcomes must also be contextualized by the significant baseline disparities between the two cohorts. As illustrated in the pre-participation wage trends, participants who received formal training consistently entered the program with significantly lower earnings histories than their non-training counterparts. In 2023, for instance, the gap in pre-program quarterly wages was approximately $3,680, with trainees earning roughly half of what non-trainees earned prior to entry.

This differential suggests that the strong performance of trainees on the Index is partly driven by a structural "catch-up" dynamic. Because these participants originate from the lower tail of the wage distribution, they possess greater "headroom" for marginal improvement. Crucially, this pattern aligns with a classic Ashenfelter dip: workers often enter training programs following a transitory earnings decline, implying that a significant portion of their subsequent wage recovery is likely mean reversion rather than a direct treatment effect of the training itself. For a worker entering with near-poverty wages, even a transition into a modest entry-level role registers as a substantial positive gain (Δw). Conversely, the non-training cohort enters with higher prior earnings, making them statistically more susceptible to "wage scars"—the well-documented phenomenon where displaced high-earners re-enter the workforce

at lower pay levels.

[Drafting Note for Future Revisions: Because our current index evaluates absolute dollar wage differences (Δw), the magnitude of this "catch-up" effect is susceptible to level-effect distortions (e.g., a $500 gain represents a fundamentally different trajectory at a $2,000 baseline versus an $8,000 baseline). Future iterations of this analysis will utilize log wage changes to isolate real percentage gains, clarifying how much of this recovery is mechanical mean reversion versus genuine programmatic upskilling.]

Consequently, the high Retrainability Index scores for the training group should be interpreted with caution. While they indicate successful re-attachment to the labor market, they do not necessarily prove that training generates a unique skill premium that outperforms the broader market. Rather, they reflect that WIOA training services effectively function as a floor for the most vulnerable, facilitating a reversion to mean earnings, while the non-training population faces the steeper challenge of replicating prior incomes.

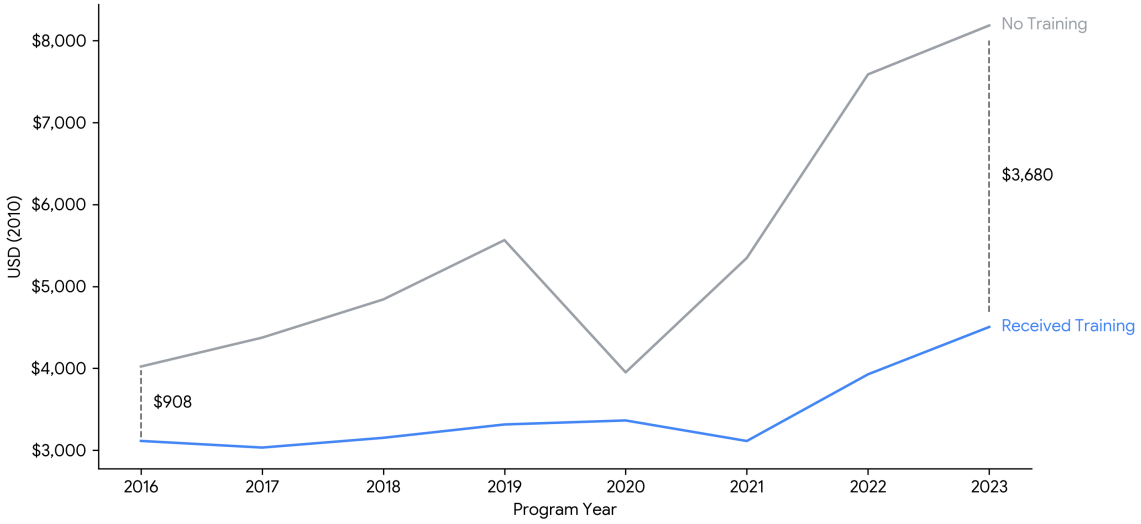


Figure 7: The average quarterly wages pre-program participation by program year.

This finding is unsurprising when viewed in conjunction with the predictive hierarchy previously noted. As suggested earlier, *Pre-Program Occupation* serves as a potential determinant of index outcomes specifically because it sets the structural "ceiling" for potential gains. The training cohort, by virtue of their lower baseline wages, disproportionately occupies the worse-off portion of this occupational ladder, exactly where marginal improvements in earnings and task complexity are statistically most achievable.

Indeed, Figures 7 and 8 explicitly illustrate this dynamic. Read together, they show trainees entering with earnings roughly half those of non-trainees (Figure 7) and then experiencing large post-program absolute dollar gains (Figure 8). For the non-training cohort, who held higher pre-participation wages, the lack of positive index movement likely reflects the difficulty of lateral or upward mobility without new credentialing. For the training cohort, the intervention offers a potential 'catch-up' effect, moving workers from a low-level equilibrium (unemployment or low-wage work) to a higher one.

However, this 'catch-up' interpretation must account for a classic Ashenfelter dip pattern: workers frequently enter training after a transitory earnings decline, meaning a significant portion of the subsequent recovery shown in Figure 8 is likely mechanical mean reversion [Ashenfelter, 1978, Card and Sullivan, 1988]. Consequently, while the data suggests that formal retraining through WIOA is associated with

baseline wage recovery for America's most vulnerable workers, we cannot definitively claim it drives unique, long-term automation resilience.

[Drafting Note for Future Revisions: We recognize that the current mapping between the absolute dollar figures—such as trainees gaining $\tilde{\$}$3,400/quarter by 2023 in Figure 8—and the normalized index values—such as Table 8's non-training wage component of 0.497—is currently difficult to follow due to the asymmetric normalization. Future drafts will transition to log wages and a standard normalization scale to make these magnitudes directly transparent and comparable.]

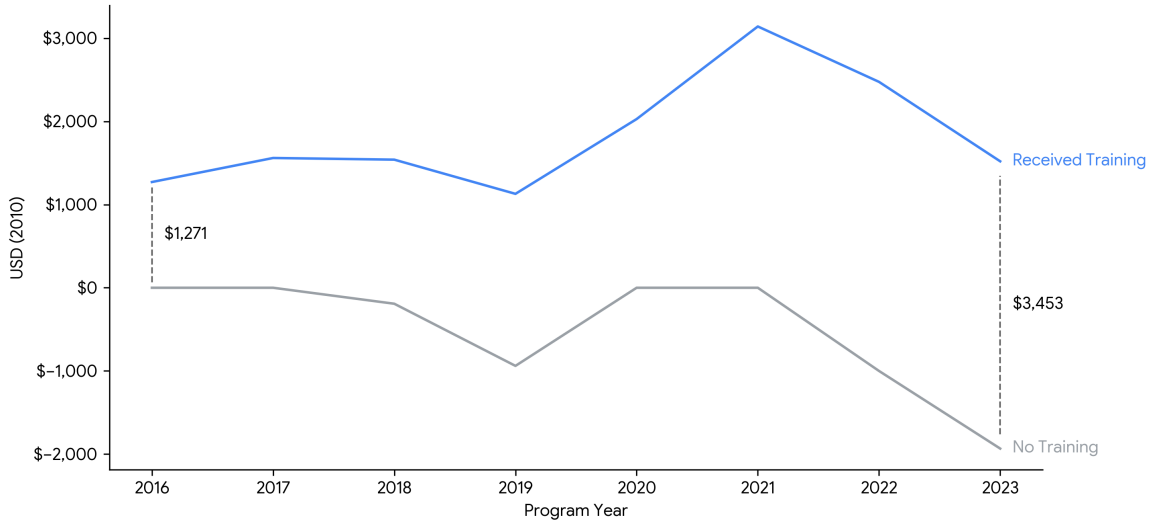


Figure 8: Average quarterly wage differences in the three quarters pre- and post-WIOA program participation, by program year.

