From AI Exposure to Training Access: Evidence from U.S. Workforce Boards

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Abstract

I link 2017-2024 administrative records from local boards under the Workforce Innovation and Opportunity Act (WIOA) to training provider listings and state funding to provide new empirical evidence on how public training systems respond to post-GenAI changes in expected skill demand. After ChatGPT's launch in 2022, boards serving more AI-exposed workers and with greater prior experience show a 3-percentage-point larger rise in training participation, about 30 additional trainees per 1,000 participants. Training content shifts much less toward AI-related fields. Eligible-provider listings expand, but listed programs do not automatically translate into funded AI training. The access response is larger in state-years with greater formula allotments, and training activity becomes more concentrated in boards with established routines. The findings show that public workforce systems can expand access when resources and delivery experience are in place. Targeted AI retraining, however, depends on whether those systems convert provider availability and fiscal support into funded participation.

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1 Introduction

Artificial intelligence raises a familiar labor-economics question in a newly urgent form: when technology changes the task content of work, can workers and institutions adjust quickly enough for public policy to matter? A large literature studies how computers, automation, and task-biased technological change alter labor demand, wage inequality, and occupational structure (Autor, Katz and Krueger, 1998; Autor, Levy and Murnane, 2003; Autor, 2015; Acemoglu and Restrepo, 2020, 2022). Recent work on AI and large language models extends this agenda by measuring which occupations, tasks, industries, firms, and places are exposed to machine-learning and GenAI capabilities (Brynjolfsson, Mitchell and Rock, 2018; Felten, Raj and Seamans, 2021; Eloundou et al., 2024). It also shows that generative AI can affect productivity in writing-intensive and customer-support tasks (Noy and Zhang, 2023; Brynjolfsson, Li and Raymond, 2025). Those exposure and productivity measures are useful because they turn a broad technological change into empirical variation. They do not, by themselves, tell us how the public training system responds.

The gap between exposure and response is especially important for AI. Exposure measures can identify where labor-market pressure may be larger, but they do not show whether institutions have the counseling capacity, provider relationships, funding flexibility, or information needed to redirect training. A local area can be highly exposed on paper and still have little ability to route participants into AI-relevant programs. Conversely, a workforce board with stronger prior training routines may be better positioned to respond even when the provider market changes gradually. The empirical question is whether public systems convert board-level AI exposure into actual services.

Public training-system adjustment is economically distinct from adjustment by workers or firms. Exposure does not itself create a training spell. Publicly subsidized retraining has to pass through a public intermediary that assesses participants, verifies eligibility, counsels them toward feasible programs, approves funding, and routes the service through providers that are allowed to receive WIOA dollars. Those upstream decisions shape which workers can eventually realize any returns from retraining. A board-level analysis therefore complements worker-level studies by examining the institutional gate through which training opportu-

nities are made available, financed, and recorded.

This paper studies that process in the U.S. Workforce Innovation and Opportunity Act (WIOA) system. Local boards sit between federal and state rules, American Job Centers, eligible-provider lists, local providers, employers, and participants. Adjustment may first appear as broader access to training, because boards can bring more participants into programs before the content of those programs changes. It may then appear in the approved provider menu or in the fiscal allocation of training activity. AI-specific content is a more downstream margin because it requires the system to match participants to relevant providers, approve the training, and record the field of service.

These institutional margins are directly relevant for policy because WIOA is a standing public infrastructure for displaced and disadvantaged workers. A large literature shows that the effects of active labor-market programs depend on program design, targeting, take-up, and implementation (Heckman, LaLonde and Smith, 1999; Schochet, Burghardt and McConnell, 2008; Attanasio, Kugler and Meghir, 2011; Card, Kluve and Weber, 2018; Katz et al., 2022; Hyman, 2022). In WIOA, technological adjustment can occur through broad training access before program content changes in a targeted way. Policy design therefore concerns both the resource envelope and the organizations that convert resources into services: staff time, provider relationships, counseling practices, fiscal procedures, and local routines that move participants from intake to approved training.

I study WIOA program years 2017 through 2024 for the 50 states and DC. A WIOA program year runs from July through the following June. The launch of ChatGPT on November 30, 2022 falls within program year 2022, which I treat as a transition year.[1] Program years 2023 and 2024 form the main post-ChatGPT period. I construct board-level AI exposure by weighting an external occupation-level GenAI exposure index with the pre-period occupational distribution of participants served by each board. The measure captures the AI exposure implied by the types of workers in a board's pre-period participant pool. Prior AI-training experience is measured from the board's own training activity from 2017 through 2019. It records earlier experience placing participants into AI-related training.

The empirical design compares changes across boards with different AI exposure and different prior AI-training experience. The main specification interacts

[1] OpenAI, "Introducing ChatGPT," November 30, 2022.

the two pre-period measures with indicators for the COVID and digital-adaptation period, the 2022 transition year, and the 2023 to 2024 post period. Board fixed effects absorb persistent differences across local systems, while state-by-year fixed effects compare boards operating under the same state policy, funding, and reporting environment. The three outcomes separate distinct margins of adjustment. Training participation measures whether participants enter training. The AI share among trainees measures how training composition changes among those who enter. AI training per participant combines access and composition into the share of all Adult and Dislocated Worker participants receiving AI-related training.

The estimates show an access-first response. In 2023 and 2024, the post-period coefficient for the main interaction is about 3 percentage points for training participation, equivalent to roughly 30 additional trainees per 1,000 Adult and Dislocated Worker participants. The participant-weighted estimate remains positive at about 1.9 percentage points. The corresponding post-period estimates for the AI share among trainees and AI training per participant are about 0.3 percentage points and are less precise. Boards therefore expand entry into training more clearly than they shift the content of training toward AI.

The mechanism evidence traces how that access response is implemented. AI-related programs and fields enter the eligible-provider menu during the transition and post periods, with less movement in the number of distinct providers. Fixed-stock specifications show that a larger listed menu does not translate one-for-one into funded AI training. The access gradient is larger in state-years with larger Adult and Dislocated Worker allotments. Quantitatively, a one standard deviation larger allotment is associated with a post-period training participation gradient about 1.6 percentage points stronger. Funding intensity, measured relative to the pre-period participant base, is instead more closely associated with the AI share among trainees. Within states, training activity also becomes more concentrated in boards with high AI exposure and stronger prior delivery experience. These patterns suggest that fiscal scale supports broad access, while the composition of training depends on how resources and existing administrative routines are used. Field-level estimates show some activity within broad AI-related training families but limited widespread entry into entirely new AI-related instructional fields.

Taken together, the results describe a public system that responds along margins that use existing routines. Fiscal scale broadens access, while resource inten-

sity can affect composition among trainees without producing the same system-output response. Targeting AI content requires an additional conversion step, from eligible programs and available resources into funded training spells with AI-relevant content. The gap between broad access and targeted AI training is the paper's central evidence on the conversion problem. Resources and provider options matter, but they produce training only when local institutions can connect participants to approved programs and finance their use.

The paper contributes most directly to research on technological change, AI exposure, and worker adjustment. Existing studies measure the tasks and occupations exposed to computers, automation, AI, and large language models, and examine effects on productivity, labor demand, wages, and skill requirements (Autor, Levy and Murnane, 2003; Autor, 2015; Brynjolfsson, Mitchell and Rock, 2018; Felten, Raj and Seamans, 2021; Alekseeva et al., 2021; Eloundou et al., 2024; Brynjolfsson, Li and Raymond, 2025). Hyman et al. (2025) provide the closest evidence by studying training choices, occupational transitions, and worker outcomes among AI-exposed WIOA trainees. I study the upstream system that determines whether training is available, funded, and allocated across local boards. The two papers therefore examine different links in the adjustment process.

The paper also speaks to the literature on publicly funded training and active labor-market policy. That literature evaluates job training, job-search assistance, sectoral programs, and adjustment assistance at the participant or program level (Heckman, LaLonde and Smith, 1999; Kluve, 2010; Schochet, Burghardt and McConnell, 2008; Attanasio, Kugler and Meghir, 2011; Crépon et al., 2013; Card, Kluve and Weber, 2018; Katz et al., 2022; Hyman, 2022). This perspective moves one step upstream. Before a training spell can generate returns, the public system must make programs eligible, guide participants toward them, approve spending, and allocate activity across local boards. Access, eligibility, and local allocation are therefore policy outcomes, not merely implementation background.

More broadly, the results connect technological adjustment to state capacity and public-sector implementation. Public action depends on fiscal resources, organizational routines, personnel, and frontline discretion as well as formal program rules (Besley and Persson, 2009, 2010; Dal Bó, Finan and Rossi, 2013; Finan, Olken and Pande, 2017; Rasul and Rogger, 2018; Best, Hjort and Szakonyi, 2023). WIOA makes that link visible in a high-income-country setting where federal rules, state

resources, and local delivery organizations jointly shape service provision. The provider menu expands, and states with larger resource envelopes show stronger access responses, but targeted AI training depends on the administrative process that turns those inputs into funded service delivery.

The rest of the paper proceeds as follows. Section 2 describes the WIOA institutional setting, data, and measurement. Section 3 lays out the board-year empirical framework and the interpretation of the main interaction. Section 4 presents the main access and AI-training margins. Section 5 studies provider supply, funded conversion, fiscal resources, delivery and throughput, and allocation across training fields. Section 6 concludes.

2 Data and Institutional Setting

2.1 WIOA Boards and Program Years

The Workforce Innovation and Opportunity Act is a federal workforce program administered by states and implemented locally.[2] Title I Adult services prioritize low-income adults and participants facing barriers to employment. Title I Dislocated Worker services primarily serve workers who have been laid off or face displacement.[3] Both programs fund career services and occupational training. Federal law and funding rules define the broad program architecture, while states administer the system, submit plans, allocate resources within federal requirements, and maintain the Eligible Training Provider List. Local workforce development boards are the governing and coordinating units in the analysis. They define local service areas, set priorities, oversee service operators, and maintain relationships with training providers and employers. American Job Centers are the physical service-delivery sites within this system. They provide intake, assessment, counseling, job-search assistance, referrals, and access to training. A board can oversee several centers, and a center can serve participants from more than one local area.

The local board's role is therefore neither the direct control of state allotments nor a passive reporting category. Boards coordinate the local institutions that

[2]U.S. Department of Labor, "Workforce Innovation and Opportunity Act," accessed June 11, 2026, https://www.dol.gov/agencies/eta/wioa.

[3]U.S. Department of Labor, "WIOA Adult and Dislocated Worker Program," accessed June 11, 2026, https://www.dol.gov/agencies/eta/workforce-investment/adult.

turn federal and state resources into services. Eligible training is generally purchased through Individual Training Accounts or related WIOA funding mechanisms from programs on the state Eligible Training Provider List.[4] A participant typically enters through intake and career services, receives assessment or counseling, is determined to need and benefit from training, chooses or is guided toward an eligible provider, and then appears in the administrative records if training is funded and recorded. This sequence explains why allotments, realized expenditures, provider listings, and board-year participation are different empirical objects. Allotments describe the assigned state resource envelope, expenditures describe realized spending, provider lists describe the approved menu, and board-year outcomes describe the participants who reach funded services.

WIOA data are reported by program year. Each program year begins in July and ends the following June.[5] The analysis uses 2017 through 2019 to measure pre-period occupational exposure and prior AI-training experience, 2020 and 2021 as the COVID and digital-adaptation period, 2022 as the ChatGPT-launch transition year, and 2023 and 2024 as the post period.

2.2 Training Outcomes

The main research universe is Adult and Dislocated Worker participants in the 50 states plus DC. Youth records and broader Title I counts are retained for validation, but the core board-year outcomes use the board-coded, deduplicated adult and dislocated-worker sample. Training service rows identify training activity and field content, while participant denominators count unique people within a board and program year. Appendix A.1 gives the denominator construction and data-source coverage.

Let N_{bt} denote adult and dislocated-worker participants in board b and program year t, T_{bt} adult and dislocated-worker training participants, and A_{bt} adult and dislocated-worker participants in AI-related training. The training participa-

[4] 20 CFR §680.100 describes the one-stop delivery system for adult and dislocated-worker services and access to Individual Training Accounts and eligible training-provider lists. See https://www.ecfr.gov/current/title-20/chapter-V/part-680.

[5] 20 CFR §683.100 defines the WIOA program year as beginning July 1 and ending June 30 of the following year. See https://www.ecfr.gov/current/title-20/chapter-V/part-683/subpart-A/section-683.100.

tion rate is T_{bt}/N_{bt}. The AI share among trainees is

$$Y_{bt} = \frac{A_{bt}}{T_{bt}}.$$

AI training per participant is

$$\widetilde{Y}_{bt} = \frac{A_{bt}}{N_{bt}} = \frac{T_{bt}}{N_{bt}} \times \frac{A_{bt}}{T_{bt}}.$$

The decomposition matters because a board can expand training without changing the AI share, or shift the portfolio among trainees without expanding overall participation. Rates with zero or unavailable denominators are coded as missing rather than zero.

Table 1 summarizes the analysis sample, main outcomes, exposure and prior-experience measures, and compact implementation context used later in the paper. The table highlights three features of the setting. First, local boards differ substantially in participant volume, so the analysis reports both unweighted and participant-weighted estimates. Second, AI-related training is a modest share of overall training, which makes it important to separate access to any training from the content of training. Third, boards, AJCs, eligible-provider lists, and state funding measure different parts of the delivery system. Boards govern local services, AJCs provide intake and navigation, provider lists define the approved menu, and state allotments define the fiscal environment in which boards operate.

2.3 Exposure and Prior AI-Training Experience

Board-level AI exposure combines the occupations in a board's pre-period participant pool with an external occupation-level measure of exposure to generative AI. For each board, I weight the exposure index by the occupation distribution of participants served from 2017 through 2019. The result is a shift-share measure of the AI exposure implied by the types of workers served by the board before the analysis period. Higher values indicate that the board served more participants from occupations whose tasks are more exposed to contemporary AI capabilities.

The main occupation-level index comes from the Budget Lab at Yale (Gimbel, Kendall and Kulsakdinun, 2026). I use it because it is designed to summarize exposure to current generative-AI capabilities, maps directly to the occupation codes

Table 1: Descriptive Statistics for Main Analysis Variables

Measure	(1) Mean	(2) SD	(3) P25	(4) Median	(5) P75	(6) N
Panel A. Analysis sample						
Boards						746
Board-years						4,847
States plus DC						51
Program years						8
Adult and DW participants	1,307.5	6,810.9	146.0	356.0	862.0	4,847
Training participants	324.8	592.9	74.0	182.0	372.0	4,847
Panel B. Main outcomes						
Training participation rate	0.554	0.281	0.342	0.583	0.793	4,431
AI share among trainees	0.127	0.118	0.035	0.103	0.186	4,409
AI training per participant	0.073	0.078	0.013	0.053	0.106	4,431
Panel C. AI exposure and prior AI-training experience						
Yale core AI exposure	0.539	0.098	0.479	0.527	0.596	567
AIOE AI exposure	0.441	0.109	0.366	0.424	0.513	567
GPT-alpha exposure	0.506	0.102	0.444	0.500	0.565	567
Prior AI-training experience	0.063	0.077	0.005	0.044	0.094	567
Pre-period AI-training share	0.123	0.120	0.027	0.101	0.180	566

Note: This table reports descriptive statistics for the main analysis sample, outcomes, AI exposure, and prior AI-training experience. The unit is the board-year for time-varying participant outcomes and the WIOA local board for pre-period exposure and prior-experience measures. The analysis sample covers the 50 states plus DC. Participant outcomes use the Adult and Dislocated Worker analysis universe. Exposure is measured from pre-period prior occupations, and prior AI-training experience is measured from pre-period AI-related training activity. WIOA program years run from July through June: PY2022 is the GenAI transition year, and PY2023 to PY2024 is the GenAI post period. Count rows report N in the final column. Distribution rows summarize board-years or boards. Appendix Table C.25 reports the mechanism context variables.

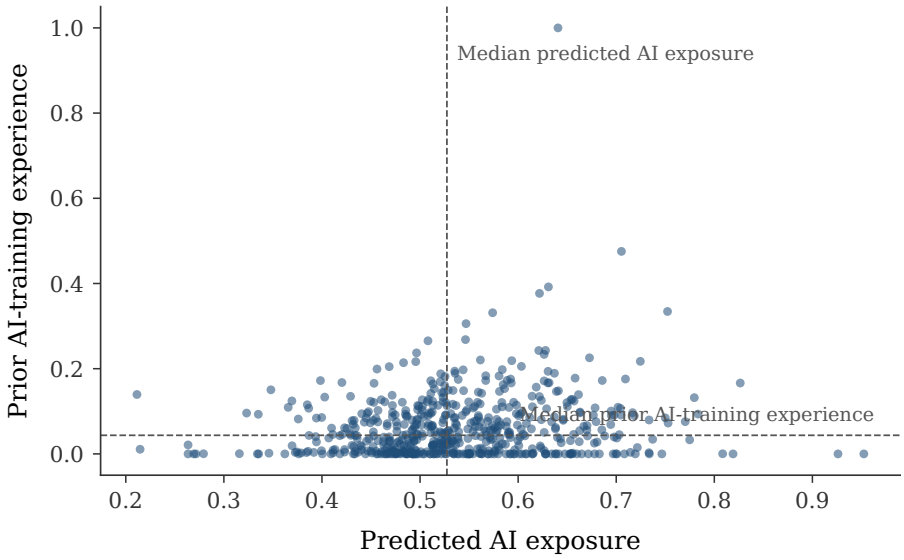
observed in WIOA, and is constructed independently of the WIOA outcomes. To assess sensitivity to this choice, I also construct board exposure using the AI Occupational Exposure index developed by Felten, Raj and Seamans (2021) and a GPT-based task-exposure measure following Eloundou et al. (2024). AIOE captures broader occupational exposure to advances in artificial intelligence, whereas GPT-based exposure emphasizes tasks potentially affected by large language models. Appendix B.1 reports the corresponding estimates.

Prior AI-training experience measures a different object. It is constructed from a board's own training activity from 2017 through 2019 and captures prior experience placing adult and dislocated-worker participants into AI-related training.

Exposure describes the occupational composition of the participant base, while this prior-experience measure describes the board's demonstrated delivery history. The empirical design uses their interaction to ask whether boards facing greater AI exposure respond more strongly when they already have relevant training routines. Appendix A.1 summarizes the construction, and Appendix B.1 reports pre-period-window robustness, including checks around the 2018 training-count anomaly.

AI exposure and prior delivery experience vary substantially across boards (Figure 1). Although the two measures are related, the relationship is far from mechanical: boards serving participant pools with similar occupational exposure often have very different histories of AI-related training, while boards with similar delivery histories serve workers with different exposure profiles. This variation allows the design to distinguish the pressure implied by the participant mix from a local system's prior experience delivering relevant training. The median lines are used only to organize descriptive trends, while the regression specifications retain both measures as standardized continuous variables.

Figure 1: AI Exposure and Prior AI-Training Experience



Notes: This figure plots the joint board-level distribution of predicted AI exposure and prior AI-training experience used in equation (3.1). The unit is the WIOA local board in the 50-state-plus-DC sample. Exposure is measured from pre-period prior occupations, and prior AI-training experience is measured from pre-period AI-related training activity. Dashed reference lines show the sample medians used to define exposure and prior-experience cells.

2.4 Provider Supply, Fiscal Resources, and Training Fields

Eligible Training Provider Lists define the programs that can receive WIOA training funds. I distinguish local physical providers from online and statewide programs, and I use the date a program entered the state list to construct annual stocks and additions.[6] These measures capture the approved provider menu. WIOA participant records separately show which listed options were actually used for funded training.

