“How Retrainable are AI-Exposed Workers?”

Ben Hyman, Ben Lahey, Karen Ni, Laura Pilossoph

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Extended Abstract

We document the extent to which AI-exposed workers can successfully retrain for AI-intensive work. We assemble a new job training dataset spanning over 2.9 million unique job training participation spells from all U.S. Workforce Investment Act (WIA) programs between 2012 – 2023. Linking occupational measures of AI exposure with earnings records observed both before and after training, we compare earnings and occupational transitions of job trainees to observationally similar AI-exposed workers who only received job search assistance services through the Wagner-Peyser program. We then construct an AI retrainability index (AIR) at the occupation level that weights transitions into more AI-intensive occupations by individual earnings returns from training. This allows us to disentangle whether AI retrainability is driven by AI skill transitions versus general returns to training.

We have three main findings: (1) About 25% to 35% of workers and occupations are “AI-retrainable”—a large number given the sample represents mostly lower-income displaced workers. (2) The share of workers that receive a positive return from AI upskilling has increased from just over 50% in 2012 to 75% in 2022, though the share transitioning to more intensive AI work remained flat over this period. (3) Positive returns to job training are driven by the most recent years when labor markets were tightest, suggesting workforce development programs may have stronger signal value when firms are forced to reach deeper into the skill market.

These preliminary results suggest that workers are not merely resorting to surviving occupations that might face AI-driven displacement in the future but are more likely to be adjusting. In ongoing work, we use a search and matching model expanding on the mismatch framework in Sahin et al. (2014) to ask whether displaced workers are over- or under-training in AI relative to the AI skills demanded in job vacancies.

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How Retrainable Are AI-Exposed Workers?

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NBER Submission Slides

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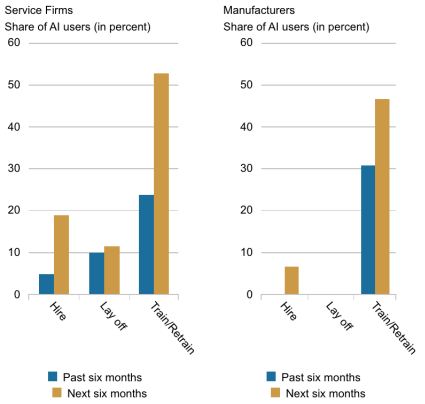
Motivation

Job Training is Understudied Margin of AI Adjustment

- AI effects on labor market flows remain prospective
  - Deming, Ong, Summers (2024): "AI could be a GPT on the scale of prior disruptive innovations..."
  - Autor (2024): "AI, if used well, can assist with restoring the middle-skill, middle-class heart of the US labor market hollowed out by automation and globalization."
- A more salient but understudied adjustment margin is **retraining workers for AI**

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- A more salient but understudied adjustment margin is **retraining workers for AI**
- NY Fed Firm Survey (Aug' 24):
  - *Due to the use of AI did your business (i) hire or onboard new employees, (ii) lay off or downsize current staff, (iii) train or retrain current stuff?*



Abel, Deitz, Emanuel, and Hyman (LSE, 2024)

Details

This Paper

- What share of AI-exposed workers can be retrained for future AI work?
- New dataset of displaced trainees:
  1. AI exposure measures at 6-digit occupation level
  2. Universe of individual job training spells from WIA/WIOA ($\sim$3m, 2012-2023); prior and post-training occupations $\rightarrow$ variation in AI exposure (intensity) and transitions
  3. Quarterly earnings for one year prior and post-training spell to measure upskilling
- Matched control group: $\sim$33m receive only Wagner-Peyser search assistance services
- AI Retrainability (AIR) index: disentangles skill returns from alternative stories