Next we present the aggregated Retrainability Index results across key programmatic and demographic subgroups. To interpret these findings, we report five summary statistics for each grouping:

- **Incidence** ($Incidence_g$): The share of participation periods within the group that achieved a positive outcome (defined as an Index score > 0.5). This functions as a "headcount ratio" for successful transitions.
- **Intensity** ($Intensity_g$): The average index score among only those participants who achieved a positive outcome. This measures the magnitude or "depth" of the success for the winners.
- **Subcomponents** ($\overline{I_n^W}$, $\overline{I_n^C}$, $\overline{I_n^M}$): The normalized mean scores for Wage Change (W), Routine Cognitive Task shift (C), and Routine Manual Task shift (M). Values above 0.5 indicate average growth/improvement, while values below 0.5 indicate regression.

The primary bifurcation in the dataset exists between the training and non-training cohorts. As detailed in (Table 8), participants who received substantive training interventions achieved an incidence score of 0.64, significantly outpacing the 0.49 baseline observed in the non-training population. Decomposing this result reveals the mechanism of impact. The "training premium" is overwhelmingly driven by the wage component ($\overline{I_n^W}$ rises from 0.497 to 0.592), whereas shifts in RTI show only marginal improvement (e.g., $\overline{I_n^C}$ rises from 0.500 to 0.511). This suggests that while formal training is associated with earnings restoration, it is not associated with a sectoral pivot away from routine work.

Table 8: Received Training

Received Training	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
No	0.49	0.57	0.497	0.500	0.499	22,686,072	48.09%
Yes	0.64	0.60	0.592	0.511	0.512	1,080,849	43.80%

Table 9 highlights the role of labor market attachment. Participants who were *Employed* at the time of entry achieved the highest incidence of positive outcomes (0.57), compared to 0.48 for those who were *Unemployed*. One explanation for this is that employed workers likely possess unobserved soft skills and professional networks that facilitate smoother transitions. Interestingly, those *Not in Labor Force* (0.52) outperform the unemployed, potentially reflecting re-entrants (e.g., students, caregivers) who face fewer structural barriers than the long-term unemployed, or else catch-up gains.

Table 9: Employment Status at Entry

Employment Status at Entry	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
Unemployed	0.48	0.57	0.494	0.499	0.499	19,955,726	46.43%
Employed	0.57	0.57	0.537	0.504	0.501	3,543,665	56.70%
Employed, but Notice of Termination	0.48	0.57	0.509	0.497	0.496	210,978	47.91%
Not in labor force	0.52	0.58	0.527	0.513	0.505	56,552	13.41%

Table 10 underscores the sensitivity of retrainability to the macroeconomic cycle. We observe a distinct "V-shaped" recovery in program efficacy corresponding to the COVID-19 shock. Incidence rates plummeted to a low of 0.43 in Program Year 2019 before rebounding sharply to 0.58 in 2020 and 0.57 in 2021. This volatility—where the wage component ($\overline{I_n^W}$) swings from 0.483 in 2019 to 0.530 in 2021—indicates that the index is highly elastic to aggregate labor demand. In tight labor markets (e.g., the post-pandemic recovery), employer barriers to entry fall, possibly boosting transition scores independent of training quality. This cyclicality warns against interpreting year-over-year index changes as purely a function of programmatic improvement.

Table 10: Program Year

Program Year	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
2016	0.50	0.57	0.506	0.501	0.500	4,401,541	44.85%
2017	0.50	0.57	0.505	0.501	0.503	3,877,284	47.51%
2018	0.48	0.57	0.499	0.500	0.501	3,403,637	51.87%
2019	0.43	0.57	0.483	0.504	0.499	3,092,935	49.92%
2020	0.58	0.58	0.529	0.504	0.499	2,250,278	48.33%
2021	0.57	0.58	0.530	0.499	0.499	2,309,217	46.43%
2022	0.49	0.58	0.489	0.495	0.497	2,207,396	55.00%

2023	0.48	0.58	0.465	0.495	0.494	2,224,633	39.72%

Table 11 disaggregates outcomes by funding stream, showing significant heterogeneity in program performance. The *Youth* stream achieves the highest incidence (0.64) and wage intensity ($(\overline{I_n^W} = 0.564)$), likely reflecting the high marginal returns to initial human capital investment for younger, less established workers. In contrast, the *Dislocated Worker* stream—typically serving older, more experienced workers—shows lower incidence (0.48) and wage scores ($\overline{I_n^W} = 0.481$), consistent with the "wage scar" literature that suggests displaced workers struggle to replicate their prior earnings.

Table 11: Funding Stream

Funding Stream	Incidence_g	Intensity_g	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
Adult	0.58	0.58	0.549	0.506	0.503	2,216,881	44.50%
Multiple	0.46	0.57	0.493	0.500	0.499	458,375	52.04%
Dislocated Worker	0.48	0.59	0.481	0.497	0.501	1,397,845	47.68%
Wagner-Peyser	0.49	0.57	0.497	0.500	0.499	19,128,661	49.27%
Youth	0.64	0.58	0.564	0.521	0.492	565,159	11.68%

Table 12 shows that *Registered Apprenticeships* are the single most effective intervention in the dataset, achieving the highest incidence rate (0.76) and wage score ($\overline{I_n^W} = 0.629$). This aligns with prior literature suggesting that training models which bypass search friction by binding skill acquisition directly to employment—such as manufacturing credentials and employer-linked models—are often significantly more effective than traditional classroom-based approaches [Brown et al., 2024]. Similarly, *Customized Training* (Incidence = 0.71) and *On-the-Job Training* (Incidence = 0.62) significantly outperform generalized services. Conversely, lighter-touch interventions such as *Job Readiness Training* (Incidence = 0.65), while seemingly successful, are associated with lower wage intensity ($\overline{I_n^W} = 0.565$) and actually regress on routine task measures ($\overline{I_n^C} = 0.475$), suggesting they facilitate rapid re-entry into similar low-quality roles rather than genuine upskilling.

Table 12: Training Service Type

Training Service Type	Incidence_g	Intensity_g	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
No Training Service	0.49	0.57	0.497	0.500	0.499	21,024,755	48.55%
On the Job Training	0.62	0.59	0.602	0.518	0.528	100,201	53.16%
Skill Upgrading	0.65	0.60	0.595	0.510	0.514	133,594	53.33%
Entrepreneurial Training	0.56	0.58	0.529	0.511	0.504	3,034	17.27%
ABE or ESL w/ Training	0.63	0.58	0.560	0.506	0.493	13,025	28.82%
Customized Training	0.71	0.56	0.593	0.509	0.502	24,710	52.00%
Occupational Skills Training	0.64	0.60	0.594	0.511	0.512	609,027	46.59%
ABE or ESL w/out Training	0.61	0.59	0.514	0.486	0.441	5,259	41.09%
Prerequisite Training	0.63	0.60	0.571	0.493	0.498	1,842	40.12%

Continued on next page

Table 12: Training Service Type

Training Service Type	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
Registered Apprenticeship	0.76	0.60	0.629	0.494	0.512	12,893	56.84%
Youth Occupational Skills Training	0.67	0.59	0.591	0.522	0.493	131,580	15.75%
Other Non-Occupational-Skills Training	0.59	0.60	0.556	0.524	0.489	11,188	27.38%
Job Readiness Training	0.65	0.61	0.565	0.475	0.476	2,812	24.32%

The demographic decomposition of the index reinforces the theory of diminishing marginal returns based on baseline advantage. Table 13 illustrates a clear negative gradient between age and retrainability. Incidence rates peak among early-career participants—reaching 0.65 for 16-year-olds and stabilizing around 0.58 for those in their early 20s—before declining steadily to 0.43 by age 60. This age penalty is driven by a divergence in wage growth potential; while younger workers ($\overline{I_n^W} \approx 0.54$) benefit from rapid initial human capital accumulation, older workers ($\overline{I_n^W} < 0.46$) face steeper barriers to replicating their peak career earnings.