The funding data measure three related fiscal margins. State Adult and Dislocated Worker formula allotments from the U.S. Department of Labor capture assigned fiscal scale. State WIOA performance reports provide realized career-service and training-service expenditures, which measure spending after state and local allocation decisions have been made. Per-participant measures describe resource intensity relative to the caseload. Formula allotments, realized spending, and spending per participant are kept separate because they correspond to different stages of the service-delivery process.

Training content is classified using instructional program codes and broader field families. Broad AI content is the main classification, while a narrower definition identifies programs with more explicit AI content. Training services are assigned to four-digit Classification of Instructional Programs fields, but detailed board-by-field cells are sparse. The main text therefore uses broader field families for readable allocation results, while Appendix D reports CIP4 estimates and field-code coverage. Detailed code cleaning and coverage are documented in Appendix A.3. The board-year panel supports the access and funding analyses, while the board-field panels support training-field allocation.

The empirical design uses these institutional objects in sequence. It first asks whether exposed boards with prior delivery experience expand training access, then examines whether approved supply, fiscal scale, realized spending, and field allocation help explain how that response is converted into funded services.

[6] CareerOneStop provides a WIOA-eligible training-program search tool. See https://www.careeronestop.org/LocalHelp/EmploymentAndTraining/find-WIOA-training-programs.aspx. TrainingProviderResults.gov reports eligible training-provider information under WIOA. See https://www.trainingproviderresults.gov/.

3 Empirical Framework

Boards differ both in the occupational exposure of their participant pools and in their prior experience delivering AI-related training. The empirical problem is to ask whether those pre-period differences predict differential adjustment after common national timing changes, while holding constant the state environment in which boards operate. The design therefore compares boards within the same state and program year. AI exposure measures the pressure implied by the participant mix, prior delivery experience measures an existing local routine, and observed WIOA-funded outcomes show whether those conditions become training services.

3.1 Adjustment Margins

Workforce-system adjustment can appear at several points in the service chain. AI exposure may create pressure for a local system to respond, and the eligible-provider menu may expand as programs enter state lists. Listed supply is still not funded WIOA use. A board must identify suitable providers, counsel participants, approve training, fund individual accounts or related services, and record the resulting activity. Observed WIOA-funded training is therefore a conversion margin rather than a direct measure of all local AI demand or all local provider capacity.

The main outcomes locate adjustment along that chain. The training participation rate measures access, meaning whether more participants enter training at all. The AI share among trainees measures composition conditional on training, meaning whether training participants are redirected toward AI-relevant content. AI training per participant combines these two forces and measures the system-level rate at which Adult and Dislocated Worker participants receive AI-related training. Content changes are downstream of access because a participant first has to enter training before the field of training can change.

Following Section 2, Y_{bt} refers to the AI share among trainees and $\widetilde{Y}_{bt}$ refers to AI training per participant. The equations below reserve O_{bt} for generic board-year outcome notation.

Provider supply and field use provide additional evidence on the same chain. Nominal eligible-provider supply can expand even if WIOA-funded use does not, especially if counseling capacity, participant fit, provider availability, or funding rules limit conversion. Field outcomes show whether boards enter new AI-related

fields or expand activity within broader field families. Those outcomes inherit the coding limits described in Appendix A.3 and Appendix D.1. Services without valid field codes are an observability constraint rather than an unobserved field allocation.

3.2 Board-Year Design

The main board-year design compares changes in outcomes across local boards with different AI exposure and different prior AI-training experience. All paper-facing board-year estimates use the 50-states-plus-DC analysis sample. Let b index boards, t index WIOA program years, and $s(b)$ denote the state containing board b. Let $Exposure_b$ be the board-level AI-exposure measure and $Capacity_b$ be the pre-period AI-training-capacity measure described in Section 2. The primary period-bin specification is

$$\begin{aligned} O_{bt} = \alpha_b + \lambda_{s(b)t} \\ &+ \sum_{\tau \in \{\text{COVID,Transition,Post}\}} \beta_\tau \left(\mathbf{1}\{t \in \tau\} \times Exposure_b \times Capacity_b\right) \\ &+ \sum_{\tau} \gamma_\tau \left(\mathbf{1}\{t \in \tau\} \times Exposure_b\right) \\ &+ \sum_{\tau} \delta_\tau \left(\mathbf{1}\{t \in \tau\} \times Capacity_b\right) + \varepsilon_{bt}. \end{aligned} \tag{3.1}$$

Here O_{bt} denotes one of the board-year outcomes: the training participation rate, the AI share among trainees, or AI training per participant. The terms α_b are board fixed effects and $\lambda_{s(b)t}$ are state-by-year fixed effects. The board fixed effects absorb time-invariant differences across local systems, including the main effects of $Exposure_b$ and $Capacity_b$. The state-by-year fixed effects absorb shocks, policies, and reporting conditions common to boards within the same state and program year, so the comparison is among boards exposed to the same state-level policy and reporting environment in a given program year. Standard errors are clustered by board. The main specifications use standardized continuous measures of AI exposure and prior AI-training experience. Median splits are used only for descriptive trends.

Intuitively, β_τ compares boards operating in the same state and year and asks whether outcomes change more where both participant exposure and prior deliv-

ery experience are higher. The coefficient is an adjustment gradient rather than a binary treatment effect. It captures the additional change associated with a one standard deviation increase in exposure when prior AI-training experience is also one standard deviation higher, net of the lower-order exposure and experience interactions. Those lower-order terms ensure that the coefficient does not simply reflect period-specific changes associated with exposure alone or prior experience alone. The baseline period is 2017 through 2019, so each period-bin coefficient is interpreted relative to that pre-period. Across the three outcomes, the same interaction asks whether the response appears as broader access, a stronger AI share among trainees, or a higher rate of AI training across all Adult and Dislocated Worker participants.

3.3 Timing and Event Studies

Timing follows WIOA program years. The omitted baseline period runs from PY2017 to PY2019. The PY2020 to PY2021 coefficients describe the COVID and digital-adaptation period rather than GenAI effects. OpenAI introduced ChatGPT on November 30, 2022, which falls in PY2022 because that WIOA program year runs from July 2022 through June 2023. The PY2022 coefficient is therefore kept separate as transition/onset evidence, while the main post-GenAI period is PY2023 to PY2024. This convention avoids folding the launch year into the main post period while still allowing the design to detect whether adjustment begins around onset.

Event-study specifications provide a more granular timing display:

$$\begin{aligned} O_{bt} = \alpha_b + \lambda_{s(b)t} \\ + \sum_{k \neq 2019} \theta_k \left(\mathbf{1}\{t = k\} \times Exposure_b \times Capacity_b \right) \\ + \text{lower-order exposure and capacity interactions } + \varepsilon_{bt}. \end{aligned} \tag{3.2}$$

The event study omits 2019 because it is the final full program year before the pandemic and immediately precedes the first major disruption in the panel. Using 2019 as the reference makes each coefficient a comparison with the last undisturbed pre-period year. The event-study coefficients θ_k trace the main interaction by program year. Pre-period coefficients show whether the interaction was already mov-

ing before the pandemic, 2020 and 2021 capture the COVID and digital-adaptation period, 2022 captures the transition year, and 2023 to 2024 provide the main GenAI comparison.

The period-bin model and the event-study model answer complementary questions. The period-bin model gives a compact main estimand for the baseline, COVID, transition, and post periods. The event study makes timing more transparent and helps interpret the post-period coefficients. Appendix Table B.13 and Appendix Figure B.7 report the main timing checks, while Appendix Figure B.8 and Appendix Tables B.15, B.16, and B.17 report exposure and prior-experience robustness. These checks show whether the broad access and AI-training patterns depend on one exposure index, one timing convention, or one prior-experience proxy.

3.4 Mechanisms and Allocation

Section 5 uses the same conceptual chain to study where adjustment appears. It asks whether the approved menu expands, whether listed supply is used in funded training, whether fiscal scale conditions access, whether activity becomes concentrated within states, and whether field use changes. Provider supply is measured through ETP listings, including date-added measures that distinguish beginning-of-program-year stocks from within-year additions. These are listed supply objects: they record programs that appear in the eligible-provider environment, not participants who receive funded training. The conversion analysis then asks whether fixed provider stock and related implementation conditions correspond to stronger WIOA-funded training responses. Appendix C.2 collects the construction and mechanism details needed to keep those objects separate.

The funding analysis augments the main board-year specification with a fourth interaction between the period indicator, AI exposure, prior AI-training experience, and a standardized state funding measure. State-by-year fixed effects absorb the funding level itself. The four-way coefficient therefore shows whether the adjustment gradient is stronger in state-years with larger Adult and Dislocated Worker allotments. Parallel models use allotments per pre-period participant to measure resource intensity. Total allotments capture the scale of the state resource envelope. Per-participant allotments capture resources relative to the pre-period

caseload.

The within-state allocation analysis uses the same main interaction with outcomes defined as each board's share of statewide training activity relative to its share of statewide participants. These outcomes show whether activity becomes more concentrated in exposed boards with established training routines, after absorbing state-year conditions shared by all boards in the state.

The training-field analysis studies whether the main board-year responses are accompanied by changes in the set or composition of training fields. Field-menu outcomes show whether boards add or activate AI-related fields. Family allocation models summarize shifts across readable field families, while detailed field-code models provide a sparser robustness check in Appendix D.1. A board can expand training access within existing fields, use providers that are already listed, or route participants through training channels that are less visible in field-coded data.

3.5 Interpretation

The design identifies differential adjustment across local workforce systems. It shows whether boards serving more AI-exposed participant pools change training activity more strongly when they enter the period with greater AI-training experience. Board fixed effects remove persistent differences across local systems, and state-by-year fixed effects compare boards operating under the same state policy, funding, and reporting environment. The outcome sequence then reveals where the response appears: training access, training composition, provider supply, fiscal resources, within-state allocation, and training fields.

The interpretation is comparative rather than structural. Board-level AI exposure is constructed from pre-period occupations, and $Capacity_b$ summarizes prior WIOA activity. Both are equilibrium characteristics of the local system. State-year fixed effects improve comparability, but they do not create randomized assignment of exposure or prior routines. The estimates therefore describe how observed public workforce activity differs across exposure and prior delivery experience, while the combined evidence from timing, funding, provider supply, and allocation helps locate adjustment without identifying a single binding friction.

4 Training Access and AI-Training Margins

The first estimates ask where adjustment becomes visible after the launch of ChatGPT: at entry into training, in the content of training among participants who enter, or in the overall rate of AI-related training. Training participation measures access to training. The AI share among trainees measures composition conditional on entering training. AI training per participant combines access and composition into the realized rate at which Adult and Dislocated Worker participants receive AI-related training.

The main result is an access-versus-composition contrast. The clearest post-GenAI response is broader training access among boards with greater AI exposure and stronger prior AI-training experience. The AI-specific composition margin and the combined AI-training-per-participant margin are weaker. This pattern directs attention to the institutions that translate exposure, provider supply, and fiscal resources into funded training.

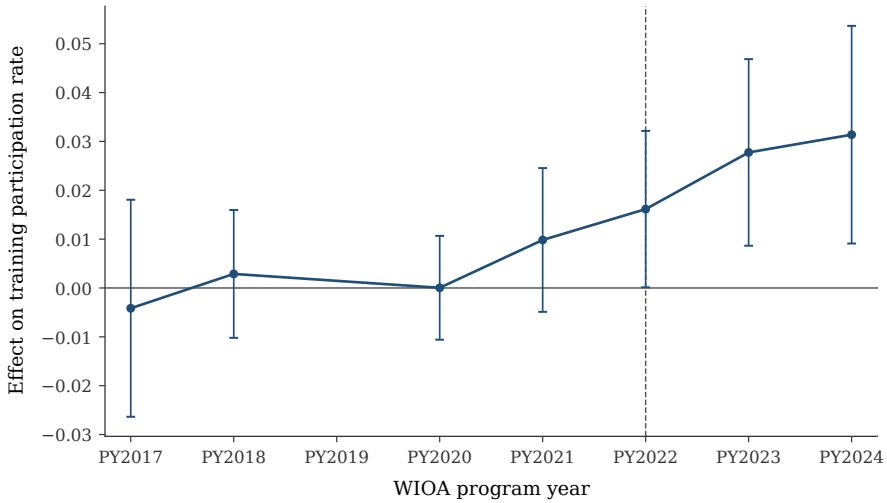
4.1 Access Versus Composition

Figure 2 displays the event-study version of the training-access margin. It plots the main interaction by program year with 2019 omitted, so the points trace differential timing relative to the immediate pre-pandemic baseline. The pre-period estimates are small and imprecise. The 2020 and 2021 coefficients precede the ChatGPT launch and capture the COVID and digital-adaptation period, while the 2022 coefficient covers a program year in which public GenAI onset occurs during the year. The main GenAI comparison is therefore 2023 and 2024.

The access path becomes more positive in the onset and post-GenAI years. The modest positive coefficients in 2020 and 2021 are consistent with an earlier phase of digital adaptation, when remote work and online service delivery expanded, while the larger 2023 to 2024 coefficient marks the stronger post-ChatGPT access response. Appendix Figures B.5 and B.6 report the corresponding AI-share and AI-training-per-participant paths because those figures are useful timing checks but less central to the main access result. They do not show the same sharp post-period pattern. The board-year response appears mainly at the gateway into training: boards with higher exposure and more prior delivery experience expand participation more clearly than they increase AI intensity among trainees.

The distinction matters because AI training per participant combines access and composition. If additional access were matched by a proportional rise in AI composition, the combined rate would rise strongly. If access expands through existing program mixes, or if AI-specific routing faces provider, counseling, eligibility, funding, or recording constraints, the combined margin can remain muted. The smaller AI-specific paths therefore motivate the mechanism evidence on provider supply, conversion, and observability.

Figure 2: Event Study: Training Participation



Notes: This figure reports event-study coefficients from equation (3.2) for the training participation rate, with vertical bars showing 95 percent confidence intervals. The omitted base year is PY2019. WIOA program years run from July through June; PY2022 contains the November 30, 2022 ChatGPT launch and is treated as the GenAI transition year. The unit is the WIOA local board by program year in the 50-state-plus-DC sample. Exposure is board-level AI exposure, prior experience is pre-period AI-training experience, and standard errors are clustered by board.

4.2 Magnitude and Interpretation

Table 2 reports the period-bin estimates from equation (3.1) for the three main outcomes. The first column shows the access margin. The second and third columns show whether the additional training is accompanied by a change in AI content among trainees or in AI training across the full participant pool.

The training participation coefficient is 0.005 in the COVID and digital bin, 0.016 in the transition year, and 0.030 in the post period, or about 0.5, 1.6, and 3.0 percentage points. The 3.0 percentage-point post estimate corresponds to about

30 additional trainees per 1,000 Adult and Dislocated Worker participants for the main one standard deviation interaction contrast. Relative to the sample mean training participation rate in Table 1, it is approximately a 5 percent increase. This translation is not an aggregate treatment effect. It describes the adjustment gradient: among boards in the same state and year, the increase in training participation is larger where AI exposure and prior AI-training experience are both higher.

The interpretation remains an adjustment contrast, not a structural elasticity. Board fixed effects absorb stable differences across local systems, and state-by-year fixed effects absorb policy, funding, and reporting conditions shared within a state and program year. The exposure and prior-experience measures are pre-period objects, but neither observed AI demand nor local delivery history is randomly assigned. The useful comparison is therefore whether predicted pressure becomes more visible in observed WIOA outcomes when a board had already demonstrated the operating ability to route participants into AI-relevant training.

Table 2: Main Board-Year Difference-in-Differences Estimates

	(1) Training participation rate	(2) AI share among trainees	(3) AI training per participant
COVID and digital	0.005	0.007**	0.004**
	(0.006)	(0.003)	(0.002)
Transition	0.016**	0.006	0.006*
	(0.008)	(0.005)	(0.003)
GenAI post	0.030***	0.003	0.003
	(0.009)	(0.006)	(0.004)
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓
Observations	3,774	3,774	3,774
Board clusters	503	503	503

Note: This table reports period-bin estimates from equation (3.1) for the three main board-year outcomes. Coefficients are exposure-by-prior-experience estimates relative to 2017 to 2019. The unit is the WIOA local board by program year, and outcomes use the Adult and Dislocated Worker analysis universe. All regressions include board and state-by-year fixed effects. Standard errors clustered by board are reported in parentheses. Exposure is board-level AI exposure, and prior AI-training experience is measured from pre-period AI-related training activity. PY2022 is the GenAI transition year, and PY2023 to PY2024 is the GenAI post period.

For the AI share among trainees, the GenAI-post coefficient is 0.003, or about 0.3 percentage points, and imprecise. For AI training per participant, the GenAI-post coefficient is also about 0.3 percentage points and imprecise. The two AI-specific estimates are much smaller than the access estimate and do not show a comparable content shift. The uncertainty around them still matters, so the estimates do not imply that AI content cannot respond. They show that the clearest post-period movement in this setting occurs at the point of entry into training. Appendix Figure B.4 visualizes the post-period estimates for the three outcomes in Table 2.

Training entry is an earlier administrative margin than AI-specific training content. Expanding access can operate through existing providers, existing counseling routines, and existing approval channels. Raising the AI share among trainees may require a more specific chain: listed provider supply in relevant fields, staff knowledge of those programs, participant readiness, funding approval, and usable training-field records. The board-year estimates therefore point to administrative conversion as the next empirical object.

4.3 Robustness and Timing

The main specification uses the Yale core exposure measure because it is the closest match to the GenAI-period interpretation. Appendix Figure B.8 compares the Yale measure with the AIOE and GPT-based measures introduced in Section 2.3. The late-period access estimates remain positive across the alternatives, although their magnitudes and precision differ.

Timing and weighting checks serve complementary purposes. Separating the COVID and digital period, the transition year, and the post period keeps pandemic-era adaptation and the onset year separate from the main post comparison. The participant-weighted access estimate is positive at about 1.9 percentage points, so the result is not driven only by small boards. Placebo and pseudo-shock checks are small and imprecise, and the raw four-cell trends are descriptive but consistent with the timing interpretation. Appendix B reports the fuller robustness matrices. These include exposure checks, participant weights, timing checks, event-study variants, raw four-cell trends, and pre-period-window checks around the 2018 anomaly.

Appendix Table B.18 separates four dimensions of prior AI-training experience:

the level of narrow-AI capacity, the pre-period share of training in narrow-AI programs, the log number of narrow-AI trainees, and the breadth of narrow-AI fields. The access result is strongest for the level measure, which most directly captures the scale of a board's prior delivery experience.

The prior-experience checks also clarify what the delivery-history measure captures. It is historical and can reflect past participant flows, provider relationships, counseling routines, funding practices, and local reporting. The robustness exercise asks whether the access pattern survives reasonable alternative summaries of that history. Across alternative exposure measures, timing definitions, participant weights, and prior-experience measures, the access coefficient remains the most consistent post-period response. The AI-content margins remain smaller across the same checks.

The result to carry forward is not simply that training rises. It is that entry into training responds more clearly than AI-specific content, which directs attention to the institutions that supply, finance, and allocate training.

5 Mechanisms of Workforce-System Adjustment

Section 4 leaves a mechanism puzzle. Boards with greater AI exposure and stronger prior AI-training experience expand training access more clearly than they change AI content. The evidence follows the service-delivery process behind that pattern. It asks whether the provider menu expands, whether listed supply becomes funded training, whether fiscal resources shape where access occurs, whether activity concentrates in boards with established routines, and whether the field portfolio changes.