Results Preview

- Key take-away: displaced AI-exposed workers are surprisingly retrainable
  - **25%** - **35**% of retraining workers and 6-digit occupations are "AI-retrainable"
  - Among high AI-exposure workers, **20%** - **25%** are AI-retrainable
  - These are large, considering low-income sample of displaced workers interfacing with publicly funded training programs
- Returns to retraining among AI-exposed are similar to general training, with positive effects concentrated in most recent years
  - Training most valuable when labor markets are tighter

Outline

1. Data and Measurement
   - AI exposure measures merged to occupational transitions around job training
   - Worker flows by AI intensity and earnings return and over time
   - Headline numbers on share retrainable

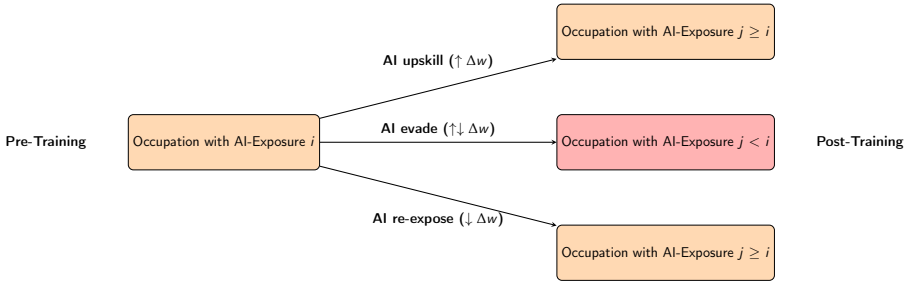
2. AI Retrainability (AIR) index and decompositions

3. Overtraining or Undertraining for Future of Work? (Including AI)
   - Job-seeker allocation model w/ frictional matching and crowd-out effects (Sahin et al., 2014)
     - We add skill heterogeneity and productivity costs from training in the "wrong" skill
   - Social planner efficiency benchmark tells us what to look for in data
     - Can measure departures from benchmark case

Data and Measurement

Data Objectives

- Goal is to index occupations by their retrainability for AI work
- Index needs to distinguish **upskill**-driven transitions to AI work from **reexposure** to AI *risk*

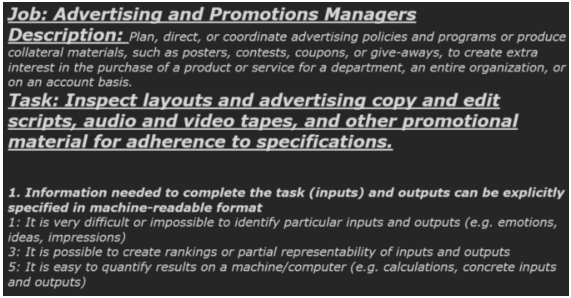


- Top branch captures "AI retrainable" transitions. Bottom branches are not AI retrainable. Distance between i and j and size of Δw let us rank retrainability in each occupation i

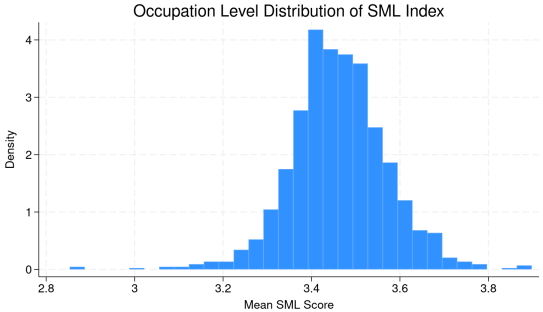
Index Input 1: Occupational AI Exposure Measure

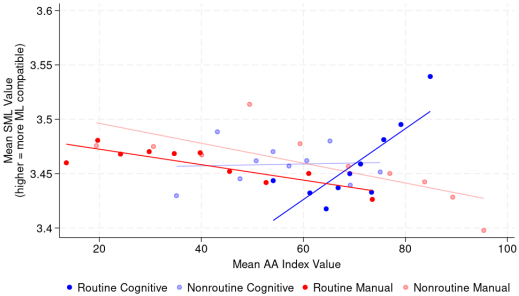
- Cannot observe whether worker's occupation, firm, or industry actually adopted AI in admin data. Instead, we follow AI exposure task measures in the literature