Table 13: Participant Age

Participant Age	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
15–19	0.61	0.57	0.550	0.522	0.499	998,023	29.30%
20–24	0.57	0.57	0.536	0.504	0.499	2,606,445	47.89%
25–29	0.54	0.57	0.523	0.500	0.500	2,990,297	51.69%
30–34	0.52	0.57	0.514	0.500	0.500	2,900,617	50.59%
35–39	0.51	0.57	0.507	0.499	0.500	2,657,943	49.84%
40–44	0.50	0.57	0.502	0.499	0.500	2,367,912	49.97%
45–49	0.48	0.57	0.495	0.499	0.500	2,286,765	50.18%
50–54	0.47	0.57	0.486	0.499	0.499	2,267,013	49.87%
55–59	0.45	0.57	0.474	0.498	0.498	2,147,507	48.42%
60–64	0.41	0.57	0.446	0.496	0.497	1,480,744	42.83%
65–69	0.39	0.56	0.440	0.496	0.497	651,488	36.28%
70–74	0.39	0.55	0.456	0.498	0.499	267,444	33.97%
75–79	0.37	0.55	0.462	0.500	0.499	96,401	31.52%
80–84	0.34	0.54	0.465	0.501	0.500	26,315	27.72%
85+	0.35	0.55	0.473	0.499	0.496	6,885	24.89%
Not available	0.54	0.57	0.503	0.500	0.503	3,952	31.20%

Our analysis of state-level outcomes reveals significant geographic heterogeneity, with incidence rates ranging from a high of 0.64 in Utah to a low of 0.35 in Puerto Rico. We observe that states with lower baseline costs of living and historically lower wages—such as Mississippi (0.55), Alabama (0.55), and Arkansas (0.50)—often achieve higher incidence rates than wealthy, high-skill economies like Massachusetts (0.43), California (0.44), and New York (0.50).

This inverse relationship supports the "catch-up" hypothesis identified earlier in the participant-level analysis. In lower-wage labor markets, the threshold for a positive index outcome is structurally lower;

a transition from unemployment to a standard entry-level role represents a significant relative wage gain (Δw). Conversely, in high-cost, high-wage states like Massachusetts, displaced workers face a potential "ceiling effect." Replicating a previous high-status salary requires a far more complex professional transition, making the marginal gains captured by the index more difficult to achieve. The low wage intensity scores in high-skill states (e.g., MA $\overline{I_n^W} = 0.470$ vs. MS $\overline{I_n^W} = 0.536$) confirm that displacement in elite labor markets often results in steeper relative wage scarring.

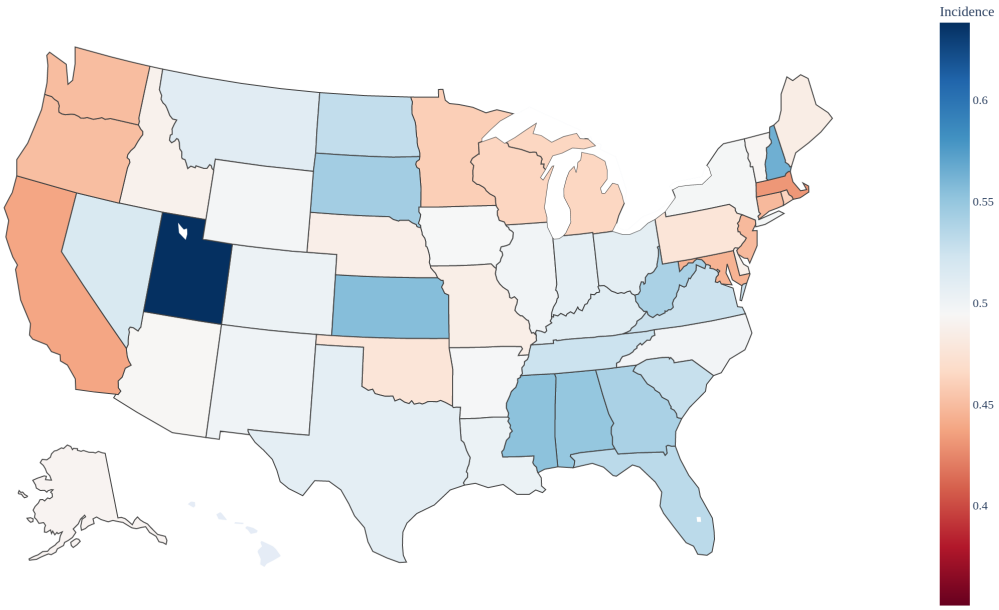


Figure 9: Incidence$_g$ by State

Utah stands as a notable structural outlier, achieving the highest incidence (0.64) alongside high wage intensity ($\overline{I_n^W} = 0.539$). This performance distinguishes it from the "catch-up" states; rather than starting from a low baseline, Utah's outcomes are likely driven by a uniquely tight labor market. During the study period, Utah consistently maintained one of the lowest unemployment rates in the nation (dropping to 2.0% in 2022), creating a high-demand environment that lowered employer barriers to entry and boosted placement rates for retrained workers independent of their starting wage.

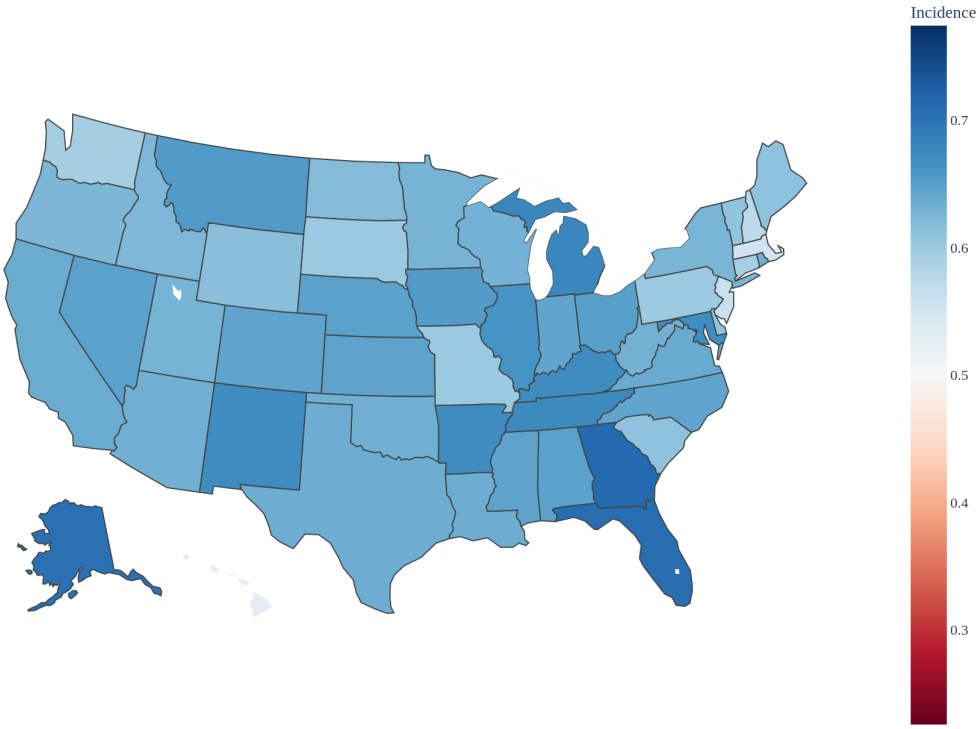


Figure 10: Incidence$_g$ by State (for participation periods that received formal training)