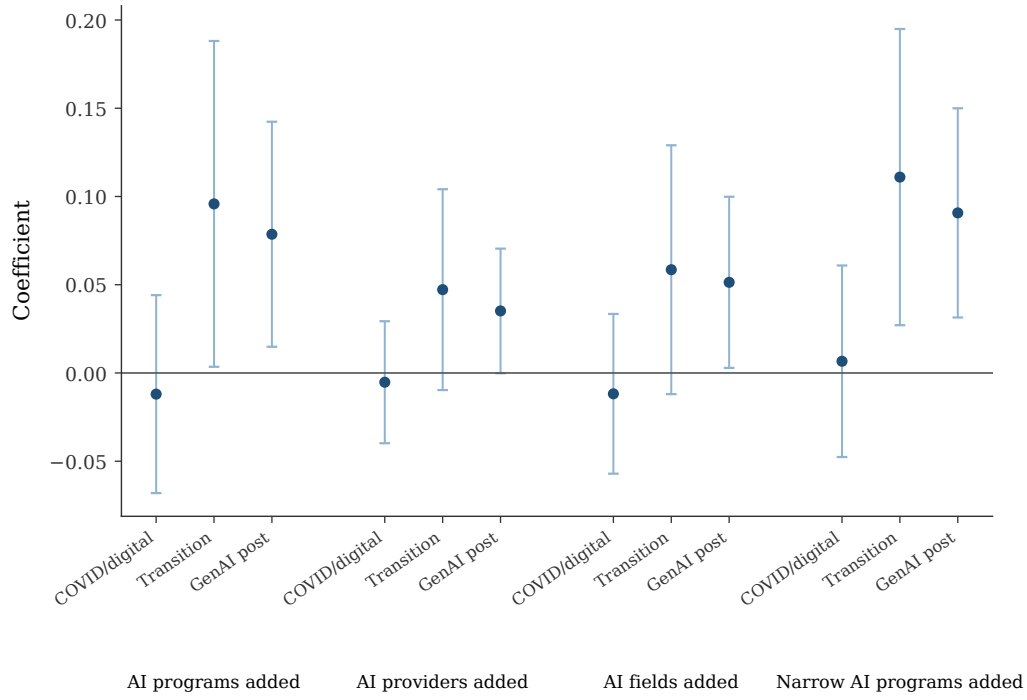
5.1 Eligible-Provider Supply

Eligible Training Provider (ETP) lists measure the approved program menu in the WIOA provider environment. They record programs that are listed and potentially available through local physical providers or online and statewide hybrid channels. They do not record participant enrollment, counseling decisions, funding approval, or completed training. A listed program can expand the menu facing a board before it appears as WIOA-funded training in a given program year.

The date-added ETP measures provide the annual supply-response margin. From observed listing dates, I construct beginning-of-year stocks and within-year additions under a no-exit assumption. Appendix A.2 describes the construction, and Appendix C.2 reports supporting local, scalable, timing, and fixed-stock tables and figures.

Figure 3 estimates the period-bin specification in equation (3.1) with additions to local AI-related programs, providers, instructional fields, and narrow-AI programs as outcomes. The transition and post-period coefficients are positive for program additions, field additions, and narrow-AI program additions. Provider entry is smaller. The pattern indicates that the eligible menu expands mainly through additional programs and fields within the provider environment, rather than through a comparably large increase in the number of provider organizations.

Figure 3: ETP Supply Response



Notes: This figure reports period-bin coefficients from equation (3.1), estimated separately for additions to local AI-related programs, providers, instructional fields, and narrow-AI programs. The unit is the WIOA local board by program year in the 50-state-plus-DC sample. All specifications include board and state-by-year fixed effects. Standard errors are clustered by board, and vertical bars show 95 percent confidence intervals. The COVID and digital period is PY2020–PY2021, the transition year is PY2022, and the GenAI post period is PY2023–PY2024.

These outcomes describe the supply available to the WIOA system. They pro-

vide the first step in the mechanism sequence because boards can finance only programs that are approved and listed. At the same time, the evidence is menu expansion rather than funded use. The expanded menu matters for adjustment only if participants are routed into those programs and the training is paid for through WIOA.

5.2 From Listed Supply to Funded Training

After establishing that the listed menu expands, I examine whether those options are translated into WIOA-funded AI training. A listed program still has to be identified as relevant, matched to a participant, approved for funding, and recorded in the administrative data.

Table 3 places the supply and conversion margins side by side. Panel A anchors the provider-list response from Figure 3. Panel B reports the common 2019 program- and provider-stock specifications. Appendix C.2 separates the underlying AI-trainee models from direct conversion-rate specifications and documents additional stock definitions where estimates are available.

Panel B tests whether the beginning-of-period stock of listed AI-relevant programs or providers predicts WIOA-funded AI trainees. The displayed 2019-stock specifications show weak connections. Given 2019 program stock, the post-period AI-trainee estimate is -0.039 with a standard error of 0.043. Given 2019 provider stock, the estimate is -0.036 with a standard error of 0.042. Appendix Tables C.28 and C.29 report direct conversion-rate checks, which are uneven across supply denominators and support samples. Appendix Figure C.16 plots the time series of AI-related program additions and WIOA-funded AI trainees. The two series move differently after the transition year, providing a descriptive view of the gap between listed supply and realized use.

Several features of WIOA make incomplete conversion plausible. Counseling, approval, participant fit, provider availability, and funding rules jointly determine whether a listed program becomes a training spell. Individual Training Accounts require participant eligibility, program eligibility, counseling, and local approval. Work-based or customized routes require employer coordination and may be less cleanly represented in field-coded training records. A listed AI-relevant program also does not ensure staff awareness, provider seats, or compatibility with local

Table 3: ETP Supply Response and WIOA Conversion

	(1) COVID and digital	(2) Transition	(3) GenAI post
Panel A. ETP supply response			
AI programs added	-0.012	0.096**	0.079**
	(0.029)	(0.047)	(0.032)
AI providers added	-0.005	0.047	0.035*
	(0.018)	(0.029)	(0.018)
AI fields added	-0.012	0.059	0.051**
	(0.023)	(0.036)	(0.025)
Narrow AI programs added	0.007	0.111***	0.091***
	(0.028)	(0.043)	(0.030)
Panel B. WIOA conversion into training			
AI trainees	-0.003	-0.006	-0.039
given PY2019 program stock	(0.024)	(0.041)	(0.043)
AI trainees	-0.013	-0.004	-0.036
given PY2019 provider stock	(0.025)	(0.039)	(0.042)
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓
Observations	3,522	3,522	3,522
Board clusters	454	454	454

Note: This table reports period-bin estimates from equation (3.1) for listed ETP supply and WIOA-funded AI training. Panel A reports additions to listed local AI-relevant ETP programs, providers, fields, and narrow-AI programs. Panel B reports fixed-stock conversion checks for WIOA-funded AI trainees using PY2019 local program or provider stock. The unit is the WIOA local board by program year. All regressions include board and state-by-year fixed effects. Standard errors clustered by board are reported in parentheses. The COVID and digital period is PY2020 to PY2021, the transition period is PY2022, and the GenAI post period is PY2023 to PY2024.

performance priorities. The evidence therefore places the provider list at the beginning of the service-delivery process, before the institutional steps that turn supply into funded training.

5.3 Fiscal Resources and Within-State Allocation

The gap between listed supply and funded use raises a fiscal question. Boards can use an expanded provider menu only within the resource environment created by state allotments and realized service spending. I therefore examine whether the

adjustment gradient is stronger when the state resource envelope is larger, and whether training activity shifts toward boards that already have relevant delivery experience.

Formula allotments come from the U.S. Department of Labor's state statutory funding files for the Adult and Dislocated Worker programs. Realized career-service and training-service expenditures come from state WIOA performance reports. Allotments measure assigned resources. Expenditures measure how states report spending those resources across service categories. The main text focuses on formula allotments and within-state activity allocation, while Appendix C.3 reports expenditure levels, spending shares, resource-intensity measures, and inference checks.

Table 4 reports the fiscal results. Panel A shows that the access gradient is stronger when fiscal scale is larger. A one standard deviation increase in Adult and Dislocated Worker allotments is associated with a 1.6 percentage-point larger post-period training participation coefficient for the main interaction. Combined with the 3.0 percentage-point coefficient in Table 2, the implied access gradient is about 4.6 percentage points one standard deviation above the mean allotment and about 1.4 percentage points one standard deviation below it. The corresponding funding interactions for the AI share and AI training per participant are negative and imprecise. Fiscal scale appears most clearly at the access margin.

Panel B measures resource intensity using allotments per pre-period participant. A one standard deviation increase in resource intensity is associated with a 3.3 percentage-point larger shift in the AI share among trainees. The access coefficient is negative and imprecise, while the AI training per participant coefficient is positive but less precise. The two panels reveal distinct fiscal margins. Fiscal scale measures the size of the state resource envelope, while resource intensity measures resources relative to the pre-period caseload. A larger envelope is most clearly associated with access, and resource intensity is more clearly associated with composition among trainees. Neither object produces a comparable, precise increase in AI training per participant. This distinction is about stages of adjustment rather than the effectiveness of spending intensity. Resources per participant can reflect costs, sparsity, service mix, and allocation choices as well as the amount of money available for broad access.

Table 5 asks where training activity is realized within a state. The access-

Table 4: Funding: Fiscal Scale and Resource Intensity

	(1) Training participation rate	(2) AI share among trainees	(3) AI training per participant
Panel A. Fiscal scale			
Assigned resources	0.016**	-0.004	-0.008
x exposure x pre-period activity	(0.008)	(0.004)	(0.006)
Observations	3,774	3,774	3,759
Board clusters	503	503	499
Panel B. Resource intensity			
Allotment per pre-period participant	-0.012	0.033***	0.024
x exposure x pre-period activity	(0.023)	(0.011)	(0.019)
Observations	3,759	3,759	3,759
Board clusters	499	499	499
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓

Note: This table reports GenAI-post moderation estimates for training participation, AI share among trainees, and AI training per participant. The unit is the WIOA local board by program year, and the sample is the Adult and Dislocated Worker analysis universe in the 50 states plus DC. Panel A uses assigned resources, defined as state-year Adult and Dislocated Worker formula allotments, as a standardized log moderator. Panel B uses assigned resources per pre-period participant as a standardized log moderator. All regressions include board and state-by-year fixed effects. Standard errors clustered by board are reported in parentheses. State-year funding main effects are absorbed by state-by-year fixed effects.

allocation outcome compares a board's share of statewide trainees with its share of statewide Adult and Dislocated Worker participants. The AI-composition outcome compares its share of statewide AI trainees with its share of all statewide trainees. The AI-output outcome compares its share of statewide AI trainees with its share of statewide participants. Panel B expresses the same comparisons as log concentration ratios.

In the log-concentration specifications, the post-period interaction implies roughly 7 percent greater training concentration and 13 percent greater AI-output concentration. The AI-composition concentration estimate is positive but less precise. These estimates show that, within states, training activity becomes more concentrated in boards with greater AI exposure and stronger prior delivery experience. The table captures where statewide service activity is realized after common state-

Table 5: Within-State Allocation and Concentration

	(1) Access allocation	(2) AI composition allocation	(3) AI output allocation
Panel A. Share allocation			
Exposure x pre-period activity	0.003*	0.004	0.007
	(0.002)	(0.004)	(0.005)
Observations	3,816	3,479	3,479
Board clusters	507	470	470
Panel B. Log concentration			
Exposure x pre-period activity	0.067***	0.067	0.125***
	(0.020)	(0.041)	(0.040)
Observations	3,759	3,198	3,198
Board clusters	499	446	446
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓

Note: This table reports GenAI-post estimates for within-state activity allocation. Access allocation aligns with the training participation margin T/N, AI composition allocation aligns with $Y = A/T$, and AI output allocation aligns with $\widetilde{Y} = A/N$. Panel A uses share-difference outcomes: access allocation compares a board's share of statewide training participants with its share of statewide participants; AI composition allocation compares its share of statewide AI-training participants with its share of statewide training participants; AI output allocation compares its share of statewide AI-training participants with its share of statewide participants. Panel B uses log concentration ratios for the same allocation margins. The unit is the WIOA local board by program year, and the sample covers the 50 states plus DC with the required positive state-year support for each margin. All regressions include board and state-by-year fixed effects. Standard errors clustered by board are reported in parentheses.

year conditions are absorbed. It locates the concentration of service activity within states rather than board-level funding allocation.

5.4 Delivery and Throughput

The remaining outcomes describe how the additional training is delivered and whether participants progress through it. Delivery-channel reallocation would be evidence that boards are reorganizing how training is provided, not only how many participants enter. Delivery measures include Individual Training Accounts, on-the-job training, customized training, apprenticeships, private providers, and online or hybrid programs. Throughput measures include completion, credential

receipt, and measurable skill gains. These outcomes help distinguish an expansion through established service channels from a broader reorganization of WIOA delivery.

Appendix Table C.37 reports the compact delivery and throughput screen, and Appendix C.4 reports the fuller delivery and throughput checks. The delivery estimates show little broad reallocation across channels. That stability is informative because it suggests that the access response operates through existing service routines rather than a rapid shift toward a different delivery model. Credential receipt and measurable skill gains increase modestly, while completion is essentially unchanged. These administrative outcomes are not measures of worker welfare or earnings. They show whether participants move through recorded training milestones after access expands.

5.5 Allocation Across Training Fields

The final mechanism margin asks whether the access and funding responses are accompanied by changes in the training fields used by local boards. A board's field menu is the set of AI-related instructional fields in which it records any trainees. Field-family outcomes aggregate detailed instructional codes into broader groups, which provides a more stable view of portfolio allocation.

Table 6 combines these two margins. Panel A reports whether boards activate AI-related fields that were absent from their pre-period menu. Panel B reports changes in the share of training, participant intensity, and activation across broader field families. The field-menu estimates are small relative to their standard errors. The family results show more movement in participant intensity and activation than in portfolio share.

The pattern complements the earlier results. Boards expand training access, provider menus, and within-state activity more clearly than they enter entirely new AI-related instructional fields. Some additional activity occurs within broad AI-related families, but the portfolio share does not shift sharply. The granular CIP4 estimates in Appendix D are sparser but provide the same scope check at a more detailed instructional level.

Together, the mechanism evidence identifies a sequence of adjustment. The approved provider menu expands, fiscal scale supports access, and statewide activity

Table 6: Training-Field Entry and Family Allocation

	(1) COVID and digital	(2) Transition	(3) GenAI post
Panel A. Field menu			
Active AI-related fields	0.042	0.064	0.034
	(0.098)	(0.146)	(0.155)
New AI-related fields	-0.019	-0.017	-0.077
	(0.057)	(0.076)	(0.081)
Any new AI-related field	0.011	0.005	0.015
	(0.016)	(0.017)	(0.018)
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓
Panel B. Family allocation			
Portfolio share	0.012***	0.015**	0.006
	(0.004)	(0.007)	(0.007)
Log participants	0.091***	0.101***	0.084**
	(0.023)	(0.032)	(0.035)
Active family	0.002	0.006	0.016*
	(0.008)	(0.008)	(0.009)
Board-by-field fixed effects	✓	✓	✓
Board-by-year fixed effects	✓	✓	✓
Field-by-year fixed effects	✓	✓	✓
Observations	3,816	3,816	3,816
Board clusters	507	507	507

Note: This table reports period-bin estimates for training-field entry and family allocation. Panel A uses board-year field-menu outcomes. Panel B uses the board-family-year allocation surface. Coefficients are exposure-by-prior-experience estimates relative to 2017 to 2019. Panel A includes board and state-by-year fixed effects. Panel B includes board-by-field, board-by-year, and field-by-year fixed effects. Standard errors clustered by board are reported in parentheses. Exposure is board-level AI exposure, and prior AI-training experience is measured from pre-period AI-related training activity. The COVID and digital period is PY2020 to PY2021, the transition period is PY2022, and the GenAI post period is PY2023 to PY2024.

becomes more concentrated in boards that already have relevant delivery experience. AI-specific content and new-field entry respond less. The remaining empirical gap is between prior experience delivering training and downstream targeting of AI content.

6 Conclusion

This paper studies how local public workforce systems respond when the occupations represented in their participant base become more exposed to AI. The strongest response appears at entry into training. In 2023 and 2024, boards with higher AI exposure and stronger prior AI-training experience increase training participation by about 3 percentage points, or roughly 30 additional trainees per 1,000 Adult and Dislocated Worker participants. The participant-weighted estimate remains positive at about 1.9 percentage points. Changes in the AI share among trainees and AI training per participant are much smaller, so the main response is broader access rather than a proportional shift toward AI-specific content.

The mechanism results show how that access response is organized. AI-related programs and fields enter the eligible-provider menu, although the number of distinct providers changes less. Fixed-stock specifications show a weaker connection between the listed menu and funded AI training. Fiscal resources matter at the upstream margin. The access gradient is stronger where Adult and Dislocated Worker allotments are larger, while allotments relative to the pre-period caseload are more closely associated with training composition. Within states, training activity also becomes more concentrated in boards with greater exposure and stronger pre-period routines. These results distinguish fiscal scale from resource intensity and show that state systems allocate activity toward local boards with established delivery capacity.

The interpretation is that existing routines make some forms of adjustment easier than others. A board that already knows which providers to use, how to counsel participants into occupational training, and how to move an approval through the WIOA process can expand access when the state resource envelope is large enough. Targeted AI content requires an additional conversion step. Staff must identify relevant programs, participants must be ready and eligible for them, providers must have usable capacity, and funding rules must allow the service to be purchased. That extra step helps explain why access responds more clearly than the AI share among trainees or AI training per participant.

The funding evidence adds to this interpretation. Provider availability and fiscal resources create room for adjustment, but their effects depend on the insti-

tutions that connect participants to programs. A larger state resource envelope supports broad access. Higher spending intensity and realized training-service expenditures describe a different allocation regime and do not produce the same access pattern. Training content therefore depends on advising, routing, approval, provider relationships, and the local routines through which funds are used.

The field results point in the same direction. Boards do not widely enter new AI-related instructional fields after the launch of ChatGPT. Instead, additional activity is more visible within existing programs and broader training families. Public workforce adaptation is therefore substantial but uneven across margins. Access, provider supply, fiscal scale, and within-state allocation respond more clearly than the detailed content of training. This is not evidence that content is immovable. It shows that changing content is farther downstream from the administrative decisions that first expand training access.

These findings contribute to research on AI and labor-market adjustment by identifying the public institution that must organize retraining before worker outcomes can change. They also extend the active labor-market-policy literature by treating access, provider eligibility, and local service allocation as policy outcomes rather than background implementation. More broadly, they connect technological adjustment to state capacity. Public programs respond not only through formal rules or available budgets, but through organizations that decide where resources are used and which participants reach training (Besley and Persson, 2010; Finan, Olken and Pande, 2017; Rasul and Rogger, 2018; Best, Hjort and Szakonyi, 2023).

The policy implication is that program eligibility is not enough. Expanding an eligible AI-training menu gives the system more options, but states and local boards also need sufficient fiscal scale, clear funding procedures, staff who can identify relevant programs, and provider relationships that make approved training usable. The distinction between total resources and resources per participant also matters. A larger resource envelope supports access, while spending intensity reflects costs, caseloads, sparsity, service mix, and allocation choices. Policy evaluation should therefore track both the number of participants who reach training and the content of the training they receive.