- Brynjolfsson, Mitchell, and Rock (2018): "Suitability for Machine Learning" (SML)
  - 7 independent human annotators evaluate 2,069 O*NET work activities ("tasks") paired with 964 6-digit occupations ("jobs") using 5-point Likert scale averaged across 23 questions



SML Measure Validations





- Left: Distribution of SML scores at 6-digit occupation level
- Right: Validation against Acemoglu and Autor (AA, 2011) task share measures, restricted to occupations in job training data
- Take-away: **AI tasks are cognitive tasks**

GenAI measure: Eloundou et al. (2024)

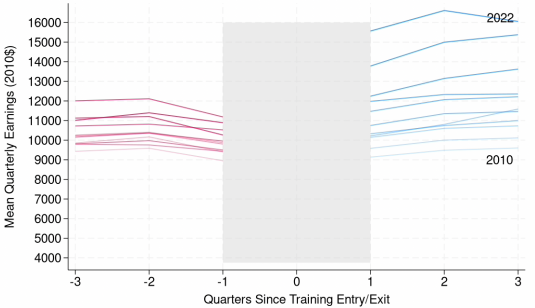
Index Input 2: Universe of WIA/WIOA Job Training Spells

- Workforce Investment Act (WIA, 1998): U.S.'s flagship workforce development program
  - Federal funds allocated to state and local workforce development boards, then to individual training accounts that can be used to enroll in certified training programs

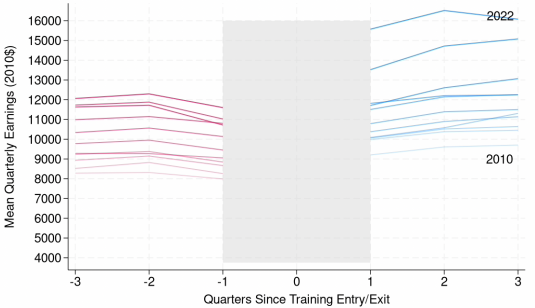
- Training participation spell-level data from PIRL tracking dataset, includes any worker interfacing with WIA (or its successor, WIOA (2014)). Examples:
  - Title I: Workforce Development Activities (N $\approx$ 3 million unique spells)
    - Adult (54%): prioritizes public service recipients and lower-income individuals
    - Dislocated Worker (35%): termination letter or lay off + rapid response services if mass layoff
    - Co-enrolled (10%), out-of-school youth program age 16-24 (1%)
  - Title III: Wagner-Peyser search assistance services (N $\approx$ 33 million unique spells)

Earnings Selection Patterns for WIA/WIOA by Program Year

(a) No Controls



(b) Residualized

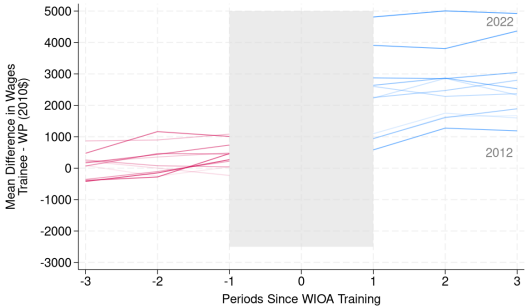


- N = 106k when restricting on 6 non-missing earnings and occupation code obs.
- AI retrainability estimated *within* cross-section of reemployed 1 quarter after exit
- *Controls*: age, sex, education, race, ethnicity, disability status, veteran status, english proficiency, single-parent, Title I program (adult, disclocated), state FEs