The demographic decomposition of the index, meanwhile, reinforces the theory of diminishing marginal returns based on baseline advantage. Table 14 illustrates that outcomes are relatively stable across *Sex* and *Race/Ethnicity*. For example, incidence rates for Black (0.52), Hispanic (0.51), and White (0.48) participants are comparable. Meanwhile, *Low Income Status* participants achieve higher incidence (0.54) and wage intensity ($\overline{I_n^W} = 0.529$) compared to their non-low-income counterparts (0.49 and 0.494, respectively), suggesting again that the program works best as a way of supporting catch-up growth for economically vulnerable populations.

Table 14: Index outcomes aggregated by Sex, Race/Ethnicity, and Low Income Status

	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
Sex							
Male	0.50	0.57	0.501	0.501	0.499	12,206,949	48.59%
Female	0.50	0.57	0.501	0.499	0.499	11,232,806	47.34%

Continued on next page

Table 14: Index outcomes aggregated by Sex, Race/Ethnicity, and Low Income Status

	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
Participant did not self-identify	0.52	0.57	0.505	0.500	0.499	327,166	40.82%
Race/Ethnicity[5]							
Hispanic	0.51	0.57	0.515	0.501	0.498	4,405,495	46.99%
Asian	0.47	0.58	0.475	0.499	0.501	565,662	42.08%
Black	0.52	0.57	0.517	0.501	0.500	5,746,133	51.68%
Native Hawaiian or Pacific Islander	0.52	0.58	0.509	0.499	0.500	86,257	40.72%
American Indian or Alaska Native	0.50	0.57	0.506	0.501	0.499	268,422	41.97%
White	0.48	0.57	0.488	0.500	0.499	10,286,848	47.77%
Multiple Race	0.51	0.58	0.509	0.501	0.501	441,107	45.41%
Not available	0.50	0.58	0.496	0.500	0.500	1,966,997	42.87%
Low Income Status							
Yes	0.54	0.58	0.529	0.503	0.499	5,264,991	41.06%
No	0.49	0.57	0.494	0.500	0.500	18,501,930	49.84%

Table 15 decomposes outcomes by educational attainment, providing further evidence for the "ceiling effect" hypothesis. Participants with the lowest formal credentials—those with *No Educational Level*—achieve an incidence rate of 0.50, comparable to those with a secondary school diploma (0.51). However, as educational attainment rises, the incidence of positive outcomes declines. Participants with a Bachelor's degree (0.46) or an advanced degree (0.43) record the lowest transition success rates in the dataset. This inverse relationship suggests that short-term WIOA interventions offer high marginal utility for low-skill workers by providing missing credentials, but offer diminishing returns for highly educated workers who face high opportunity costs and steeper barriers to replicating their previous occupational status.

Table 15: Highest Education Level

Highest Education Level	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
NaN	0.59	0.54	0.509	0.499	0.484	6,069	7.73%
No Educational Level Completed	0.50	0.56	0.509	0.502	0.496	4,011,506	45.22%

Continued on next page

[5]Race/ethnicity does not include Hispanic unless otherwise specified.

Table 15: Highest Education Level

Highest Education Level	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
Attained secondary school diploma	0.51	0.57	0.510	0.500	0.497	8,320,409	49.28%
Attained a secondary school equivalency	0.51	0.57	0.515	0.501	0.497	1,916,778	47.61%
The participant with a disability receives a certificate of atten-dance/completion as a result of successfully completing an Individualized Education Program (IEP)	0.50	0.57	0.509	0.500	0.500	24,601	42.05%
Completed one of more years of postsecondary education	0.50	0.57	0.502	0.500	0.501	3,613,511	49.05%
Attained a postsecondary technical or vocational certificate (non-degree)	0.51	0.58	0.509	0.500	0.501	704,162	50.18%
Attained an Associate's degree	0.49	0.58	0.499	0.499	0.502	1,504,500	48.52%
Attained a Bachelor's degree	0.46	0.59	0.472	0.498	0.506	2,681,229	46.47%
Attained a degree beyond a Bachelor's degree	0.43	0.60	0.446	0.500	0.506	984,156	44.99%

5 Conclusion

This paper has introduced the *Retrainability Index* as a novel instrument for evaluating the efficacy of US active labor market programming (ALMP) provided by the Workforce Innovation and Opportunity Act (WIOA). First, we find that success is associated with *program structure*, *local economy*, and *timing*. The hierarchy of feature importance reveals that local labor market characteristics—specifically economic diversity—and an individual's labor market attachment at entry are strongly correlated with successful outcomes. Rates of success is therefore geographically varied; a worker's ability to benefit from WIOA programming appears bounded by the complexity of their local economy and the availability of suitable work in their locality. Second, we identify a potential "age penalty": older workers experience lower rates of WIOA success, as captured by our Index, possibly driven by their detachment from the labor market. Third, while formal retraining interventions are associated with wage premiums, they are not associated with worker movement into less automation-susceptible labor. Indeed, most participants cycle back into industries with similar technological vulnerabilities, achieving income recovery without necessarily securing long-term automation resilience. Finally, we note that the WIOA system appears best suited at facilitating "catch-up" income growth for its most vulnerable participants. It appears less effective at protecting workers from automation risk. Meanwhile, individuals from more affluent regions, industries, and backgrounds seem to experience a ceiling effect, whereby WIOA participation does not appear to substantively boost their wages or reduce their RTI scores.

What our analysis suggests, therefore, is that the United States' major public active labor market programming and retraining scheme is primarily a 'second-chance' intervention most helpful at boosting wages for its most vulnerable participants. By contrast, it seems poorly suited to support scenarios where significant portions of the labor market must upskill into new forms of work. If new technologies, particularly AI, do indeed result in widespread labor displacement, our analysis suggests the United States' existing public programming is unprepared.

A Index Construction Methodology

A.1 Subcomponent Details

Wage difference refers to the gap between an individual's average quarterly wages in the pre-participation window and the post-participation window. This provides a direct measure of earnings progression associated with the participation in job retraining or other workforce development programs. The change in routine cognitive and routine manual task intensity associated with the industry subsector in which the individual is employed before and after program participation proxies the technological vulnerability of the work performed, allowing us to assess whether participants transition into occupations or industries that rely less on routine, automatable tasks.