The empirical design measures differential adjustment across boards and states rather than a single binding friction. It combines pre-period exposure and training routines with common state-year conditions, national provider data, funding mea-

sures, and training allocation. That design improves comparability within state-years, but the exposure and prior-experience measures remain equilibrium characteristics of local workforce systems. The outcome sequence is useful because it locates where adjustment appears. It shows access, resources, and allocation moving more clearly than targeted AI content.

The paper also opens several directions for future work. Administrative data that link board-level funding, staffing, provider contracts, caseworker practices, and participant outcomes would help identify the constraints behind the conversion process. Governance and institutional incentives may shape which boards receive attention and resources. Worker-level earnings and occupational transitions would show whether access expansion produces durable adaptation. These questions extend the paper's main lesson: technological exposure becomes policy-relevant when public institutions translate it into funded service delivery. The public workforce system responds to the AI shock, but it responds first through access, resources, and allocation. Targeted AI training requires the additional administrative work that connects those upstream margins to program content.

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A Data Construction and Measurement

This appendix section collects construction details that are necessary for reading the data section but too detailed for the main text. It documents the analysis universe, denominators, outcome rates, AI measurement surfaces, WIOA operational capacity, provider-supply timing, valid CIP coverage, and field-code observability choices.

A.1 Analysis Universe, Outcomes, and Denominators

This subsection documents the denominator and outcome objects introduced in Section 2. The central distinction is between participant denominators, training participants, AI-training participants, and service rows. Rates are participant-based, while service records provide training activity and field content.

The WIOA participant and service records provide the administrative base for the board-year panel. The participant side supplies the adult and dislocated-worker denominator, while the service side identifies training activity and provides the field information needed for AI-content and allocation measures. Table A.1 documents the main source layers and helps readers distinguish the WIOA participant and service records from ETP listings, AJC records, board geography, exposure crosswalks, and field references.

The board-year spine is defined at the local board by program-year level. Table A.2 shows how the main adult and dislocated-worker sample compares with broader Title I and stream-specific universes. This matters because the paper's main rates use unique participants in the adult and dislocated-worker sample as denominators; service counts are informative about activity but are not participant counts.

Outcome rates follow the denominator discipline in Section 2. Table A.3 shows the numerators and denominators for the three main outcomes. It also reports services without valid CIP4 codes as a field-code coverage measure. Rates with zero or unavailable denominators are treated as missing. A missing rate means that the relevant participant or trainee base is unavailable rather than that no AI training occurred.

The board-field panels extend the board-year spine to field surfaces used in allocation analyses. Table A.4 separates the readable family panel from the more

granular patched CIP4 panel and its balance-support surface. The table also flags services without valid CIP4 support as an observability category rather than a substantive field.

Prior AI-training experience is measured from pre-period WIOA training behavior. Table A.5 reports the main prior-experience measure from PY2017 to PY2019 and the alternative windows used to address the 2018 training-count anomaly. These rows support the interpretation of the measure as revealed historical WIOA operating experience rather than external provider supply or an exogenous engineering constraint.

A.2 ETP Date-Added Provider Supply

This subsection explains the annual ETP provider measures. Listing dates define beginning-of-year stocks and within-year additions under the no-exit assumption. AJC reach remains a separate service layer.

The ETP program dictionary identifies listed provider programs and the listing date used to place programs into annual program-year stocks and additions. Table A.6 reports coverage, parse success, assignment-year rows, board-year support, and the no-exit assumption. The active-stock and additions measures capture nominal eligible-provider supply, with a current-list survivorship caveat because historical exits are not observed.

AJC reach is reported in this construction appendix because it is part of the institutional capacity stack, but it is not provider supply. Table A.7 distinguishes usable geography, boards with observed centers, true zero-center boards, and boards where geography or support is missing. The table provides the coverage summary needed to interpret the reach measure.

A.3 CIP Validity and Field-Code Coverage

This subsection documents the field-code validity choices that determine which training services enter coded field-allocation surfaces. The patched CIP4 surface removes invalid zero-like codes, recovers supported four-digit CIP4 values, and leaves invalid or unrecoverable services outside substantive field cells.

CIP validity matters because the field-allocation analysis interprets changes across coded instructional fields. Table A.8 shows how the validity patch removes

zero-like artifacts, recovers supported raw four-digit codes, and reduces the active CIP4 field count.

Services without valid CIP4 codes remain observable as training services even when they cannot be assigned to a substantive instructional field. Table A.9 shows that valid-CIP coverage varies sharply by service type, especially in work-based and customized training. This is why services without valid CIP4 codes are an interpretation constraint rather than a field that can be analyzed like health, information technology, or business training.

A.4 AI Measurement and Field Classification

This subsection connects the paper's AI content labels and exposure measures. The main text uses broad-content AI as the primary training-content measure, narrow AI as a restrictive alternative, Yale core as the primary GenAI-pressure index, and AIOE and GPT-alpha as robustness measures.

The exposure measures and content labels play different roles. Yale core, AIOE, and GPT-alpha are predicted exposure measures built from external occupation-level indices and pre-period occupational information. Broad-content and narrow AI are content labels for training programs and fields. Target-SOC and CIP-SOC high-exposure labels are sensitivity labels that connect training content to exposed occupations, but they are not substitutes for the main broad-content definition.

Table A.10 reports how common each label is in the constructed training data and makes clear which labels are content based, exposure based, or union sensitivity measures. Figure A.3 then shows how these labels overlap. Together, the table and figure help readers see why the main analysis uses broad-content AI while preserving narrower and exposure-based alternatives for measurement robustness.

The field surfaces inherit these labels differently. The family surface groups fields into stable categories for allocation interpretation, while the patched CIP4 surface keeps more granular instructional codes when valid CIP4 information is observed. Table A.11 lists the most common broad-content AI fields as a reader-facing check on the content label. The measurement displays in this subsection should therefore be read together with Appendix A.3.

Table A.1: Data Source Coverage

Source	(1) Rows / records	(2) States / boards / providers
WIOA PIRL participant/service data	3,705,314	3,338,455
ETP provider-program list	77,085	9,197
Board geography	2,882	509
AJC reach data	2,177	54
AI exposure crosswalk	889	87
CIP-SOC / field references	8,789	388

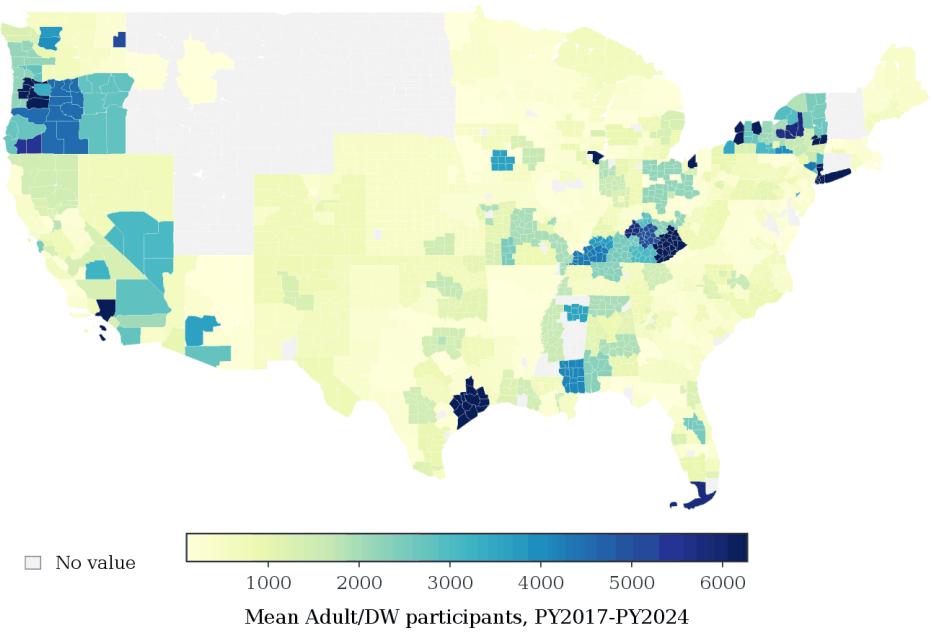
Note: This table summarizes the data sources used to construct the analysis panels. WIOA participant and service records cover program years 2017 to 2024. ETP provider-program listings use the current TrainingProviderResults.gov extract and Date Added to State ETP List field where available. Board geography and AJC reach data are current-snapshot files. AI exposure crosswalks and CIP-SOC field references are frozen reference files. WIOA participant records supply denominators and outcomes; ETP listings describe provider-program supply; board geography, AJC records, and AI exposure crosswalks support maps, operational context, and exposure assignment.

Table A.2: Analysis Universe and Denominators

Universe	(1) Board-years	(2) Boards	(3) Participants	(4) Training participants	(5) Training rate
Adult/DW main	4,431	668	6,337,688	1,574,429	0.248
Title I all	4,439	671	7,354,343	1,908,381	0.259
Adult	4,373	648	4,215,798	1,141,306	0.271
Dislocated Worker	4,390	666	2,874,794	528,903	0.184
Youth	4,302	621	1,077,273	365,526	0.339

Note: This table reports analysis-universe coverage and denominators. The sample covers the 50 states plus DC from program years 2017 to 2024. Adult and Dislocated Worker board-years define the main analysis universe. Title I, Adult, Dislocated Worker, and Youth rows report comparison denominators used for universe checks and stream-specific descriptive context. Training rate is training participants divided by participants.

Figure A.1: Mean Adult and Dislocated Worker Participants by WIOA Board



Notes: This figure shows the board mean of Adult and Dislocated Worker participants, pooling program years 2017 to 2024. Board-level values are assigned to county polygons using the board-county crosswalk; counties served by multiple matched boards receive the mean board value, and counties without matched board values are shown as no value. The color scale is continuous.

Table A.3: Outcome Construction Summary

Outcome	(1) Numerator	(2) Denominator	(3) Board-years	(4) Mean	(5) Median
Training participation rate	1,574,429	6,337,688	4,431	0.554	0.583
AI share among trainees	206,063	1,574,429	4,409	0.127	0.103
AI training per participant	206,063	6,337,688	4,431	0.073	0.053
Narrow AI share	105,424	1,574,429	4,409	0.063	0.034
Narrow AI per participant	105,424	6,337,688	4,431	0.036	0.018
Services without valid CIP4	540,660	1,707,075			

Note: This table reports the construction of the main board-year outcomes. Training participation is training participants divided by participants. AI share is AI-related training participants divided by training participants. AI training per participant is AI-related training participants divided by participants. Narrow AI uses the restrictive AI-content label. Services without valid CIP4 are reported as a service-record observability measure rather than a board-year outcome.

Table A.4: Board-Field Panel Construction Summary

Panel	(1) Rows	(2) Fields	(3) Missing	(4) Unit
Family panel	58,164	12	0.000	board-family-year
Patched CIP4 active panel	434,556	376	0.009	board-CIP4-year
Balance-support panel	1,880,636	388	0.009	board-field-year
Valid-CIP support row	1,724,856	1	0.009	service

Note: This table reports board-field panel construction for 4,847 board-year observations. A family groups detailed instructional fields into broader training categories used for readable allocation results. CIP4 is the four-digit instructional program code used for the granular field surface. Missing is the share of panel or support rows without a valid substantive field code after cleaning.

Table A.5: Pre-Period AI-Training Capacity Construction

Capacity measure	(1) Boards non-missing	(2) Positive-capacity boards	(3) Mean	(4) P25	(5) Median	(6) P75
Main AI broad per participant	567	470	0.063	0.005	0.044	0.094
AI broad share among trainees	566	470	0.123	0.027	0.101	0.180
Narrow AI capacity	567	450	0.027	0.001	0.013	0.037
Field breadth	567	478	9.959	5.000	9.000	14.000
Excluding-2018 robustness	643	520	0.061	0.003	0.042	0.092
2019-only robustness	577	488	0.071	0.012	0.055	0.104

Note: This table reports pre-period AI-training capacity measures constructed from program years 2017 to 2019. WIOA program years run from July through June. The excluding-2018 robustness row uses program years 2017 and 2019, and the 2019-only robustness row uses program year 2019. Capacity measures are constructed from WIOA participant and service records. The main capacity measure is broad AI training per Adult and Dislocated Worker participant.

Table A.6: ETP Date-Added Construction Summary

Measure	Value
date range start	2,014
date range end	2,024
local assignment-year rows	449,976
scalable assignment-year rows	549,408
board-year rows	4,847

Note: This table reports the construction of annual ETP stocks and additions from program listing dates. ETP provider-program records are downloaded from TrainingProviderResults.gov. The Date Added to State ETP List field is assigned to WIOA program years to construct beginning-of-year stocks and within-year additions. Historical exit dates are not observed, so annual stock construction carries listed programs forward after their observed listing date.

Table A.7: AJC Reach Coverage Summary

Measure	(1) Boards	(2) Share of boards	(3) Board-years
WIOA boards	746	1.000	5,968
Usable geography	529	0.709	4,232
Boards with any AJC	495	0.664	3,960
Boards with comprehensive AJC	474	0.635	3,792
True zero-AJC boards	34	0.046	272
Missing due to no geography/support	217	0.291	1,736

Note: This table reports coverage of American Job Center measures across local boards and board-years. Rows distinguish usable geography, observed centers, zero-center boards, and support gaps. Board-years equal boards multiplied by the eight program years in the panel.

Table A.8: CIP Validity Patch Before and After

Measure	(1) Before	(2) After	(3) Change
zero-like CIP4 services	8,196	0	-8,196
zero-like main rows	2,264.0	0.000	-2,264.0
valid raw 4-digit recoveries	0	4,278	4,278
invalid-to-missing services	0	3,918	3,918
CIP4 fields	737.0	382.0	-355.0
active CIP4 rows	375,470	364,063	-11,407
Rows without valid CIP4 codes	3,916.0	4,146.0	230.0
Field-code export rows	458,727	444,931	-13,796

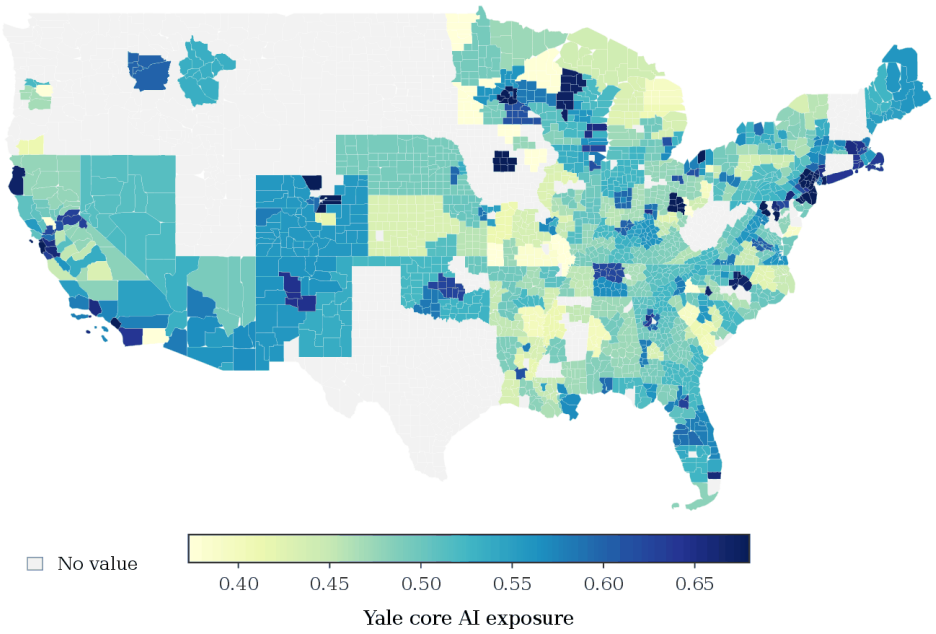
Note: This table reports how the field-code cleaning rules change the detailed instructional-field panel. The cleaning removes zero-like four-digit CIP codes, recovers supported raw four-digit codes when a valid source code is available, and assigns invalid or unrecoverable field codes to missing field-code status. CIP4 fields are four-digit instructional-program codes used in the granular field-allocation surface.

Table A.9: Valid CIP4 Coverage by Service Type

Service type	(1) Training services	(2) Services without valid CIP4	(3) Share without valid CIP4
All training services	1,732,396	561,290	0.324
On-the-job training	170,539	155,675	0.913
Customized training	37,453	19,316	0.516
Registered apprenticeship	38,032	11,714	0.308
occupational skills	1,192,339	298,845	0.251
Individual training account	1,157,754	295,791	0.255
Private provider	399,172	83,288	0.209
Online	28,800	8,525	0.296
Hybrid	67,035	11,756	0.175

Note: This table reports field-code coverage across training service types. Services without valid CIP4 codes remain observable as training services but cannot be assigned to a substantive instructional field. The final column is the share of training services without valid CIP4 codes.

Figure A.2: Board-Level Yale Core AI Exposure



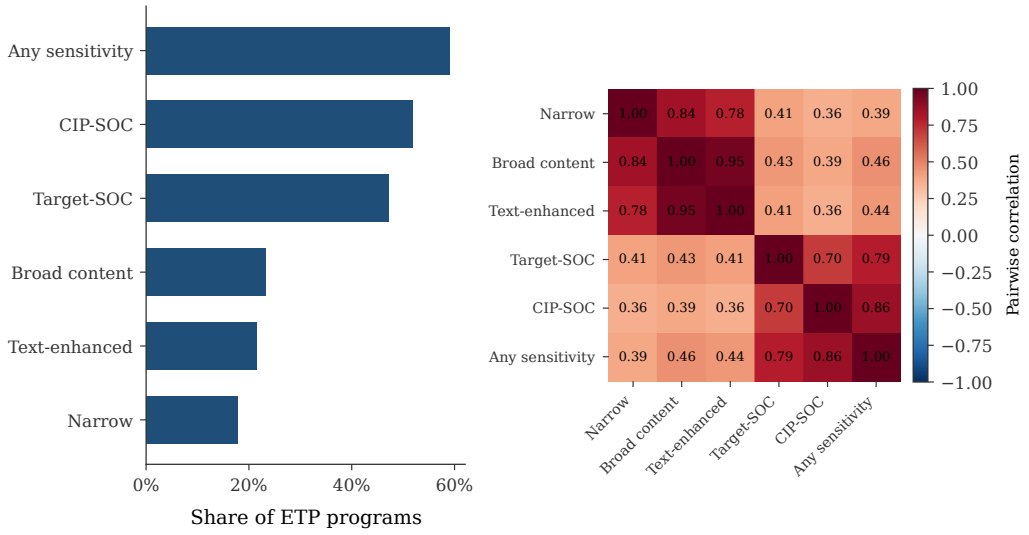
Notes: The map shows pre-period predicted AI exposure from PY2017 to PY2019 prior occupations in the 50-state-plus-DC sample. Board-level values are assigned to county polygons using the board-county crosswalk; counties served by multiple matched boards receive the mean board value, and counties without matched board values are shown as no value. The color scale is continuous.

Table A.10: AI Classification Label Shares

Label	(1) Count	(2) Share
AI narrow	13,660	0.177
AI broad content	17,922	0.232
Text-enhanced	16,641	0.216
Target-SOC high exposure	36,369	0.472
CIP-SOC high exposure	40,028	0.519
Any-relevant sensitivity	45,570	0.591

Note: This table reports AI classification label shares in the constructed provider-program and field records. Broad AI is the main content label for AI-related training. Narrow AI is a more restrictive content label. Text-enhanced identifies text-based AI-relevant programs. Target-SOC high exposure and CIP-SOC high exposure are exposure-based sensitivity labels. Any-relevant sensitivity is the union of the content and exposure-based sensitivity labels.