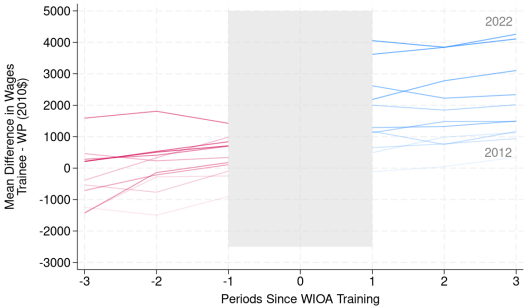
With Zeros

NN-Matched Returns to WIA/WIOA by Program Year

(a) Low Initial AI Exposure



(b) High Initial AI Exposure



- *Exact Match*: year of participation, SML quintile of prior occupation
- *Fuzzy Match*: sex, age at participation, indicators for: Hispanic/Latino, disability, adult vs. dislocated, limited-English, low-income, TANF, veteran, SSI/SSDI, $\geq$ HS, $\geq$ SomeCollege

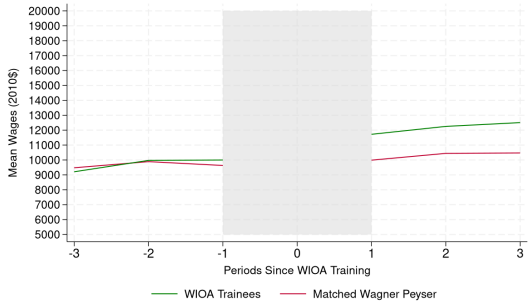
Rothstein et al. (2022)

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Rothstein et al. (2022)

Summary Statistics and Attrition Balance

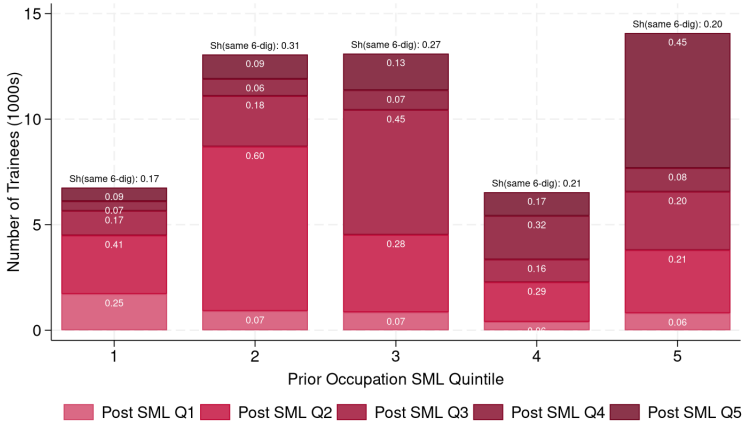
	Nonmissing Occ Codes		Missing Occ Codes		Nonmiss - Miss	
	Mean/SD (1)	# Trainees (2)	Mean/SD (3)	# Trainees (4)	Δ/SE (5)	% Diff (6)
A. Demographic Characteristics						
Female	0.49	106,359	0.50	448,040	-0.013***	-2.60
	[0.50]		[0.50]		(0.0017)	
Age	39.1	106,359	38.2	367,168	0.96***	2.45
	[11.1]		[11.0]		(0.038)	
Asian	0.041	86,069	0.035	385,684	0.0065***	15.8
	[0.20]		[0.18]		(0.00070)	
Black	0.30	88,836	0.30	389,467	0.00024	0.079
	[0.46]		[0.46]		(0.0017)	
White	0.67	93,224	0.64	403,466	0.021***	3.10
	[0.47]		[0.48]		(0.0017)	
Hispanic/Latino	0.17	101,195	0.16	405,705	0.016***	9.36
	[0.38]		[0.36]		(0.0013)	
Disability Status	0.027	103,912	0.026	424,510	0.00067	2.46
	[0.16]		[0.16]		(0.00056)	
No HS Diploma/GED	0.046	106,359	0.058	448,040	-0.012***	-27.1
	[0.21]		[0.23]		(0.00078)	
HS Diploma/GED	0.46	106,359	0.46	448,040	0.0019	0.41
	[0.50]		[0.50]		(0.0017)	
Some College	0.20	106,359	0.19	448,040	0.0059***	2.97
	[0.40]		[0.39]		(0.0013)	
College Degree Plus	0.29	106,359	0.28	448,040	0.0079***	2.71
	[0.45]		[0.45]		(0.0015)	
Total Obs.		**106,359**		**448,040**		