Formally, let $w_{n,t}$ denote the quarterly wage of individual n in quarter t. We index quarters relative to the first quarter of WIOA participation, with $\tau = 0$ representing the participation quarter. Define the pre- and post-period sets as $\mathscr{P} = \{-3,-2,-1\}$ and $\mathscr{Q} = \{1,2,3,4\}$, respectively. The average pre- and post-participation wages for individual n are:

$$\overline{w}_n^{\text{pre}} = \frac{1}{|\mathscr{P}|} \sum_{\tau \in \mathscr{P}} w_{n,\tau}, \tag{1}$$

$$\overline{w}_n^{\text{post}} = \frac{1}{|\mathscr{Q}|} \sum_{\tau \in \mathscr{Q}} w_{n,\tau}. \tag{2}$$

We define the change in wages as:

$$\Delta w_n = \bar{w}_n^{\text{post}} - \bar{w}_n^{\text{pre}}. \tag{3}$$

To quantify the extent to which participants transition into more or less routine forms of work, we measure changes in routine task intensities along two dimensions: routine *cognitive* tasks and routine *manual* tasks. Let p_{ij} denote the employment share of occupation i within industry subsector j, and let N denote the total number of occupations. Occupation-level task intensities are fixed parameters taken from O*NET and related sources [Acemoglu and Autor, 2011].

$$r^{C_i} = \text{routine cognitive task intensity of occupation } i,$$
$$r^{M_i} = \text{routine manual task intensity of occupation } i.$$

Industry subsector-level routine task intensities are defined as employment-share-weighted averages of the task intensities of the occupations that comprise each subsector:

$$R^{C_j} = \sum_{i=1}^{N} p_{ij}\, r^{C_i}, \tag{4}$$

$$R^{M_j} = \sum_{i=1}^{N} p_{ij}\, r^{M_i}. \tag{5}$$

For each period of participation n, we define the change in routine task intensity as the difference in the subsector-level intensities associated with a participant's pre- and post-participation employment:

$$\Delta R_n^C = R_n^{C_y} - R_n^{C_x}, \tag{6}$$

$$\Delta R_n^M = R_n^{M_y} - R_n^{M_x}, \tag{7}$$

where $R_n^{C_x}$ and $R_n^{C_y}$ denote the routine cognitive intensities of the subsectors of pre-program and post-program employment, respectively (and analogously for manual routine intensity).

A.1.1 Interpreting Industry Subsector Routine Task Intensity

A methodological limitation is that subsector-level routine task intensity is only weakly correlated with the occupation-level task intensities of the specific jobs held by WIOA participants To quantify this discrepancy between occupation and industry subsector routine task intensity, we exploit the subset of participation periods for which both pre- and post-program occupation codes are observed (approximately 1.2% of participation periods), comparing changes in actual occupation-level routine task intensities (Δr) with changes computed using our subsector-level proxies (ΔR).

The empirical relationship is indeed weak. The fitted relationships

$$\Delta r_n^C \approx 0.25\,\Delta R_n^C + 0.043 \quad (R^2 = 0.013), \tag{8}$$

$$\Delta r_n^M \approx 0.25\,\Delta R_n^M + 0.098 \quad (R^2 = 0.027), \tag{9}$$

indicate that subsector-level changes explain only 1–3% of the variation in occupation-level task changes for the subset with complete data. These patterns imply substantial within-subsector occupational heterogeneity.

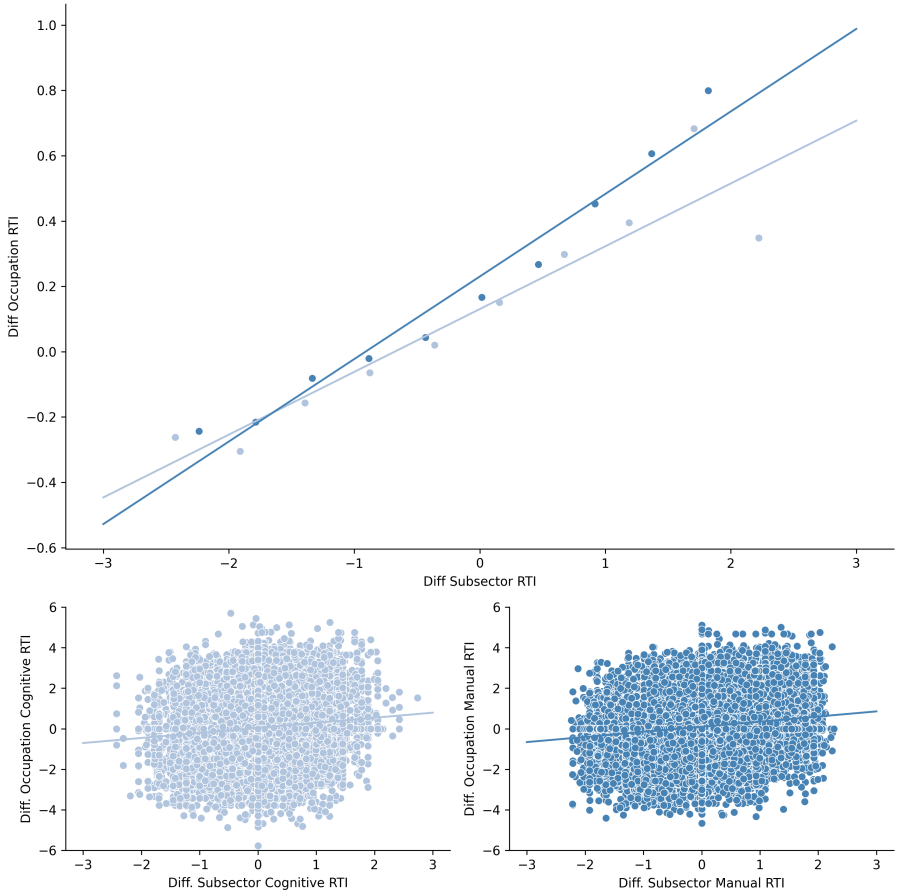


Figure 11: Comparison of occupation-level and subsector-level changes in routine cognitive (bottom left) and routine manual (bottom right) task intensity with scatter plot binned by subsector-level changes (top).

This arises because industries contain heterogeneous mixtures of occupations with vastly different routine task intensity compositions. Despite the low correlation with individual job tasks, we retain the subsector-level index as a measure of sectoral exposure. As noted in Equation (6), R^{C_j} and R^{M_j} quantify the technological environment that prevails in the subsector as a whole. In the context of workforce

development, placing a participant into a sector with low Routine Task Intensity (RTI) is a valuable outcome regardless of their specific entry-level role, as it implies a transition into an ecosystem with greater long-term resilience against automation [Acemoglu and Restrepo, 2019]. Therefore, ΔR_n^M and ΔR_n^C should be interpreted as the change in the *technological vulnerability of the labor market segment* the participant occupies, rather than a precise measure of their daily ergonomic or cognitive functions.

To address the sparsity of occupation codes in future iterations of this index, we propose estimating the expected change in occupation-level task intensity conditional on observable characteristics. Throughout this analysis, subsector-level routine task intensities are treated as *industry characteristics* that proxy for the routine intensity of the sectoral environment into which participants are placed, rather than as approximations of individual job-level tasks. This distinction allows the index to function as a macro-indicator of workforce mobility toward resilient industries, even in the absence of granular occupational coding.

A.2 Normalization & Aggregation Details

Let each observation $n = 1, \ldots, N$ correspond to a completed period of participation. For each n, we denote the raw difference variables as:

$$D_n^W \equiv \Delta w_n, \qquad D_n^C \equiv \Delta R_n^C, \qquad D_n^M \equiv \Delta R_n^M$$

where D_n^W represents the real wage change, and D_n^C, D_n^M represent the changes in routine cognitive and routine manual task intensities associated with the participant's transition between industry subsectors.