Figure A.3: AI Classification Distribution and Overlap



Notes: This figure reports AI-label shares and pairwise overlap for provider-program and field-classification records. The bar chart reports label shares, and the heatmap reports pairwise correlations among binary labels. Broad AI is the main training-content label. Narrow AI is a more restrictive content label. Text-enhanced identifies text-based AI-relevant programs. Target-SOC high exposure and CIP-SOC high exposure are exposure-based sensitivity labels. Any-relevant sensitivity is the union of the content and exposure-based sensitivity labels.

Table A.11: AI Classification Top Broad-Content Fields

Rank	CIP6	CIP4	Programs	States	Providers
1	111003	1110	1,268	48	557
2	110901	1109	964	45	490
3	110103	1101	892	46	391
4	111006	1110	797	47	431
5	110101	1101	677	44	358
6	110201	1102	640	43	341
7	111001	1110	594	43	316
8	110801	1108	429	38	264
9	110501	1105	335	32	150
10	110202	1102	280	33	131

Note: This table reports the largest AI-related instructional fields in the ETP program data. Broad-content AI is the main training-content label. Narrower and exposure-based labels are used as measurement checks. Rows are ETP program records with valid instructional-field coding.

B Robustness for Main Results

This appendix section gathers robustness evidence for the main board-year results. The checks keep the main estimand fixed while varying exposure metrics, capacity definitions, timing windows, AI-content definitions, and analysis universes. It also holds visual summaries that support the main access-versus-composition interpretation without adding more main-text floats.

The purpose is to show whether the access and AI-training margins are tied to a single measurement choice or survive across prespecified alternatives.

B.1 Board-Year Robustness Checks

This subsection collects the prespecified robustness checks that support the main board-year access and AI-training results. The exhibits vary exposure measures, prior-experience definitions, prior-experience windows, analysis universes, AI definitions, and timing displays while preserving the underlying locked outcomes.

The first table compares Yale core, AIOE, and GPT-alpha exposure variants. Table B.14 shows whether the main access pattern is specific to the Yale core GenAI-pressure measure or also appears under broader AI and LLM/task-exposure indices. This matters because the Yale measure is closest to the paper's GenAI interpretation, while AIOE and GPT-alpha capture different exposure concepts.

The prior-experience definition and window exhibits separate revealed WIOA operating experience from alternative pre-period summaries. Tables B.15, B.16, and B.17 vary the prior-experience object across outcomes. Table B.24 then compares the main window from PY2017 to PY2019 with the PY2017 plus PY2019 window that excludes the 2018 anomaly and with the PY2019-only measure. The event-study and raw-trend figures show the same robustness logic visually across program-year timing.

The remaining tables and figures document universe, AI-definition, and timing sensitivity. They check the measurement and support conditions introduced in Section 2 while preserving the main outcome definitions.

Figure B.4 gives the compact visual decomposition behind the Section 4 interpretation. It places the post-GenAI estimates for training participation, AI share among trainees, and AI training per participant on the same scale, so readers can

see the access-versus-composition contrast without adding a separate model family.

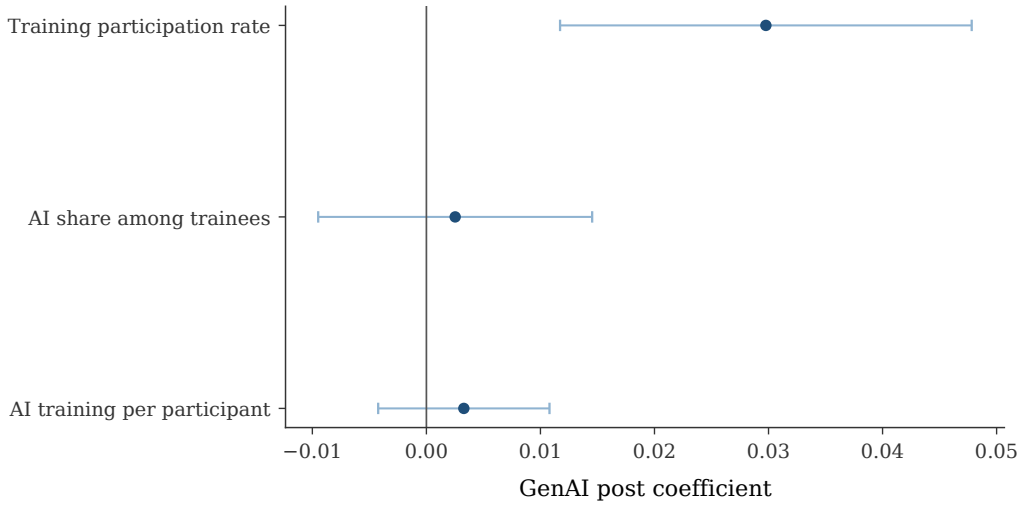
The main-text timing discussion keeps the training-access event study in Section 4. Figures B.5 and B.6 provide the AI-specific event-study paths using the same locked specification and style. They support the same interpretation without adding more main-text floats.

The participant-weighted, placebo, and four-cell trend exhibits provide the main timing checks. Table B.12 asks whether the access estimate survives weighting boards by Adult and Dislocated Worker participant counts. Table B.13 reports pre-period and pseudo-shock checks, and Figure B.7 shows the corresponding raw four-cell training-access pattern.

Figure B.8 shows the corresponding training-participation timing pattern under the three exposure measures. The figure supports the access result without requiring the exposure indices to be identical.

Table B.18 summarizes the main prior-experience heterogeneity check for the access margin. It keeps the delivery-history interpretation visible while leaving the main text focused on the core event-study and difference-in-differences exhibits.

Figure B.4: Access-versus-Composition Decomposition



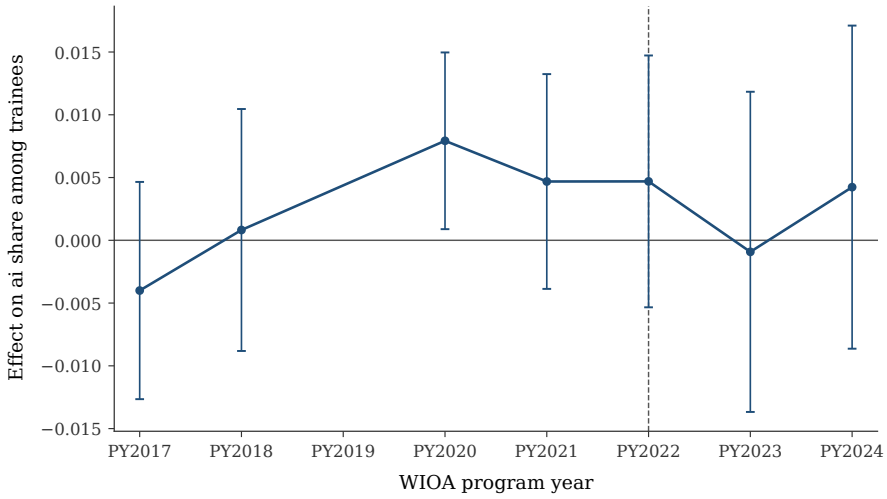
Notes: This figure plots the post-period estimates from equation (3.1) for the three main board-year outcomes. The unit is the WIOA local board by program year in the 50-state-plus-DC sample. Training participation measures access to training, the AI share among trainees measures training composition among participants who receive training, and AI training per participant combines the access and composition margins. Estimates include board and state-by-year fixed effects, with standard errors clustered by board. Vertical bars show 95 percent confidence intervals. Exposure is board-level AI exposure and prior AI-training experience is measured from pre-period AI-related training activity. PY2023 to PY2024 are the GenAI post years.

Table B.12: Participant-Weighted Board-Year Estimates

	(1) Training participation rate	(2) AI share among trainees	(3) AI training per participant
GenAI post	0.019***	0.005	0.003
	(0.007)	(0.005)	(0.003)
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓
Participant weights	✓	✓	✓
Observations	3,774	3,759	3,774
Board clusters	503	499	503

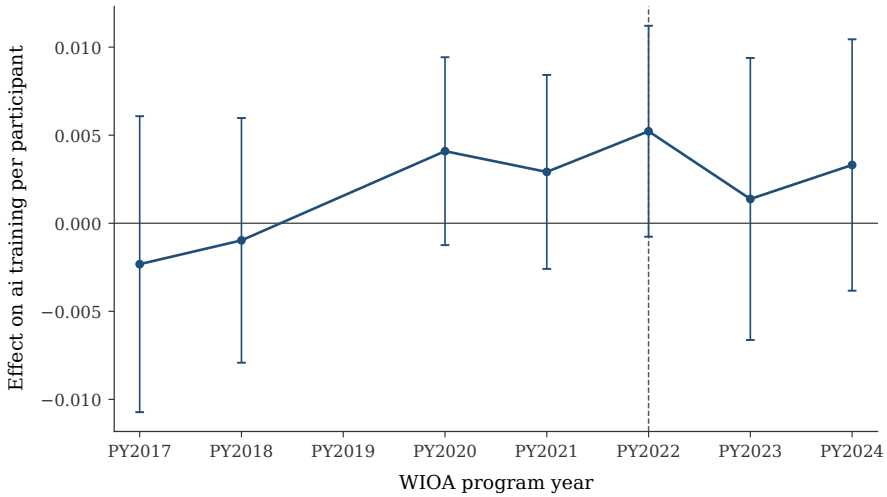
Note: This table reports participant-weighted versions of the estimates in Table 2. Adult and Dislocated Worker participant counts are analytic weights. The unit is the WIOA local board by program year in the 50-state-plus-DC sample. All regressions include board and state-by-year fixed effects. Standard errors clustered by board are reported in parentheses.

Figure B.5: Event Study: AI Share Among Trainees



Notes: This figure reports event-study coefficients from equation (3.2) for the AI share among trainees, with vertical bars showing 95 percent confidence intervals. The omitted base year is PY2019. WIOA program years run from July through June; PY2022 contains the November 30, 2022 ChatGPT launch and is treated as the GenAI transition year. The unit is the WIOA local board by program year in the 50-state-plus-DC sample. Exposure is board-level AI exposure, prior AI-training experience is measured from pre-period AI-related training activity, and standard errors are clustered by board.

Figure B.6: Event Study: AI Training per Participant



Notes: This figure reports event-study coefficients from equation (3.2) for AI training per participant, with vertical bars showing 95 percent confidence intervals. The omitted base year is PY2019. WIOA program years run from July through June; PY2022 contains the November 30, 2022 ChatGPT launch and is treated as the GenAI transition year. The unit is the WIOA local board by program year in the 50-state-plus-DC sample. Exposure is board-level AI exposure, prior AI-training experience is measured from pre-period AI-related training activity, and standard errors are clustered by board.

Table B.13: Placebo and Timing Diagnostics

	Coefficient	Obs.	Clusters
Placebo 2018–2019	0.006	1,399	476
	(0.014)		
Pseudo-shock 2020–2021	0.005	2,398	502
	(0.006)		
Transition-inclusive 2022–2024	0.023***	3,774	503
	(0.007)		
Post 2023 only	0.023***	3,335	503
	(0.007)		
Post 2024 only	0.023***	3,774	503
	(0.008)		
Board fixed effects	✓		
State-by-year fixed effects	✓		

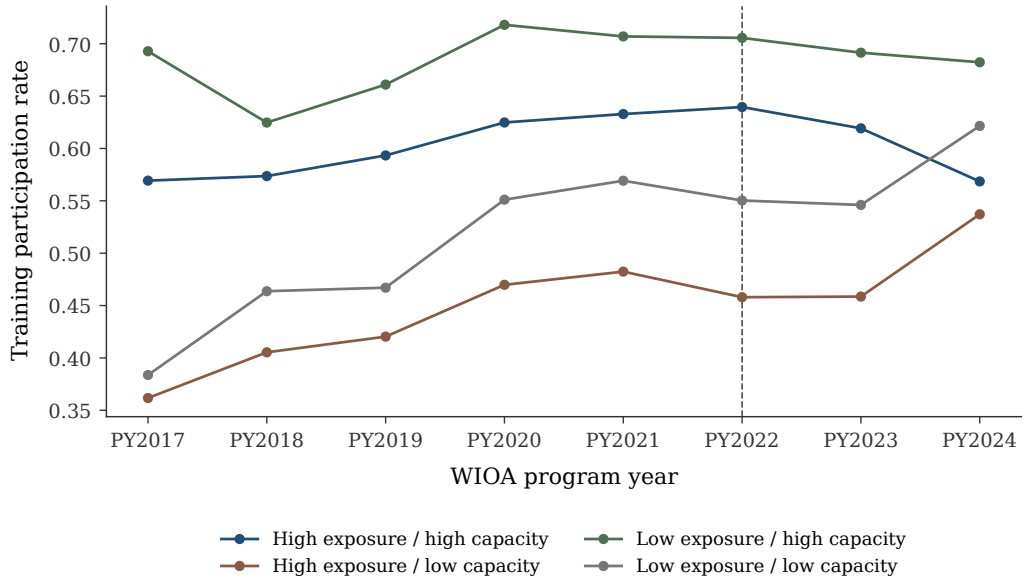
Note: This table reports placebo and timing checks for column (1) of Table 2. The outcome is training participation. Coefficients use the exposure-by-capacity structure from the main board-year specification. All regressions include board and state-by-year fixed effects. Standard errors clustered by board are reported in parentheses.

Table B.14: Yale, AIOE, and GPT Exposure Robustness

	(1) Yale core	(2) AIOE	(3) GPT-alpha
COVID and digital	0.005	0.003	0.013*
	(0.006)	(0.005)	(0.007)
Transition	0.016**	0.011	0.019*
	(0.008)	(0.007)	(0.010)
GenAI post	0.030***	0.022**	0.028***
	(0.009)	(0.009)	(0.011)
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓
Observations	3,810	3,810	3,810
Board clusters	508	508	508

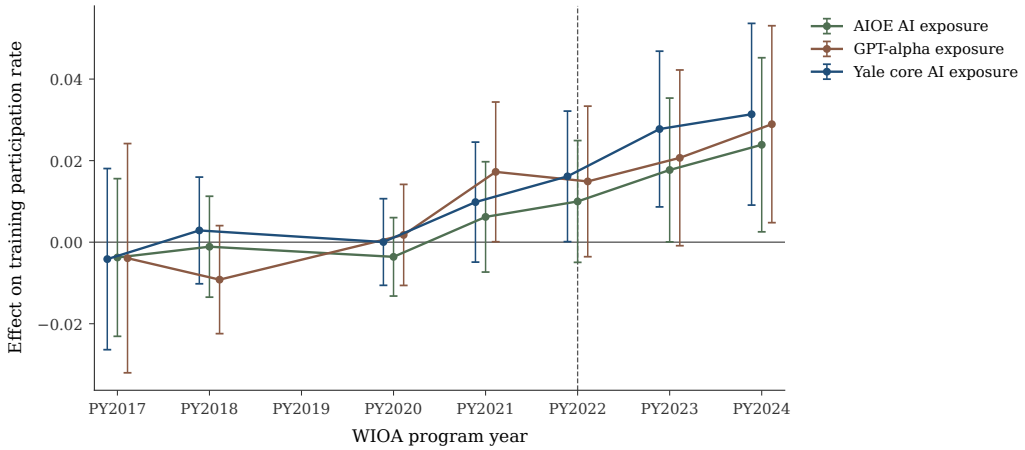
Note: This table reports exposure-measure robustness checks for the training-participation result in column (1) of Table 2. The unit is the WIOA local board by program year. Columns use Yale core, AIOE, and GPT-alpha exposure measures interacted with pre-period AI-training capacity. All regressions include board and state-by-year fixed effects. Standard errors clustered by board are reported in parentheses.

Figure B.7: Four-Cell Training-Access Trends



Notes: This figure plots raw board-year means of the training participation rate by high and low exposure and prior AI-training experience cells. High and low are defined as above and below the sample medians of board-level AI exposure and prior AI-training experience. The unit is the WIOA local board by program year in the 50-state-plus-DC analysis sample. The vertical dashed line marks PY2022, the GenAI transition year.

Figure B.8: Exposure Robustness Event Study



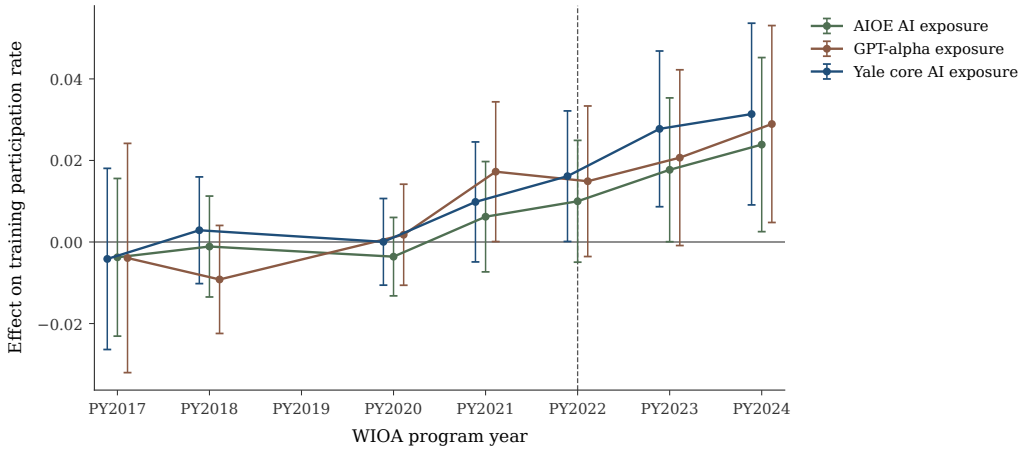
Notes: This figure plots event-study coefficients for the training participation rate using Yale core, AIOE, and GPT-alpha exposure measures. The figure is an exposure-measure robustness check for Figure 2. Vertical bars show 95 percent confidence intervals, and the omitted base year is PY2019. The unit is the WIOA local board by program year in the 50-state-plus-DC sample. Prior AI-training experience is measured from pre-period AI-related training activity. PY2022 is the GenAI transition year. Series are horizontally dodged so confidence intervals remain readable.

Table B.15: Capacity Definition Robustness: Training Participation

	(1) Narrow capacity	(2) Narrow share	(3) Log narrow trainees	(4) Narrow field breadth
COVID and digital	0.002	-0.001	-0.004	-0.006
	(0.006)	(0.005)	(0.005)	(0.005)
Transition	0.008	-0.000	-0.005	-0.005
	(0.007)	(0.007)	(0.008)	(0.008)
GenAI post	0.015*	0.010	0.002	0.004
	(0.009)	(0.008)	(0.009)	(0.009)
Board fixed effects	✓	✓	✓	✓
State-by-year fixed effects	✓	✓	✓	✓
Observations	3,774	3,774	3,774	3,774
Board clusters	503	503	503	503

Note: This table reports capacity-definition robustness checks for the training-participation result in column (1) of Table 2. The unit is the WIOA local board by program year. Capacity measures are narrow-AI capacity, narrow-AI training share, log narrow-AI trainees, and narrow-AI field breadth. All regressions include board and state-by-year fixed effects. Standard errors clustered by board are reported in parentheses.