- Similar to both CPS-Unemployed and CPS-DWS

Summary Statistics and Attrition Balance

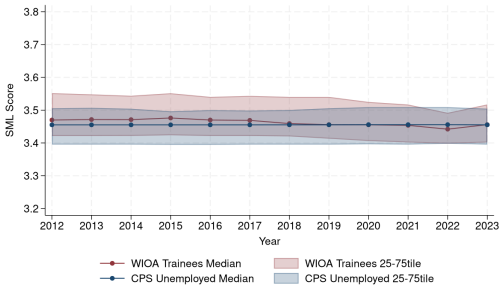
	Nonmissing Occ Codes		Missing Occ Codes		Nonmiss - Miss	
	Mean/SD (1)	# Trainees (2)	Mean/SD (3)	# Trainees (4)	Δ/SE (5)	% Diff (6)
B. Social Benefits						
Disadvantaged Adult Status	0.50	106,359	0.65	448,040	-0.14***	-28.6
	[0.50]		[0.48]		(0.0016)	
Dislocated Worker Status	0.49	106,359	0.38	448,040	0.11***	22.3
	[0.50]		[0.49]		(0.0017)	
Low-income Status	0.44	104,964	0.42	416,495	0.020***	4.48
	[0.50]		[0.49]		(0.0017)	
TANF Recipient	0.011	87,281	0.013	370,048	-0.0024***	-21.7
	[0.10]		[0.12]		(0.00043)	
SNAP Recipient	0.22	72,810	0.21	216,498	0.011***	5.09
	[0.41]		[0.40]		(0.0017)	
Other Public Assistance Recipient	0.26	82,292	0.21	351,378	0.044***	17.2
	[0.44]		[0.41]		(0.0016)	
C. Pre-Separation Employment						
Employed at Participation	0.31	106,359	0.40	448,040	-0.089***	-28.6
	[0.46]		[0.49]		(0.0017)	
Real Wages 1Q Before	9923.8	106,359	9500.2	448,040	423.7***	4.27
	[10975.0]		[12173.4]		(40.8)	
Real Wages 2Q Before	10477.0	106,359	9952.3	448,040	524.8***	5.01
	[9452.0]		[11173.7]		(37.1)	
Real Wages 3Q Before	10323.9	106,359	9734.1	448,040	589.7***	5.71
	[9023.1]		[9900.8]		(33.2)	
Total Obs.		**106,359**		**448,040**		

Transitions in AI Intensity



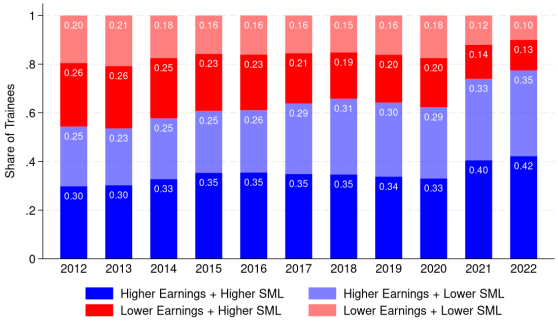
- Trainees' initial occupations are high AI exposure

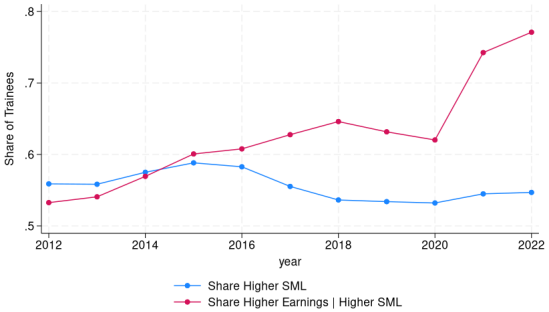
Composition of Trainees by Initial AI Exposure is Flat Over Time