Outlier Treatment

To ensure the index is not distorted by extreme outliers (e.g., data entry errors or non-representative wage jumps), we apply winsorization. This process caps extreme values at the 1st and 99th percentiles, preserving the distribution's shape while limiting the influence of tails **?**. Let $Q_{0.01}^k$ and $Q_{0.99}^k$ denote the 1st and 99th percentiles for variable $k \in \{W, C, M\}$. The winsorized value $\widetilde{D}_n^k$ is defined as:

$$\widetilde{D}_n^k = \min\{\max(D_n^k, Q_{0.01}^k), Q_{0.99}^k\}.$$

Normalization

Standard min-max normalization is insufficient for this index because the value of zero change represents a critical reference point (the status quo). We therefore employ asymmetric normalization around a reference point which fixes the value of "no change" at 0.5. Thus, the normalized score I_n^k is calculated using a piecewise linear function:

$$I_n^k = \begin{cases} 0.5 + 0.5 \left(\dfrac{\widetilde{D}_n^k}{Q_{0.99}^k} \right) & \text{if } \widetilde{D}_n^k > 0, \\ 0.5 - 0.5 \left(\dfrac{\widetilde{D}_n^k}{Q_{0.01}^k} \right) & \text{if } \widetilde{D}_n^k < 0, \\ 0.5 & \text{if } \widetilde{D}_n^k = 0. \end{cases}$$

This transformation yields normalized components $I_n^W, I_n^C, I_n^M \in [0, 1]$, where a score of 1.0 represents the best observed positive outcome, 0.0 the worst, and 0.5 maintenance of the status quo.

Weighting

The final individual index is a weighted linear combination of the three normalized components. We assign a 50% weight to wage growth (reflecting immediate economic benefits) and split the remaining

50% equally between the two resilience metrics (cognitive and manual task exposure). However, we illustrate in Appendix A.2.1 that the index shows low sensitivity to the particular choice of weights.

$$\text{Index}_n = 0.5 \cdot I_n^W + 0.25 \cdot (1 - I_n^C) + 0.25 \cdot (1 - I_n^M). \tag{10}$$

Aggregation

Because the index is defined at the level of the participation period, it can be flexibly aggregated to any administrative or geographic unit without loss of consistency. Let $g \in \mathcal{G}$ be a group from a grouping of interest (i.e., State, a Local Workforce Development Board (WDB), Industry Subsector). Furthermore, let $g^+ \subseteq g$ be the set of participation periods such that $\text{Index}_n > 0.5$. Then, let N_g be the number of items in grouping g and $N_{g^+} = |g^+|$ be the number of such participation periods. We then define the share of participant periods that experience a positive outcome and the intensity of these positive outcomes as

$$\text{Incidence}_g = \frac{N_{g^+}}{N_g} \tag{11}$$

$$\text{Intensity}_g = \frac{1}{N_{g^+}} \sum_{n \in g^+} \text{Index}_n \tag{12}$$

Subsequently, we define the group-level index as their product:[6]

$$\text{Index}_g = \text{Incidence}_g \cdot \text{Intensity}_g = \frac{1}{N_g} \sum_{n \in g^+} \text{Index}_n. \tag{13}$$

However, we observe that there is a high degree of correlation between Index_g and Incidence_g and a low degree of variability in Intensity_g across key groupings as shown in Table 16. This table summarizes the Spearman correlation between Index_g and Incidence_g for key aggregations. We observe that the the Index_g is highly correlated ($\rho > 0.9$) with Incidence_g suggesting that the the latter serves as a reliable proxy for the data. Thus, because $\text{Index}_g \propto \text{Incidence}_g$, we report the aggregate index simply as $\text{Index}'_g = \text{Incidence}_g$, or the share of participation periods for which positive outcomes were experienced.

Table 16: Summary of Spearman Correlations between Index_g and Incidence_g

Grouping	ρ
Workforce Board	0.9861
Employment Status at Entry	1.0000
Program Year	0.9524
Pre-Program Occupation	0.9748
Received Training Indicator	1.0000
Funding Stream	1.0000
Training Service Type	0.9066
Age	0.9910
State	0.9851
Race/Ethnicity	0.9643
Low Income Status	1.0000
Highest Educational Level	0.9333
Routine Cognitive Intensity (Pre-Program)	0.9763
Routine Manual Intensity (Pre-Program) 0.9763 Sex	0.5000

[6] We construct our index similarly to the United Nations Development Programme's Global Multidimensional Poverty Index (MPI) which is the product of the incidence of multidimensional poverty and its intensity. Further technical details about the MPI can be found in Alkire and Foster (2011) **?**.

A.2.1 Assessing Subcomponent Weight Sensitivity

To assess the robustness of the Retrainability Index to alternative value judgments on indicator weighting, we conducted a Monte Carlo sensitivity analysis on a 10% sample of the dataset. For each of 500 simulations, a random weight vector was drawn from a Dirichlet distribution, and the index was recomputed. Results were compared to the baseline using Spearman rank correlations (ρ) and absolute changes in percentile rank (Table 17).

Table 17: Summary of Monte Carlo Sensitivity Results (500 Simulations)

Grouping	**# Groups**	**Mean ρ**	**Min ρ**	**Median Pct. Shift**	**Max Pct. Shift**
Participation Period (Index_n)	1,138,977	0.861	0.664	0.042	0.778
Local Workforce Board (WDB)	640	0.929	0.835	0.037	0.847
Employment Status at Entry	4	0.841	0.200	0.070	0.140
Program Year	8	0.960	0.905	0.039	0.128
Pre-Program Occupation	1,254	0.848	0.651	0.034	0.936
Received Training Indicator	2	1	1	0	0
Funding Stream	5	0.990	0.900	0	0.020
Training Service Type	14	0.741	0.327	0.116	0.454
Participant Age	87	0.985	0.943	0.010	0.286
State	52	0.981	0.944	0.027	0.174
Race / Ethnicity	8	0.968	0.905	0.019	0.115
Low Income Status	2	1	1	0	0
Highest Educational Level	10	0.941	0.745	0.026	0.198
Routine Cognitive Intensity (Pre-Program)	699	0.862	0.705	0.047	0.948
Routine Manual Intensity (Pre-Program)	699	0.862	0.705	0.047	0.948
Sex	3	0.572	0.500	0.285	0.285

At the individual participant period level ($N \approx 1.14$ million), the index demonstrates *high robustness*: the mean Spearman correlation is approximately $\rho \approx 0.86$, and the median percentile rank shift is only 4.2%. Similar stability emerges the groupings *Local Workforce Board*, *Program Year*, *Received Training Indicator*, *Funding Stream*, *Participant Age*, *State*, *Race*, and *Low Income Status*, and *Highest Educational Level* ($\rho > 0.9$). Higher sensitivity appears for smaller groupings, such as *Training Service Types*, where the ranking of specific interventions (e.g., On-the-Job Training vs. Classroom Training) is more sensitive to whether the index prioritizes wages or task resilience. Overall, the analysis confirms that the index is structurally stable and not driven by specific weighting choices.

B Detailed Index Results Tables

B.1 State

Table 18: Index outcomes aggregated by state.