Figure B.9: Event-Study Robustness: Training Participation



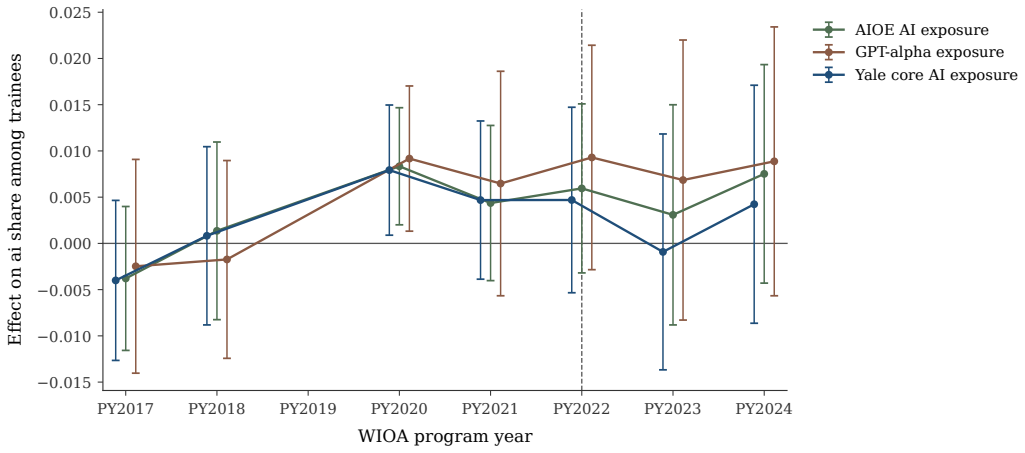
Notes: This figure reports robustness event-study coefficients from equation (3.2) for training participation, with vertical bars showing 95 percent confidence intervals. The omitted base year is PY2019. WIOA program years run from July through June; PY2022 contains the November 30, 2022 ChatGPT launch and is treated as the GenAI transition year. The unit is the WIOA local board by program year in the 50-state-plus-DC sample. Exposure and prior-experience measures use the labeled robustness definitions. Standard errors are clustered by board, and series are horizontally dodged so confidence intervals remain readable.

Table B.16: Capacity Definition Robustness: AI Share Among Trainees

	(1) Narrow capacity	(2) Narrow share	(3) Log narrow trainees	(4) Narrow field breadth
COVID and digital	0.004	0.004	-0.001	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)
Transition	0.001	0.005	-0.003	-0.003
	(0.005)	(0.005)	(0.004)	(0.004)
GenAI post	-0.003	0.005	-0.003	-0.004
	(0.005)	(0.006)	(0.004)	(0.004)
Board fixed effects	✓	✓	✓	✓
State-by-year fixed effects	✓	✓	✓	✓
Observations	3,759	3,759	3,759	3,759
Board clusters	499	499	499	499

Note: This table reports capacity-definition robustness checks for the AI-share-among-trainees result in column (2) of Table 2. The unit is the WIOA local board by program year. Capacity measures are narrow-AI capacity, narrow-AI training share, log narrow-AI trainees, and narrow-AI field breadth. All regressions include board and state-by-year fixed effects. Standard errors clustered by board are reported in parentheses.

Figure B.10: Event-Study Robustness: AI Share



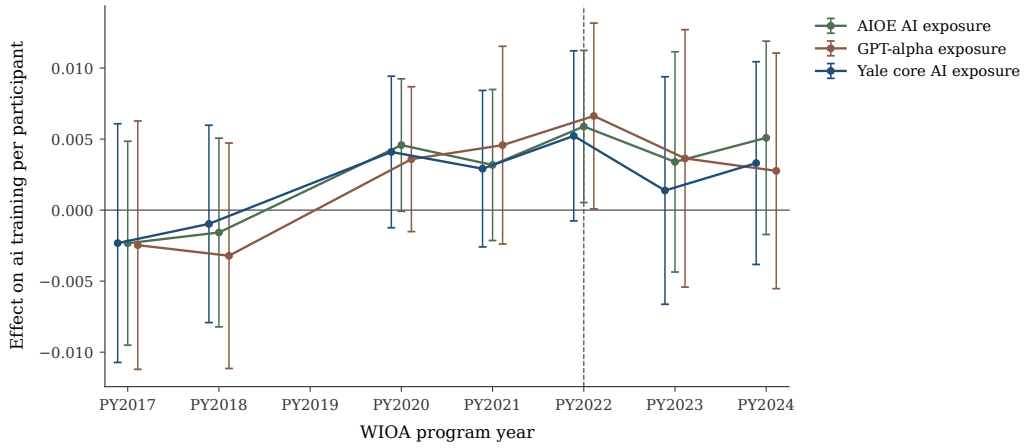
Notes: This figure reports robustness event-study coefficients from equation (3.2) for the AI share among trainees, with vertical bars showing 95 percent confidence intervals. The omitted base year is PY2019. WIOA program years run from July through June; PY2022 contains the November 30, 2022 ChatGPT launch and is treated as the GenAI transition year. The unit is the WIOA local board by program year in the 50-state-plus-DC sample. Exposure and prior-experience measures use the labeled robustness definitions. Standard errors are clustered by board, and series are horizontally dodged so confidence intervals remain readable.

Table B.17: Capacity Definition Robustness: AI Training per Participant

	(1) Narrow capacity	(2) Narrow share	(3) Log narrow trainees	(4) Narrow field breadth
COVID and digital	0.002	-0.000	-0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Transition	0.002	0.001	-0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
GenAI post	-0.001	0.001	-0.002	-0.002
	(0.004)	(0.004)	(0.003)	(0.003)
Board fixed effects	✓	✓	✓	✓
State-by-year fixed effects	✓	✓	✓	✓
Observations	3,774	3,774	3,774	3,774
Board clusters	503	503	503	503

Note: This table reports capacity-definition robustness checks for the AI-training-per-participant result in column (3) of Table 2. The unit is the WIOA local board by program year. Capacity measures are narrow-AI capacity, narrow-AI training share, log narrow-AI trainees, and narrow-AI field breadth. All regressions include board and state-by-year fixed effects. Standard errors clustered by board are reported in parentheses.

Figure B.11: Event-Study Robustness: AI Training per Participant



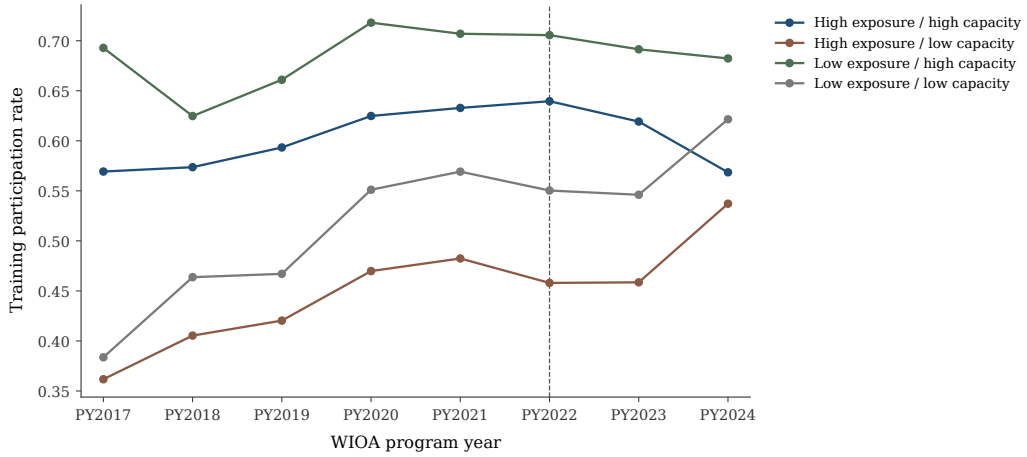
Notes: This figure reports robustness event-study coefficients from equation (3.2) for AI training per participant, with vertical bars showing 95 percent confidence intervals. The omitted base year is PY2019. WIOA program years run from July through June; PY2022 contains the November 30, 2022 ChatGPT launch and is treated as the GenAI transition year. The unit is the WIOA local board by program year in the 50-state-plus-DC sample. Exposure and prior-experience measures use the labeled robustness definitions. Standard errors are clustered by board, and series are horizontally dodged so confidence intervals remain readable.

Table B.18: Alternative Narrow-AI Capacity Measures: Training Participation

	(1) Narrow capacity	(2) Narrow share	(3) Log narrow trainees	(4) Narrow field breadth
COVID and digital	0.002	-0.001	-0.004	-0.006
	(0.006)	(0.005)	(0.005)	(0.005)
Transition	0.008	-0.000	-0.005	-0.005
	(0.007)	(0.007)	(0.008)	(0.008)
GenAI post	0.015*	0.010	0.002	0.004
	(0.009)	(0.008)	(0.009)	(0.009)
Board fixed effects	✓	✓	✓	✓
State-by-year fixed effects	✓	✓	✓	✓
Observations	3,774	3,774	3,774	3,774
Board clusters	503	503	503	503

Note: This table reports alternative narrow-AI capacity measures for the training-participation outcome. The unit is the WIOA local board by program year. The four capacity measures are the level of narrow-AI capacity, the pre-period share of training in narrow-AI programs, the log number of narrow-AI trainees, and the breadth of narrow-AI fields. All regressions include board and state-by-year fixed effects. Standard errors clustered by board are reported in parentheses.

Figure B.12: Raw Exposure-Capacity Trends: Training Participation



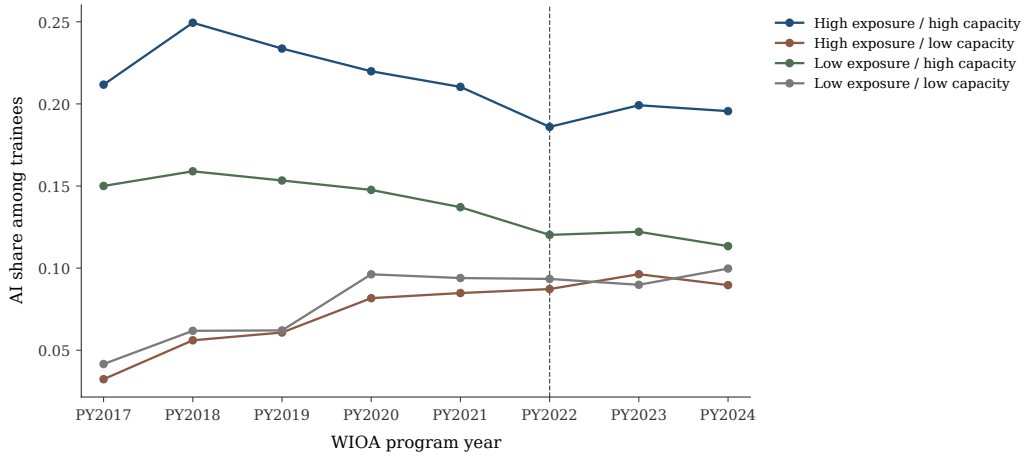
Notes: The figure plots raw board-year means of training participation for the four exposure-prior-experience groups in the 50-state-plus-DC sample. WIOA program years run from July through June; PY2022 contains the November 30, 2022 ChatGPT launch and is treated as the GenAI transition year. The series are descriptive and are not fixed-effect adjusted.

Table B.19: Capacity-Window Robustness: Training Participation

	(1) Capacity excluding PY2018	(2) Capacity measured in PY2019	(3) Share excluding PY2018	(4) Share measured in PY2019
COVID and digital	0.002	-0.002	-0.004	-0.005
	(0.006)	(0.006)	(0.005)	(0.005)
Transition	0.014*	0.011	0.004	0.002
	(0.008)	(0.008)	(0.008)	(0.008)
GenAI post	0.029***	0.022**	0.019**	0.014*
	(0.009)	(0.009)	(0.009)	(0.009)
Board fixed effects	✓	✓	✓	✓
State-by-year fixed effects	✓	✓	✓	✓
Observations	3,774	3,774	3,774	3,774
Board clusters	503	503	503	503

Note: This table reports capacity-window robustness checks for the training-participation estimates in Table 2. The unit is the WIOA local board by program year in the Adult and Dislocated Worker analysis universe. Columns vary the pre-period AI-training-capacity measure by excluding PY2018, using PY2019 only, or measuring the pre-period AI-training share. All specifications include board and state-by-program-year fixed effects. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

Figure B.13: Raw Exposure-Capacity Trends: AI Share Among Trainees



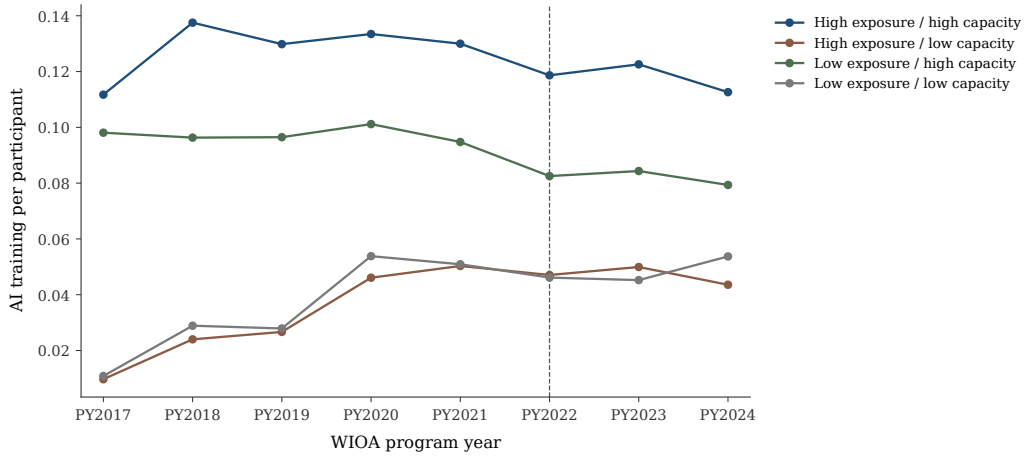
Notes: The figure plots raw board-year means of the AI share among trainees for the four exposure-prior-experience groups in the 50-state-plus-DC sample. WIOA program years run from July through June; PY2022 contains the November 30, 2022 ChatGPT launch and is treated as the GenAI transition year. The series are descriptive and are not fixed-effect adjusted.

Table B.20: Capacity-Window Robustness: AI Share Among Trainees

	(1) Capacity excluding PY2018	(2) Capacity measured in PY2019	(3) Share excluding PY2018	(4) Share measured in PY2019
COVID and digital	0.007**	0.001	0.006**	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Transition	0.005	-0.001	0.007	0.004
	(0.005)	(0.006)	(0.005)	(0.005)
GenAI post	0.001	-0.001	0.009	0.007
	(0.006)	(0.006)	(0.006)	(0.006)
Board fixed effects	✓	✓	✓	✓
State-by-year fixed effects	✓	✓	✓	✓
Observations	3,759	3,759	3,759	3,759
Board clusters	499	499	499	499

Note: This table reports capacity-window robustness checks for the AI-share-among-trainees estimates in Table 2. The unit is the WIOA local board by program year in the Adult and Dislocated Worker analysis universe. Columns vary the pre-period AI-training-capacity measure by excluding PY2018, using PY2019 only, or measuring the pre-period AI-training share. All specifications include board and state-by-program-year fixed effects. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

Figure B.14: Raw Exposure-Capacity Trends: AI Training per Participant



Notes: The figure plots raw board-year means of AI training per participant for the four exposure-prior-experience groups in the 50-state-plus-DC sample. WIOA program years run from July through June; PY2022 contains the November 30, 2022 ChatGPT launch and is treated as the GenAI transition year. The series are descriptive and are not fixed-effect adjusted.

Table B.21: Capacity-Window Robustness: AI Training per Participant

	(1) Capacity excluding PY2018	(2) Capacity measured in PY2019	(3) Share excluding PY2018	(4) Share measured in PY2019
COVID and digital	0.004*	0.000	0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Transition	0.006	0.002	0.005	0.002
	(0.003)	(0.004)	(0.004)	(0.004)
GenAI post	0.003	0.001	0.005	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Board fixed effects	✓	✓	✓	✓
State-by-year fixed effects	✓	✓	✓	✓
Observations	3,774	3,774	3,774	3,774
Board clusters	503	503	503	503

Note: This table reports capacity-window robustness checks for the AI-training-per-participant estimates in Table 2. The unit is the WIOA local board by program year in the Adult and Dislocated Worker analysis universe. Columns vary the pre-period AI-training-capacity measure by excluding PY2018, using PY2019 only, or measuring the pre-period AI-training share. All specifications include board and state-by-program-year fixed effects. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

Table B.22: Training Participation Across WIOA Participant Universes

	(1) Title I	(2) Adult	(3) Dislocated Worker	(4) Youth
COVID and digital	0.005	0.006	0.007	0.004
	(0.004)	(0.006)	(0.006)	(0.007)
Transition	0.015***	0.016**	0.008	0.011
	(0.006)	(0.008)	(0.008)	(0.008)
GenAI post	0.023***	0.033***	0.017	0.016**
	(0.007)	(0.009)	(0.011)	(0.007)
Board fixed effects	✓	✓	✓	✓
State-by-year fixed effects	✓	✓	✓	✓
Observations	3,779	3,779	3,779	3,779
Board clusters	503	503	503	503

Note: This table reports training-participation estimates across WIOA participant universes. The unit is the WIOA local board by program year. Columns define the participant denominator as Title I, Adult, Dislocated Worker, or Youth participants. All specifications include board and state-by-program-year fixed effects and use predicted AI exposure interacted with pre-period AI-training capacity. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

Table B.23: AI-Training Outcomes Under Alternative AI Definitions

	(1) Text-enhanced share	(2) Text-enhanced per participant	(3) Target-SOC share	(4) Target-SOC per participant
COVID and digital	-0.001	-0.000	0.002	0.002
	(0.002)	(0.001)	(0.004)	(0.003)
Transition	-0.004	0.000	0.001	0.002
	(0.003)	(0.002)	(0.008)	(0.005)
GenAI post	-0.005	-0.002	0.002	0.006
	(0.004)	(0.003)	(0.007)	(0.005)
Board fixed effects	✓	✓	✓	✓
State-by-year fixed effects	✓	✓	✓	✓
Observations	3,759	3,759	3,759	3,759
Board clusters	499	499	499	499

Note: This table reports AI-training outcome estimates under alternative AI definitions. The unit is the WIOA local board by program year in the Adult and Dislocated Worker analysis universe. Text-enhanced columns use the text-enhanced AI label, and target-SOC columns use the target-SOC AI label. All specifications include board and state-by-program-year fixed effects and use predicted AI exposure interacted with pre-period AI-training capacity. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

Table B.24: Pre-Period Window Robustness

	(1) 2017-2019 baseline	(2) Excluding 2018	(3) 2019 only
Panel A. Training participation rate			
COVID and digital	0.005	0.002	-0.002
	(0.006)	(0.006)	(0.006)
Transition	0.016**	0.014*	0.011
	(0.008)	(0.008)	(0.008)
GenAI post	0.030***	0.029***	0.022**
	(0.009)	(0.009)	(0.009)
Panel B. AI share among trainees			
COVID and digital	0.007**	0.007**	0.001
	(0.003)	(0.003)	(0.003)
Transition	0.006	0.005	-0.001
	(0.005)	(0.005)	(0.006)
GenAI post	0.003	0.001	-0.001
	(0.006)	(0.006)	(0.006)
Panel C. AI training per participant			
COVID and digital	0.004**	0.004*	0.000
	(0.002)	(0.002)	(0.002)
Transition	0.006*	0.006	0.002
	(0.003)	(0.003)	(0.004)
GenAI post	0.003	0.003	0.001
	(0.004)	(0.004)	(0.004)
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓
Observations	3,774	3,774	3,774
Board clusters	503	503	503

Note: This table reports pre-period-window robustness checks for the three outcomes in Table 2. Panel A reports the training participation rate, Panel B reports the AI share among trainees, and Panel C reports AI training per participant. The unit is the WIOA local board by program year in the Adult and Dislocated Worker analysis universe. Columns compare the PY2017–PY2019 baseline capacity measure with variants that exclude PY2018 or use PY2019 only. All specifications include board and state-by-program-year fixed effects. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

C Provider Supply and Administrative Conversion

This appendix section supports the mechanism discussion by separating listed provider supply from observed WIOA-funded use. It includes local ETP supply checks, conversion evidence, funding data and fiscal-context exhibits, AJC reach summaries, date-added timing evidence, delivery-channel screens, throughput screens, and static cost/funding context.