- No change in composition of WIA/WIOA trainee AI exposure over time
- Four potential explanations:
  1. Composition of retraining workers is not (yet) reflecting large AI layoffs
  2. AI-impacted workers do not interface with publicly funded programs
  3. SML measure is poor / noisy
  4. Retrained workers succesfully adjust without reallocation

But This Masks Important Changes in Flow Types





Headline Results: Share AI-Retrainable

AI Retrainability Statistic		Trainees		Trainees - Matched	
		Full Sample	High Initial AI Exposure	Full Sample	High Initial AI Exposure
Sh. Spells	$\Delta SML \geq 0$ & $\Delta w \geq 0$	35.3%	21.0%	28.2%	24.8%
Sh. Occs	$\Delta SML \geq 0$ & $\Delta w \geq 0$	35.2%	12.0%	26.7%	23.7%
Sh. Spells	$\Delta SML^{GenAI} \geq 0$ & $\Delta w \geq 0$	40.4%	23.6%	35.3%	24.2%
Sh. Occs	$\Delta SML^{GenAI} \geq 0$ & $\Delta w \geq 0$	38.5%	9.0%	37.3%	19.4%

- High initial AI exposure $\equiv SML_i \geq p50(SML)$
- Selection adjustment for share AI-retrainable:
  - Full sample: 35% - 40% $\rightarrow$ 25% - 35%
  - High AI exposure: 10% - 20% $\rightarrow$ 20% - 25%

Baseline Earnings: Full Sample vs. High Exposure

AI Retrainability Index

AI Retrainability Index

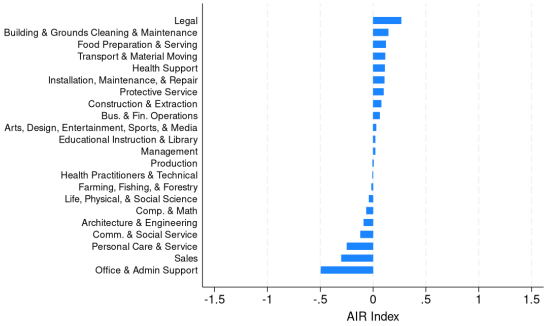
$$AIR_i = \sum_j \frac{1}{n_{ij}} \Delta SML_{ij}^{\sigma} * \mathcal{M}(\Delta \log(\overline{Y_{ij}})) \tag{1}$$

- n_{ij}: number of trainees flowing from occupation i to j, capturing probability of reemployment in occupations of varying AI-intensities
- $\Delta SML_{ij}^{\sigma} = \frac{SML_j - SML_i}{SD(SML_j - SML_i)}$: normalized difference in mean SML scores from transitioning
- $\Delta \log(\overline{Y_{ij}}) = \overline{\log(Y_j) - \log(Y_i)}$: mean return to occupational training over all n_{ij}
- $\mathcal{M} \in [0, 1]$: MinMax transformation that allows us to circumvent multiplying negative wage returns by negative SML changes

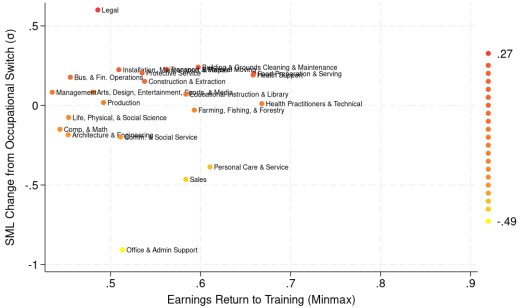
$$\mathcal{M}(\Delta \log(\overline{Y_{ij}})) = \frac{\Delta \log(\overline{Y_{ij}}) - \min(\Delta \log(\overline{Y_{ij}}))}{\max(\Delta \log(\overline{Y_{ij}})) - \min(\Delta \log(\overline{Y_{ij}}))} \tag{2}$$