State	Incidence_g	Intensity_g	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
AK	0.49	0.58	0.516	0.501	0.506	66,861	32.62%
AL	0.55	0.57	0.528	0.503	0.499	409,400	60.28%
AR	0.50	0.56	0.496	0.499	0.495	535,924	65.04%
AS	NaN	NaN	NaN	NaN	NaN	386	0.00%
AZ	0.49	0.57	0.505	0.499	0.502	312,363	53.25%
CA	0.44	0.58	0.475	0.498	0.500	1,528,270	48.67%

Continued on next page

Table 18: Index outcomes aggregated by state

State	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
CO	0.50	0.58	0.508	0.501	0.498	482,724	49.20%
CT	0.45	0.57	0.479	0.498	0.503	242,955	46.68%
DC	0.50	0.59	0.502	0.494	0.499	50,702	5.77%
DE	0.49	0.57	0.492	0.496	0.496	75,131	57.48%
FL	0.53	0.57	0.529	0.502	0.503	1,490,985	36.40%
GA	0.54	0.58	0.521	0.499	0.498	1,053,086	43.85%
GU	NaN	NaN	0.506	NaN	NaN	8,270	0.00%
HI	NaN	NaN	0.467	NaN	NaN	26,762	0.00%
IA	0.50	0.57	0.520	0.497	0.495	368,611	39.22%
ID	0.49	0.57	0.492	0.502	0.503	95,330	62.25%
IL	0.50	0.58	0.504	0.496	0.502	271,335	55.40%
IN	0.51	0.56	0.496	0.501	0.496	540,837	66.91%
KS	0.56	0.57	0.525	0.502	0.501	144,036	56.24%
KY	0.51	0.57	0.501	0.497	0.494	390,371	48.30%
LA	0.50	0.57	0.506	0.499	0.497	300,431	47.67%
MA	0.43	0.58	0.470	0.503	0.504	720,444	34.45%
MD	0.44	0.57	0.482	0.502	0.502	288,351	58.18%
ME	0.48	0.57	0.496	0.502	0.491	40,158	53.38%
MI	0.46	0.56	0.483	0.499	0.497	1,125,773	56.37%
MN	0.46	0.58	0.471	0.498	0.502	208,743	53.47%
MO	0.48	0.59	0.503	0.501	0.500	542,594	57.38%
MP	NaN	NaN	NaN	NaN	NaN	1,132	0.00%
MS	0.55	0.57	0.536	0.507	0.505	347,540	54.04%
MT	0.51	0.57	0.506	0.501	0.498	144,075	44.84%
NC	0.50	0.57	0.501	0.502	0.499	941,698	63.54%
ND	0.53	0.57	0.517	0.501	0.500	35,359	52.99%
NE	0.49	0.57	0.494	0.499	0.497	82,871	56.86%
NH	0.56	0.59	0.464	0.512	0.503	97,222	1.03%
NJ	0.45	0.58	0.472	0.498	0.503	515,558	31.26%
NM	0.50	0.57	0.511	0.501	0.496	180,600	43.75%
NV	0.52	0.58	0.520	0.499	0.498	252,047	47.96%
NY	0.50	0.58	0.495	0.499	0.499	1,809,911	44.22%
OH	0.51	0.58	0.509	0.498	0.504	237,582	41.59%
OK	0.48	0.57	0.481	0.496	0.494	115,862	45.53%
OR	0.45	0.57	0.478	0.501	0.497	964,447	56.07%
PA	0.48	0.58	0.490	0.497	0.501	503,201	53.57%
PR	0.35	0.58	0.504	0.598	0.564	132,379	9.41%
PW	NaN	NaN	NaN	NaN	NaN	236	0.00%
RI	0.46	0.58	0.487	0.494	0.503	32,521	55.80%
SC	0.53	0.57	0.513	0.498	0.498	401,373	53.23%
SD	0.54	0.56	0.524	0.503	0.500	63,095	54.78%
TN	0.53	0.57	0.516	0.502	0.497	288,317	55.35%
TX	0.51	0.57	0.507	0.500	0.501	2,888,672	51.41%
UT	0.64	0.57	0.539	0.502	0.498	1,142,357	40.91%
VA	0.53	0.57	0.513	0.501	0.498	235,366	58.86%
VI	0.54	0.57	0.521	0.492	0.487	9,131	26.73%

Continued on next page

Table 18: Index outcomes aggregated by state

State	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
VT	0.49	0.57	0.509	0.503	0.496	23,588	47.02%
WA	0.45	0.58	0.483	0.500	0.503	571,458	11.05%
WI	0.46	0.57	0.483	0.498	0.494	163,373	59.88%
WV	0.54	0.57	0.509	0.499	0.497	211,532	33.59%
WY	0.50	0.57	0.517	0.500	0.495	53,585	25.87%

Table 19: Index outcomes aggregated by state (for participation periods that received training)

State	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
AK	0.71	0.61	0.625	0.506	0.531	6,200	29.02%
AL	0.65	0.59	0.598	0.518	0.514	36,100	50.51%
AR	0.67	0.60	0.604	0.519	0.507	6,642	53.82%
AS	NaN	NaN	NaN	NaN	NaN	11	0.00%
AZ	0.63	0.59	0.586	0.509	0.536	29,063	48.42%
CA	0.64	0.61	0.596	0.514	0.502	139,677	41.23%
CO	0.65	0.60	0.591	0.511	0.506	20,222	58.06%
CT	0.59	0.60	0.565	0.512	0.518	14,521	36.75%
DC	0.77	0.63	0.599	0.455	0.446	3,010	4.12%
DE	0.61	0.60	0.561	0.507	0.510	3,892	53.75%
FL	0.71	0.60	0.624	0.516	0.508	79,655	40.75%
GA	0.71	0.61	0.646	0.525	0.506	30,181	50.01%
GU	NaN	NaN	0.555	NaN	NaN	416	0.00%
HI	NaN	NaN	0.588	NaN	NaN	1,161	0.00%
IA	0.66	0.60	0.625	0.494	0.495	5,408	28.74%
ID	0.62	0.59	0.584	0.519	0.527	3,467	58.75%
IL	0.66	0.61	0.612	0.504	0.520	57,792	48.19%
IN	0.64	0.59	0.586	0.512	0.508	17,314	64.33%
KS	0.65	0.60	0.587	0.513	0.523	5,329	57.67%
KY	0.67	0.60	0.597	0.505	0.492	17,895	52.12%
LA	0.64	0.60	0.606	0.514	0.528	15,787	46.56%
MA	0.56	0.58	0.536	0.510	0.488	23,994	28.41%
MD	0.67	0.59	0.581	0.506	0.495	13,401	55.32%
ME	0.61	0.60	0.563	0.525	0.491	3,352	45.67%
MI	0.68	0.60	0.608	0.510	0.513	37,991	43.82%
MN	0.63	0.61	0.580	0.513	0.506	9,964	39.47%
MO	0.60	0.61	0.583	0.508	0.508	18,841	51.68%
MP	NaN	NaN	NaN	NaN	NaN	213	0.00%
MS	0.65	0.59	0.623	0.523	0.546	18,402	64.46%
MT	0.66	0.60	0.558	0.507	0.479	2,592	44.02%
NC	0.64	0.59	0.586	0.514	0.507	36,924	59.84%
ND	0.62	0.60	0.598	0.510	0.533	1,745	57.02%
NE	0.65	0.59	0.588	0.501	0.503	2,940	50.07%
NH	0.57	0.59	0.583	0.519	0.510	3,367	19.66%

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Table 19: Index outcomes aggregated by state (for participation periods that received training)