These exhibits provide mechanism and implementation support. WIOA operational capacity, provider listings, and participant outcomes remain distinct analysis objects.

C.1 Mechanism and Implementation Context

This subsection collects context variables for provider supply, service infrastructure, and implementation throughput. The table separates these objects from the main descriptive table so the main text can focus on the analysis sample, outcomes, exposure, and core prior-experience measures.

C.2 Provider Supply and Conversion Details

This subsection collects provider-supply and conversion exhibits that support Section 5. The ETP exhibits distinguish listed program supply from observed WIOA-funded training, while the AJC exhibit records the service-infrastructure layer used for implementation context.

ETP local physical supply measures listed provider-program availability assigned to a local board area. Table C.26 shows whether predicted AI pressure is associated with additions to listed AI programs, providers, and fields. This is a nominal supply margin: it records what appears on eligible-provider lists, not whether Adult and Dislocated Worker participants use those listings.

The conversion tables keep that distinction visible. Table C.27A compares fixed listed supply with WIOA-funded AI trainees, and Table C.27B reports conversion relative to fixed 2019 AI program stock. Together they show whether provider availability translates into participant training outcomes without changing the outcome definitions.

Figure C.16 provides the visual summary of the gap between listed AI program additions and WIOA-funded AI training participants. It is an appendix support figure because Figure 3 and Table 3 carry the main-text supply and conversion evidence.

The direct conversion-rate exhibits extend that same distinction. Table C.28 describes the skewed distribution of AI trainees per listed supply object, and Table C.29 reports conversion-rate checks using alternative supply denominators. Table C.30 shows that AJC moderation is weak in these data.

AJC reach is the service-infrastructure layer. Table C.31 summarizes the distribution of total and comprehensive American Job Centers and the reach index across boards with usable support. The AJC measure captures intake, counseling, navigation, referral, and local service footprint. It is separate from ETP provider supply.

The date-added timing figure documents when listed provider supply enters the annual panel. Figure C.18 helps readers assess listing-date coverage, heaping, and the timing support for beginning-of-program-year stocks and within-program-year additions. It supports the interpretation of provider supply as nominal availability under the no-exit assumption, with current-list survivorship as a caveat.

C.3 Funding Data and Fiscal Context

This subsection supports the fiscal-resource and within-state allocation discussion in Section 5. The exhibits separate assigned resources, realized spending, resource intensity, and within-state activity allocation. Assigned resources are formula allotments at the state-year level. Realized spending records career- and training-service expenditures after allocation and implementation choices have been made. Resource-intensity measures divide assigned resources or realized spending by pre-period participants. The distinction is important because these objects answer different mechanism questions and should not be collapsed into a single funding measure.

Figure C.19 and Figure C.20 summarize the expenditure and resource-intensity trends used to read the regression support. They provide descriptive fiscal context. Resource-intensity moderation is integrated into main-text Table 4. This appendix

retains realized-spending and inference-sensitivity checks.

C.4 Delivery, Throughput, and Cost Context

This subsection collects implementation screens that support the mechanism discussion. The delivery-channel and throughput tables show whether the main response is accompanied by broad changes in service delivery or recorded completion and credential margins. The cost and funding table provides static descriptive context for current eligible-provider listings.

These exhibits describe the administrative environment in which provider listings must become funded WIOA training. They provide supporting context for the mechanism interpretation.

Table C.25: Mechanism and Implementation Variables

Measure	(1) Mean	(2) SD	(3) Median	(4) N
Panel A. Field and capacity context				
Active AI-related fields	0.5	5.9	0.0	434,556
Pre-period AI field breadth	9.96	7.45	9.00	567
Panel B. Provider and implementation context				
Local AI ETP programs added	2.29	8.20	0.00	4,009
PY start local AI ETP stock	7.65	21.48	0.00	4,009
AJCs per 10,000 pre-period participants	34.30	47.04	17.94	514
Individual training account share	0.701	0.313	0.820	4,409
Credential rate among trainees	0.204	0.197	0.179	4,409
Skill-gain rate	0.383	0.251	0.376	4,431

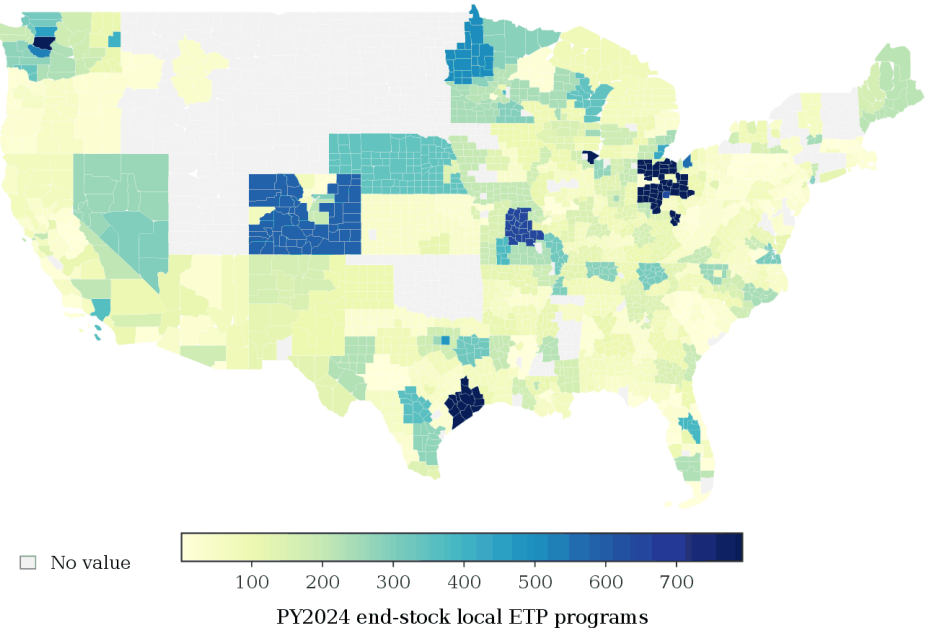
Note: This table reports mechanism and implementation variables used in Section 5 and Appendix C. Field and provider measures are board-year or board-field-year counts, AJC reach is measured at the local-board level, and training-administration rates use Adult and Dislocated Worker training records. ETP measures describe listed eligible-provider supply rather than WIOA-funded participant training.

Table C.26: Local ETP Supply Responses

	(1) COVID and digital	(2) Transition	(3) GenAI post
AI programs added	-0.012	0.096**	0.079**
	(0.029)	(0.047)	(0.032)
AI providers added	-0.005	0.047	0.035*
	(0.018)	(0.029)	(0.018)
AI fields added	-0.012	0.059	0.051**
	(0.023)	(0.036)	(0.025)
Narrow AI programs added	0.007	0.111***	0.091***
	(0.028)	(0.043)	(0.030)
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓
Observations	3,522	3,522	3,522
Board clusters	454	454	454

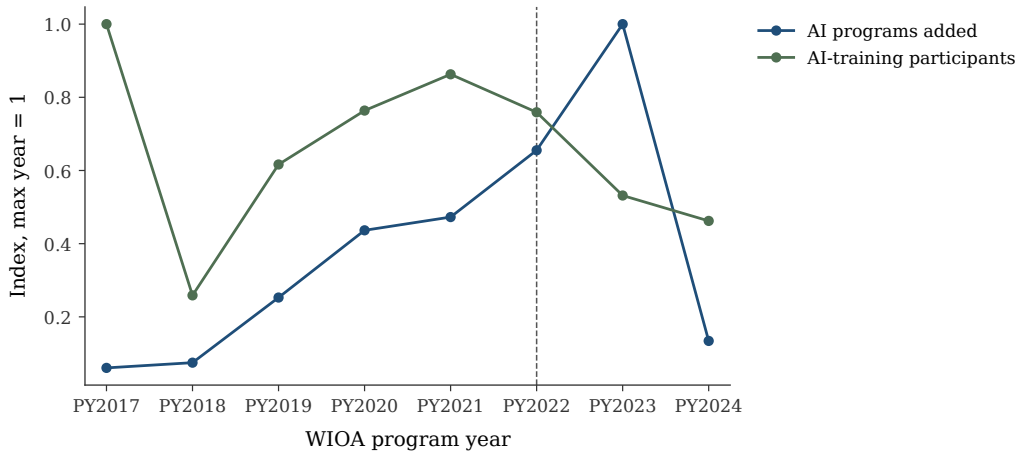
Note: This table reports period-bin estimates for local eligible-training-provider supply responses. The unit is the WIOA local board by program year. Outcomes are log one plus newly listed local AI-related programs, providers, fields, or narrow-AI programs. All specifications include board and state-by-program-year fixed effects and interact predicted AI exposure with pre-period AI-training capacity. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

Figure C.15: PY2024 Local ETP Program Stock



Notes: The map shows the PY2024 end-of-year stock of local physical ETP programs assigned to each WIOA board in the 50-state-plus-DC sample. Board-level values are assigned to county polygons using the board-county crosswalk; counties served by multiple matched boards receive the mean board value, and counties without matched board values are shown as no value. The color scale is continuous.

Figure C.16: Supply-to-Use Gap



Notes: The figure compares annual AI program additions with WIOA-funded AI training participants. Each series is indexed to its own maximum year, so the display compares timing and relative movement rather than levels, units, or regression coefficients. WIOA program years run from July through June; PY2022 contains the November 30, 2022 ChatGPT launch and is treated as the GenAI transition year.

Table C.27A: WIOA-Funded AI Trainees and Fixed ETP Stock

	(1) COVID and digital	(2) Transition	(3) GenAI post
Panel A. Fixed PY2019 stock			
AI trainees	-0.003	-0.006	-0.039
given program stock	(0.024)	(0.041)	(0.043)
AI trainees	-0.013	-0.004	-0.036
given provider stock	(0.025)	(0.039)	(0.042)
Panel B. Fixed PY2022 stock			
AI trainees	0.010	0.014	-0.002
given program stock	(0.019)	(0.027)	(0.032)
AI trainees	0.004	0.019	0.006
given provider stock	(0.022)	(0.030)	(0.038)
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓
Observations, PY2019 rows	3,520	3,520	3,520
Board clusters, PY2019 rows	453	453	453
Observations, PY2022 rows	3,506	3,506	3,506
Board clusters, PY2022 rows	450	450	450

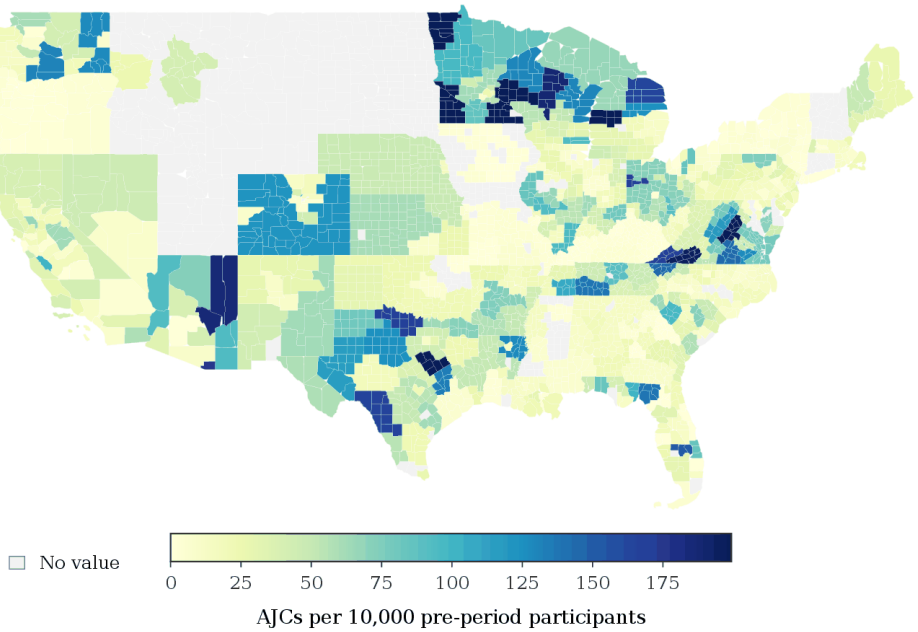
Note: This table reports period-bin estimates relating WIOA-funded AI trainees to fixed local ETP stock. The outcome is log one plus WIOA-funded AI trainees. Fixed stock is measured as local AI-related ETP program or provider stock at the start of PY2019 or PY2022, as labeled by panel and row. The unit is the WIOA local board by program year among board-years with nonmissing fixed stock. All specifications include board and state-by-program-year fixed effects, interact predicted AI exposure with prior AI-training experience, and cluster standard errors by board. The COVID and digital period is PY2020–PY2021, the transition year is PY2022, and the GenAI post period is PY2023–PY2024.

Table C.27B: Conversion Relative to Fixed 2019 AI Program Stock

	(1) COVID and digital	(2) Transition	(3) GenAI post
Conversion with PY2019 program stock	4.524* (2.464)	-2.598* (1.508)	-2.371 (1.896)
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓
Observations	910	910	910
Board clusters	115	115	115

Note: This table reports direct conversion-rate estimates relative to fixed PY2019 local AI program stock. The outcome is WIOA-funded AI trainees per 100 listed AI programs among board-years with positive fixed PY2019 program stock. The unit is the WIOA local board by program year in the positive-stock support sample. The specification includes board and state-by-program-year fixed effects, interacts predicted AI exposure with prior AI-training experience, and clusters standard errors by board. The COVID and digital period is PY2020–PY2021, the transition year is PY2022, and the GenAI post period is PY2023–PY2024.

Figure C.17: AJCs per 10,000 Pre-Period Participants



Notes: The map shows current-snapshot American Job Center counts divided by mean PY2017 to PY2019 Adult and Dislocated Worker participants, scaled per 10,000 participants in the 50-state-plus-DC sample. Board-level values are assigned to county polygons using the board-county crosswalk; counties served by multiple matched boards receive the mean board value, and counties without matched board values are shown as no value. The color scale is continuous.

Table C.28: Conversion-Rate Descriptives

Period	Mean	Median	P25	P75	N	Zero-use share
Panel A. AI trainees per 100 local AI programs						
Baseline	1,809.5	376.9	92.1	1,254.2	315	0.143
COVID and digital	1,961.5	514.3	125.0	1,515.0	391	0.102
Transition	1,511.7	368.8	135.2	1,100.0	294	0.088
GenAI post	613.0	153.2	46.4	500.0	799	0.149
Panel B. AI trainees per 100 local AI providers						
Baseline	2,476.6	933.3	200.0	2,485.7	315	0.143
COVID and digital	3,093.1	1,407.7	545.0	3,475.0	391	0.102
Transition	2,528.1	1,212.5	443.5	3,018.8	294	0.088
GenAI post	1,211.3	625.0	184.5	1,441.7	799	0.149
Panel C. AI trainees per 100 fixed 2019 AI programs						
Baseline	1,940.1	366.7	70.0	1,212.5	377	0.170
COVID and digital	3,147.0	670.8	174.2	1,918.8	270	0.130
Transition	1,496.8	600.0	177.5	1,408.8	135	0.148
GenAI post	1,006.7	305.6	84.6	975.0	264	0.182
Panel D. AI trainees per 100 fixed 2022 AI programs						
Baseline	1,384.9	250.0	65.5	950.0	797	0.120
COVID and digital	1,740.6	494.8	150.0	1,500.0	582	0.081
Transition	1,511.7	368.8	135.2	1,100.0	294	0.088
GenAI post	954.0	200.0	46.2	723.2	579	0.192
Panel E. AI training per participant per local AI program						
Baseline	0.051	0.016	0.004	0.062	315	0.143
COVID and digital	0.044	0.016	0.006	0.048	391	0.102
Transition	0.038	0.014	0.005	0.040	294	0.088
GenAI post	0.028	0.008	0.002	0.025	798	0.149

Note: This table reports conversion-rate descriptive statistics by period bin. Baseline pools PY2017–PY2019, COVID and digital pools PY2020–PY2021, Transition is PY2022, and GenAI post pools PY2023–PY2024. Conversion ratios link observed WIOA-funded broad-AI training use to positive listed-supply denominators. Zero-use shares are computed among board-years with positive denominators.

Table C.29: WIOA AI Training Relative to Listed AI Supply

	Fixed 2019 programs	Fixed 2022 programs	Local providers	Log AI trainees
COVID and digital	649.1	-82.755	206.1	0.162**
	(491.0)	(80.584)	(333.5)	(0.066)
Transition	164.3	257.9***	105.5	0.213**
	(360.6)	(96.334)	(499.5)	(0.084)
GenAI post	220.3	255.6**	-50.139	0.241***
	(370.9)	(103.0)	(456.9)	(0.084)
Observations	910	1,848	1,448	1,448
Board fixed effects	✓	✓	✓	✓
State-by-year fixed effects	✓	✓	✓	✓

Note: This table reports board-year estimates of WIOA-funded AI training relative to listed local AI supply. Fixed-program and local-provider columns use AI trainees per 100 listed AI programs or providers among board-years with positive denominators, and the log AI-trainees column uses log one plus AI trainees. All specifications include board and state-by-program-year fixed effects and interact predicted AI exposure with pre-period AI-training capacity. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

Table C.30: AJC Reach and the Exposure-by-Prior-Experience Response

	Training access	AI use	Conv.
COVID and digital AJC moderation	0.007	0.000	1,079.4**
	(0.009)	(0.004)	(509.0)
Transition AJC moderation	0.011	0.003	-462.6
	(0.012)	(0.007)	(430.5)
GenAI post AJC moderation	0.004	0.005	-263.4
	(0.012)	(0.007)	(427.3)
Observations	3,517	3,510	910
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓

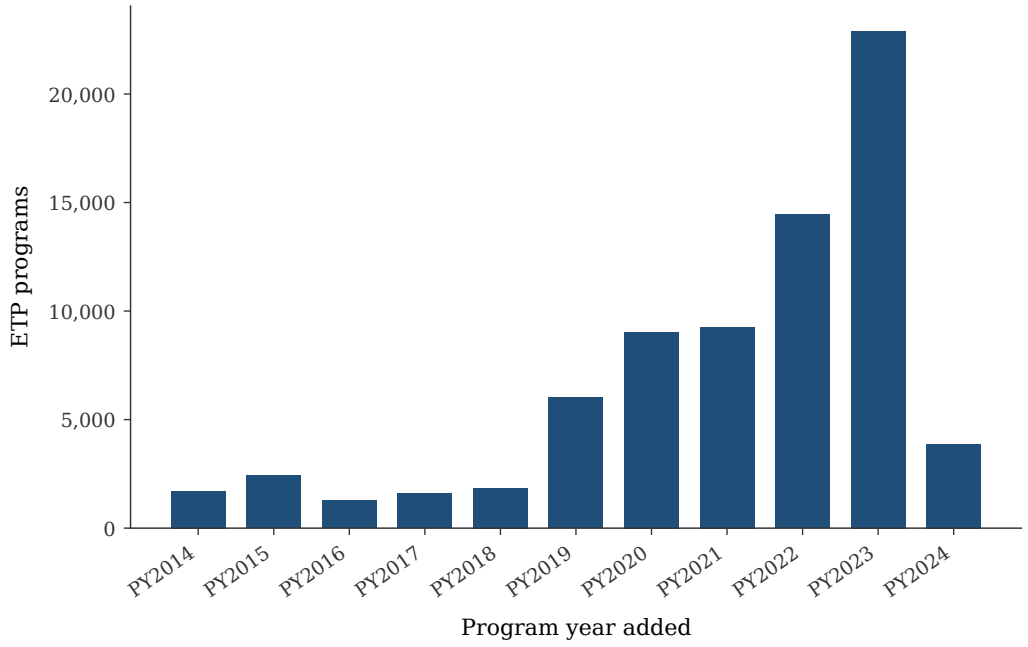
Note: This table reports exposure-by-prior-experience-by-AJC-reach period-bin coefficients from board-year specifications. Training access is the training participation rate, AI use is AI training per participant, and conversion is AI trainees per 100 fixed PY2019 AI programs among board-years with positive fixed stock. AJC reach measures local service-infrastructure coverage. Specifications include board and state-by-program-year fixed effects. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

Table C.31: American Job Center Reach

Measure	(1) Mean	(2) Median	(3) Std. dev.	(4) N
AJC total	3.612	3.000	3.586	529
Comprehensive AJC	1.779	1.000	1.921	529
AJC reach index	2.696	2.000	2.499	529

Note: This table reports American Job Center reach measures at the WIOA local-board level. AJC total counts all American Job Centers mapped to the board, comprehensive AJC counts comprehensive centers, and the AJC reach index combines local center counts used in the board-level moderation specifications.