State	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
NJ	0.56	0.60	0.523	0.501	0.506	35,381	30.92%
NM	0.67	0.60	0.599	0.517	0.500	14,172	43.19%
NV	0.65	0.60	0.615	0.510	0.531	12,226	37.01%
NY	0.63	0.58	0.562	0.507	0.502	51,964	34.24%
OH	0.65	0.59	0.598	0.513	0.522	44,144	33.76%
OK	0.63	0.59	0.569	0.500	0.513	10,339	44.40%
OR	0.62	0.60	0.593	0.517	0.517	17,691	53.84%
PA	0.60	0.60	0.570	0.501	0.526	36,807	51.51%
PR	0.40	0.57	0.542	0.643	0.603	11,100	9.99%
PW	NaN	NaN	NaN	NaN	NaN	54	0.00%
RI	0.63	0.58	0.574	0.506	0.497	5,391	49.16%
SC	0.61	0.59	0.580	0.500	0.525	16,161	49.24%
SD	0.60	0.59	0.578	0.498	0.521	1,211	52.85%
TN	0.68	0.60	0.623	0.519	0.517	32,530	47.00%
TX	0.64	0.60	0.589	0.507	0.514	53,915	51.25%
UT	0.63	0.61	0.589	0.510	0.515	8,986	53.66%
VA	0.64	0.59	0.593	0.508	0.509	16,771	46.82%
VI	0.65	0.59	0.579	0.508	0.480	891	33.00%
VT	0.61	0.59	0.561	0.527	0.512	904	42.04%
WA	0.59	0.60	0.571	0.501	0.493	19,922	9.62%
WI	0.63	0.60	0.573	0.507	0.493	11,891	45.12%
WV	0.63	0.61	0.585	0.495	0.501	9,785	10.44%
WY	0.62	0.62	0.595	0.518	0.528	1,144	36.63%

B.2 Regional Economic Indicators (Workforce Board Level)

Table 20: Index outcomes aggregated by Workforce Development Board (WDB) characteristics, where continuous measures are binned into interpretable ranges.

	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
WDB Unemployment Rate							
1–2%	0.44	0.59	0.465	0.497	0.499	10,245	60.80%
2–3%	0.49	0.58	0.492	0.499	0.500	1,189,976	50.21%
3–4%	0.50	0.57	0.497	0.498	0.500	5,583,296	51.07%
4–5%	0.51	0.57	0.507	0.501	0.500	4,656,720	45.82%
5–6%	0.54	0.57	0.518	0.502	0.499	3,087,183	45.70%
6–7%	0.51	0.57	0.512	0.503	0.498	1,257,492	47.56%
7–8%	0.51	0.57	0.514	0.505	0.501	684,421	50.59%
8–9%	0.48	0.57	0.499	0.506	0.499	649,924	43.67%
9–10%	0.48	0.57	0.502	0.505	0.500	257,699	42.04%
10%+	0.51	0.58	0.515	0.505	0.500	405,211	43.94%
Not available	0.48	0.57	0.489	0.499	0.498	5,984,754	47.92%

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Table 20: Index outcomes aggregated by WDB characteristics

	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
WDB High Household Debt-to-Income Ratio							
< 1	0.51	0.58	0.508	0.501	0.502	698,921	46.83%
1–2	0.51	0.57	0.506	0.500	0.500	10,659,074	48.77%
2–3	0.51	0.57	0.505	0.501	0.499	5,938,243	47.94%
3–4	0.45	0.58	0.481	0.499	0.502	475,613	38.70%
Not available	0.48	0.57	0.489	0.499	0.498	5,995,070	47.13%
WDB Median Age							
25–29	0.54	0.58	0.525	0.501	0.506	17,754	45.46%
30–34	0.49	0.57	0.505	0.501	0.502	1,497,407	50.06%
35–39	0.51	0.58	0.504	0.500	0.501	8,442,660	46.95%
40–44	0.51	0.57	0.505	0.500	0.498	6,748,678	49.10%
45–49	0.51	0.57	0.513	0.502	0.499	1,099,791	45.04%
50–54	0.49	0.57	0.507	0.503	0.502	95,037	42.15%
Not available	0.48	0.57	0.489	0.499	0.498	5,865,594	47.94%
WDB Population (per sq km)							
< 10	0.51	0.57	0.510	0.500	0.496	847,684	44.24%
10–50	0.53	0.57	0.516	0.501	0.498	5,403,196	50.95%
50–200	0.51	0.57	0.506	0.500	0.499	5,305,370	48.23%
200–1000	0.48	0.58	0.494	0.501	0.504	4,590,913	46.74%
1000–4000	0.48	0.58	0.495	0.501	0.504	558,499	46.68%
4000+	0.49	0.59	0.494	0.501	0.500	815,790	36.71%
Not available	0.48	0.57	0.489	0.499	0.498	6,245,469	47.87%
WDB Diversity Index							
25–50	0.48	0.58	0.496	0.498	0.503	1,172,258	47.37%
50–75	0.47	0.58	0.491	0.500	0.503	4,678,679	46.97%
75–10	0.50	0.57	0.505	0.500	0.499	5,632,934	48.50%
100+	0.54	0.57	0.518	0.501	0.497	6,315,201	48.88%
Not available	0.48	0.57	0.489	0.499	0.498	5,967,849	47.11%
WDB Population							
< 100K	0.52	0.57	0.513	0.501	0.498	6,142,960	50.22%
100K–1M	0.51	0.57	0.504	0.501	0.501	8,574,230	47.62%
1M+	0.48	0.58	0.492	0.500	0.503	3,421,138	44.57%
Not available	0.48	0.57	0.488	0.499	0.498	5,628,593	47.79%
WDB Mean Commuting Time (Min)							
< 15	0.51	0.58	0.521	0.501	0.504	23,070	17.99%
15-30	0.51	0.57	0.508	0.501	0.499	15,328,256	48.76%
30-45	0.46	0.58	0.486	0.500	0.503	2,566,977	42.94%
Not available	0.48	0.57	0.489	0.499	0.498	5,848,618	47.90%
WDB Median Income Level							
\$10–15K	0.30	0.57	0.507	0.649	0.581	86,409	5.37%
\$15–20K	0.52	0.57	0.521	0.507	0.502	418,306	47.80%
\$20–25K	0.52	0.57	0.517	0.502	0.499	2,932,805	50.82%

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Table 20: Index outcomes aggregated by WDB characteristics

	Incidence$_g$	Intensity$_g$	$\overline{I_n^W}$	$\overline{I_n^C}$	$\overline{I_n^M}$	Count	% w/ Index
\$25–30K	0.52	0.57	0.513	0.501	0.498	5,490,576	48.60%
\$30–35K	0.51	0.57	0.505	0.501	0.500	4,691,710	46.40%
\$35–40K	0.48	0.58	0.493	0.498	0.501	2,355,626	50.66%
\$40–45K	0.48	0.59	0.485	0.497	0.502	1,074,207	47.31%
\$45–50K	0.47	0.59	0.473	0.496	0.502	518,575	42.15%
\$50–60K	0.44	0.59	0.455	0.493	0.502	279,836	32.51%
\$60–75K	0.39	0.60	0.399	0.490	0.504	51,382	35.45%
\$75K+	0.45	0.60	0.454	0.493	0.497	1,895	61.42%
Not available	0.48	0.57	0.489	0.499	0.498	5,865,594	47.94%
WDB Metro Status (USDA Rural-Urban Continuum Codes)							
Metro:							
1M+	0.48	0.58	0.491	0.500	0.503	5,596,833	46.45%
250K–1M	0.49	0.57	0.503	0.501	0.500	1,760,940	47.92%
$<$ 250K	0.50	0.57	0.507	0.501	0.497	314,979	49.14%
Metro Adjacent:							
20K+	0.52	0.57	0.516	0.500	0.502	387,741	38.53%
5K–20K	0.53	0.58	0.520	0.501	0.496	78,845	49.38%
$<$ 5K	0.67	0.58	0.605	0.542	0.521	282	19.15%
Nonmetro							
20K+	0.50	0.57	0.512	0.500	0.496	209,230	47.68%
5K–20K	0.53	0.57	0.526	0.504	0.500	159,021	50.77%
Not available	0.51	0.57	0.503	0.500	0.498	15,259,050	48.60%

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