Figure C.18: ETP Date-Added Timing and Coverage



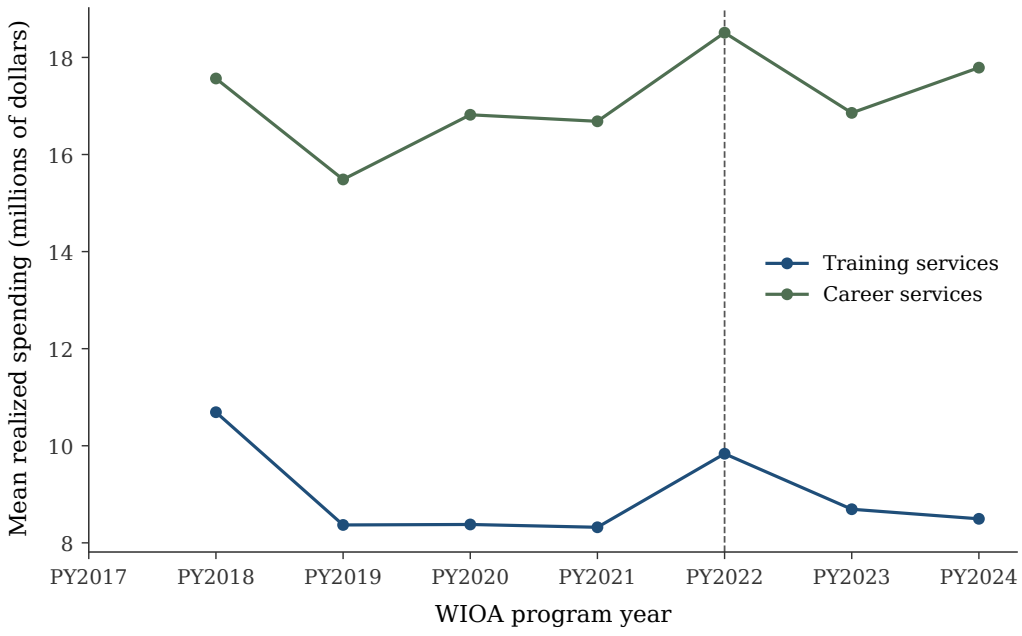
Notes: The histogram places ETP provider-program listing dates into WIOA program years. Date-added information is interpreted as listing or active-start evidence. Historical exits are not observed, so beginning-of-year stocks use a no-exit assumption and should be read with the current-list survivorship caveat.

Table C.32: State Funding Coverage and Spending by Program Year

	Assigned resources	Training spending	Career spending	Training share	States with spending data
PY2017	36.7				0
PY2018	38.5	10.7	17.6	0.395	43
PY2019	35.2	8.4	15.5	0.363	51
PY2020	35.3	8.4	16.8	0.343	51
PY2021	35.7	8.3	16.7	0.355	51
PY2022	36.3	9.8	18.5	0.369	33
PY2023	36.6	8.7	16.9	0.352	51
PY2024	36.7	8.5	17.8	0.346	50

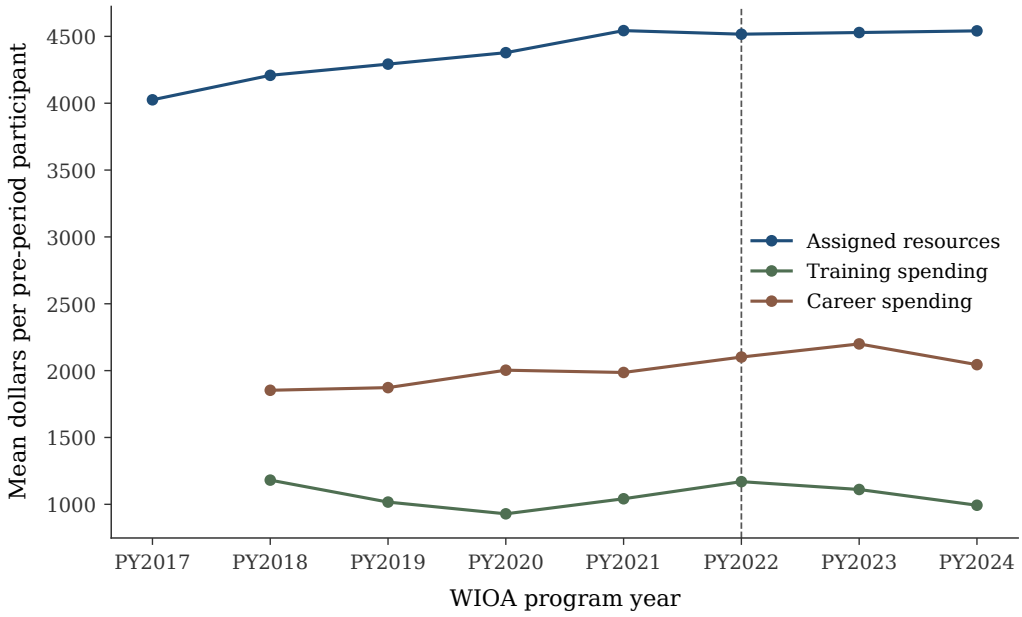
Note: This table reports funding coverage and descriptive statistics by WIOA program year for the 50 states plus DC. Assigned resources are Adult and Dislocated Worker formula allotments. Realized training spending and realized career spending are state-year service-expenditure measures reported where expenditure data are available. Training share is training spending divided by the sum of training and career spending. Dollar values are state-year means in millions.

Figure C.19: Career and Training Service Expenditure Trends



Notes: This figure plots mean state career-service and training-service expenditures by program year. Values are in millions of dollars for the 50 states plus DC where expenditure data are available. WIOA program years run from July through June; PY2022 is the GenAI transition year and PY2023 to PY2024 are the GenAI post years. PY2017 lacks realized expenditure coverage in this extract, and PY2022 has partial expenditure coverage.

Figure C.20: Funding per Pre-Period Participant Trends



Notes: This figure plots state-year mean assigned resources and realized service spending per pre-period participant. Assigned resources are formula allotments divided by pre-period participant counts. Realized training and career spending per pre-period participant are expenditure-intensity measures where spending data are available. The sample covers the 50 states plus DC. Higher per-participant amounts can reflect costs, sparsity, existing service regimes, or allocation choices.

Table C.33: Realized Career and Training Spending as Moderators

	(1) Training participation rate	(2) AI share among trainees	(3) AI training per participant
Panel A. Realized spending levels			
Training spending × access	0.003		
	(0.010)		
Career spending × access	0.016		
	(0.012)		
Training-spending share × access	-0.027***		
	(0.010)		
Training spending × AI share		-0.007*	
		(0.004)	
Career spending × AI share		-0.003	
		(0.004)	
Training spending × AI training per participant			-0.010
			(0.007)
Career spending × AI training per participant			-0.006
			(0.006)
Panel B. Realized spending per pre-period participant			
Training-spending intensity × access	-0.048***		
	(0.013)		
Career-spending intensity × access	-0.020		
	(0.014)		
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓

Note: This table reports GenAI-post moderation estimates using realized career- and training-service spending measures. Training spending is standardized log state-year Adult and Dislocated Worker training-service expenditures. Career spending is standardized log state-year Adult and Dislocated Worker career-service expenditures. The training-spending share is training expenditures divided by training plus career-service expenditures. Spending intensity is realized spending per pre-period Adult and Dislocated Worker participant. The unit is the WIOA local board by program year in states with expenditure support. Regressions include board and state-by-program-year fixed effects, and standard errors are clustered by board. Realized expenditures are allocation measures, not exogenous shocks.

Table C.34: Inference Sensitivity for Funding and Within-State Concentration Estimates

	(1) Estimate	(2) Board SE	(3) State SE	(4) Two-way SE	(5) Obs.
Panel A. Funding moderation					
Assigned resources × training access	0.016	0.008	0.008	0.008	3,774
Training spending × training access	0.003	0.010	0.011	0.011	3,185
Panel B. Within-state concentration					
Training concentration	0.067	0.020	0.025	0.025	3,759
AI-output concentration	0.125	0.040	0.042	0.042	3,198
Board fixed effects	✓	✓	✓	✓	
State-by-year fixed effects	✓	✓	✓	✓	

Note: This table reports inference-sensitivity checks for selected funding and within-state concentration estimates. The estimate column is common across clustering specifications; only the standard-error estimator changes across columns (2)–(4). Funding rows report the GenAI-post four-way interaction among exposure, prior AI-training experience, and the funding moderator. Concentration rows report the GenAI-post exposure-by-prior-experience interaction for log within-state concentration outcomes. All models include board and state-by-year fixed effects, and the unit is the board-year. State clustering is defined at the state/DC level, and the two-way specification clusters by board and state.

Table C.35: Realized Spending Moderation on a Common Analysis Sample

	(1) Training participation rate	(2) AI training per participant
Current training spending x access	0.003	
	(0.011)	
Current career spending x access	0.016	
	(0.012)	
Current training spending		-0.010
× AI training per participant		(0.007)
Current career spending		-0.006
× AI training per participant		(0.006)
Lagged training spending x access	0.010	
	(0.009)	
Lagged career spending x access	0.021*	
	(0.012)	
Lagged training spending		-0.017**
× AI training per participant		(0.007)
Lagged career spending		-0.006
× AI training per participant		(0.007)
Board fixed effects	✓	✓
State-by-year fixed effects	✓	✓

Note: This table reports complete-case expenditure checks for current and lagged realized spending measures. The unit is the WIOA local board by program year with required expenditure support. Spending rows use state-year realized training-service and career-service expenditures. Specifications include board and state-by-program-year fixed effects. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

Table C.36: Within-State Training Allocation and Concentration

	(1) Estimate	(2) Obs.	(3) Clusters
Training share minus participant share	0.003*	3,816	507
	(0.002)		
AI-training share minus participant share	0.007	3,479	470
	(0.005)		
Log training concentration	0.067***	3,759	499
	(0.020)		
Log AI-training concentration	0.125***	3,198	446
	(0.040)		
Log training concentration × assigned resources	0.037**	3,759	499
	(0.017)		
Log AI-training concentration × assigned resources	0.014	3,198	446
	(0.044)		
Log training concentration × training-spending share	-0.066***	3,177	494
	(0.025)		
Log AI-training concentration × training-spending share	-0.040	2,731	444
	(0.049)		
Board training share within state-year	0.003*	3,816	507
	(0.002)		
Board AI-training share within state-year	0.006	3,479	470
	(0.005)		

Note: This table reports within-state allocation and concentration estimates. Share rows compare a board's statewide activity share with its statewide participant share, and concentration rows use log ratios for training or AI-training activity within state-years. Assigned-resource rows interact concentration with Adult and Dislocated Worker formula allotments, and training-spending-share rows interact concentration with realized training spending divided by training plus career spending. Specifications include board and state-by-program-year fixed effects. Standard errors are clustered by board and shown in parentheses on the row immediately below each estimate.

Table C.37: Delivery Channels and Training Progress

	(1) COVID and digital	(2) Transition	(3) GenAI post
Online training share	0.002	0.000	
	(0.002)	(0.002)	
Hybrid training share	0.001	0.001	
	(0.004)	(0.003)	
Private-provider training share	0.001	0.002	0.004
	(0.004)	(0.006)	(0.009)
Training completion rate	0.004	-0.007	-0.001
	(0.004)	(0.007)	(0.007)
Credential rate among trainees	-0.004	0.001	0.007*
	(0.005)	(0.006)	(0.004)
Measurable-skill-gain rate	0.002	0.009	0.017*
	(0.005)	(0.007)	(0.009)
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓
Observations	1,840	1,840	1,840
Board clusters	472	472	472

Note: This table reports delivery-channel and training-progress estimates by period bin. The unit is the WIOA local board by program year in the Adult and Dislocated Worker training sample with delivery-channel support. Outcomes are training delivery shares, completion rates, credential rates, and measurable-skill-gain rates. All specifications include board and state-by-program-year fixed effects and interact predicted AI exposure with prior AI-training experience. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

Table C.38: Delivery-Channel Responses

	(1) COVID and digital	(2) Transition	(3) GenAI post
Online training share	0.002	0.000	
	(0.002)	(0.002)	
Hybrid training share	0.001	0.001	
	(0.004)	(0.003)	
Private-provider training share	0.001	0.002	0.004
	(0.004)	(0.006)	(0.009)
On-the-job training share	-0.004	0.001	-0.005
	(0.002)	(0.006)	(0.006)
Customized training share	-0.002	-0.002	-0.003
	(0.001)	(0.001)	(0.002)
Apprenticeship share	0.000	0.001	0.001
	(0.001)	(0.001)	(0.002)
Individual account share	0.007	0.001	0.010
	(0.004)	(0.008)	(0.009)
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓
Observations	1,840	1,840	1,840
Board clusters	472	472	472

Note: This table reports delivery-channel estimates by period bin. The unit is the WIOA local board by program year in the Adult and Dislocated Worker training sample with delivery-channel support. Outcomes are shares of training records delivered through the listed channels or funded through individual training accounts. All specifications include board and state-by-program-year fixed effects and interact predicted AI exposure with pre-period AI-training capacity. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

Table C.39: Training Completion, Credentials, and Skill Gains

	(1) COVID and digital	(2) Transition	(3) GenAI post
Completion rate	0.004	-0.007	-0.001
	(0.004)	(0.007)	(0.007)
Credential rate	-0.004	0.001	0.007*
	(0.005)	(0.006)	(0.004)
Measurable-skill-gain rate	0.002	0.009	0.017*
	(0.005)	(0.007)	(0.009)
AI completion rate	0.009	0.006	0.006
	(0.008)	(0.010)	(0.009)
AI credential rate	0.004	0.009	0.014**
	(0.009)	(0.008)	(0.006)
Board fixed effects	✓	✓	✓
State-by-year fixed effects	✓	✓	✓
Observations	3,759	3,759	3,759
Board clusters	499	499	499

Note: This table reports training completion, credential, and measurable-skill-gain estimates by period bin. The unit is the WIOA local board by program year in the Adult and Dislocated Worker analysis universe. AI completion and AI credential outcomes restrict the numerator to AI-related training records. All specifications include board and state-by-program-year fixed effects and interact predicted AI exposure with pre-period AI-training capacity. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

Table C.40: ETP Program Costs, Duration, and ITA Funding

Measure	(1) Mean	(2) Median	(3) Std. dev.	(4) N
Local AI cost median	7,324.7	5,958.9	6,536.0	3,319
Local AI duration median	39.879	32.000	37.653	2,850
Scalable AI cost median	5,283.8	4,697.0	3,620.5	4,434
Local AI ITA funds	142,895	8,234.0	492,472	4,009

Note: This table reports descriptive statistics for listed ETP program costs, listed program duration, and local individual training account funding. The unit is the board-year with available ETP cost, duration, or funding data. Cost and duration measures are static current-listing measures rather than historical prices. Local AI ITA funds summarize listed individual training account funding linked to local AI-related programs.

D Field Allocation and Field-Code Coverage

This appendix section records how the paper reads field-allocation evidence under incomplete field-code observability. It keeps the family surface, patched CIP4 surface, and services without valid CIP4 codes conceptually separate.

The exhibits support a clear measurement boundary for field allocation. Coded field shifts are informative, while incomplete valid-CIP coverage and work-based channels limit what field-coded outcomes can reveal.

D.1 Field Allocation Surfaces

This subsection supports the field-allocation discussion by keeping the family and patched CIP4 surfaces separate. Family groups are readable and stable; patched CIP4 is more granular but more exposed to field-code missingness and validity limits.

The family surface is the main reader-facing allocation surface because it groups training into stable field families. Table D.41 shows the fuller family allocation evidence behind the compact main-text discussion. The table describes coded training-family allocation, with uncoded content outside the field-family surface.

The patched CIP4 surface is more granular and closer to instructional-program coding, but its support is thinner. Table D.42 reports the granular robustness results. Readers can connect the field-allocation surface to the CIP-validity and field-code coverage construction details in Appendix A.3.

Table D.41: Family-Level Training Allocation

	(1) COVID and digital	(2) Transition	(3) GenAI post
Portfolio share	0.012***	0.015**	0.006
	(0.004)	(0.007)	(0.007)
Log participants	0.091***	0.101***	0.084**
	(0.023)	(0.032)	(0.035)
Active family	0.002	0.006	0.016*
	(0.008)	(0.008)	(0.009)
Board-by-field fixed effects	✓	✓	✓
Board-by-year fixed effects	✓	✓	✓
Field-by-year fixed effects	✓	✓	✓
Observations	41,965	41,965	41,965
Board clusters	508	508	508

Note: This table reports family-level training allocation estimates. The unit is the board-family-year in the Adult and Dislocated Worker training sample with valid field families. Outcomes are the family portfolio share, log participants, and an active-family indicator. Specifications include board-by-field, board-by-year, and field-by-year fixed effects and interact predicted AI exposure with pre-period AI-training capacity. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.

Table D.42: Detailed CIP4 Allocation Robustness

	(1) COVID and digital	(2) Transition	(3) GenAI post
Log participants	-0.023***	-0.015	-0.029***
	(0.008)	(0.011)	(0.011)
Portfolio share	-0.000	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)
Active CIP4 field	-0.010*	-0.005	-0.013**
	(0.005)	(0.006)	(0.007)
Board-by-field fixed effects	✓	✓	✓
Board-by-year fixed effects	✓	✓	✓
Field-by-year fixed effects	✓	✓	✓
Observations	311,034	311,034	311,034
Board clusters	512	512	512

Note: This table reports detailed CIP4 allocation robustness estimates. The unit is the board-CIP4-year in the Adult and Dislocated Worker training sample after field-code cleaning. Outcomes are log participants, portfolio share, and an active-CIP4-field indicator. Specifications include board-by-field, board-by-year, and field-by-year fixed effects and interact predicted AI exposure with pre-period AI-training capacity. Standard errors are clustered by board and shown in parentheses on the row immediately below each coefficient.