AIR Index, 2-Digit SOC Rankings

(a) Index Rankings

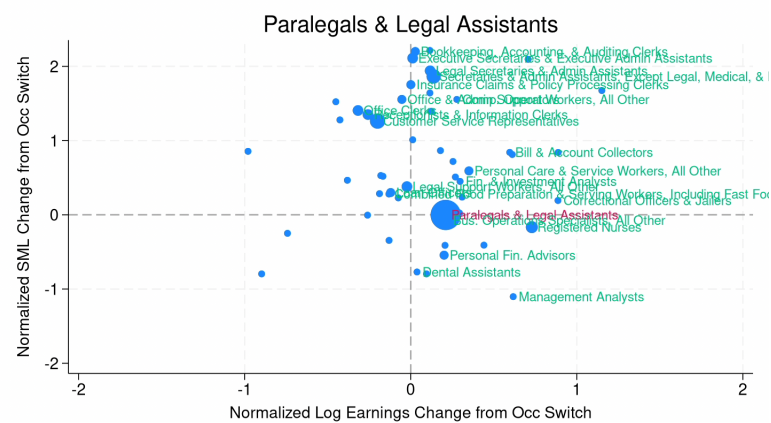


(b) Decomposition



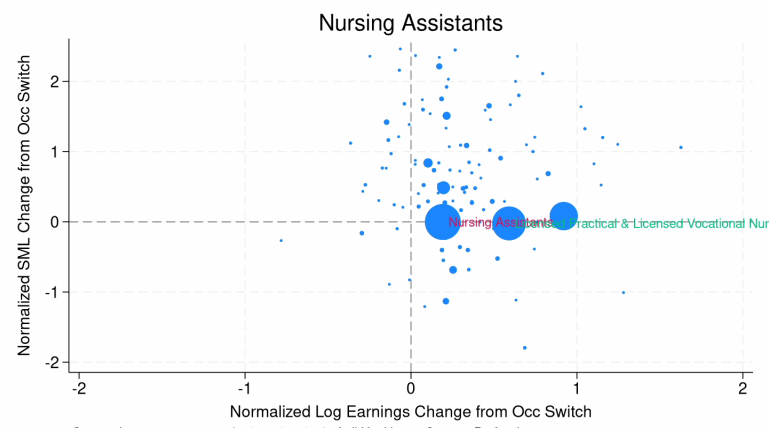
6-Digit Deep Dive for High Ranked Occupations (1/2)

- Legal (AIR rank = 1/23) by main 6-digit occupation



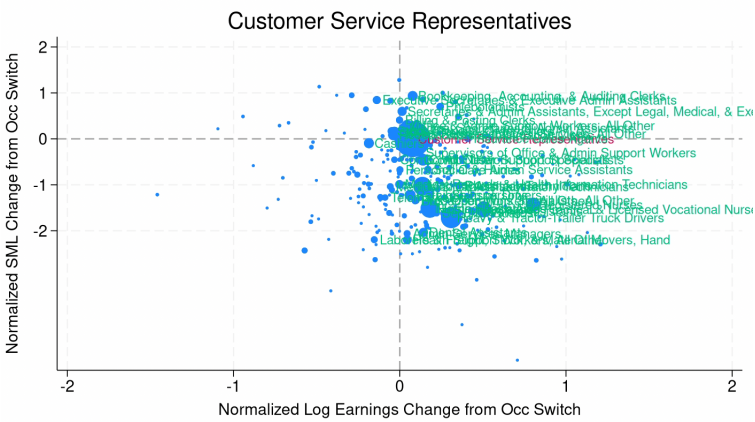
6-Digit Deep Dive for High Ranked Occupations (2/2)

- Health Support (AIR rank = 5/23) by main 6-digit occupation



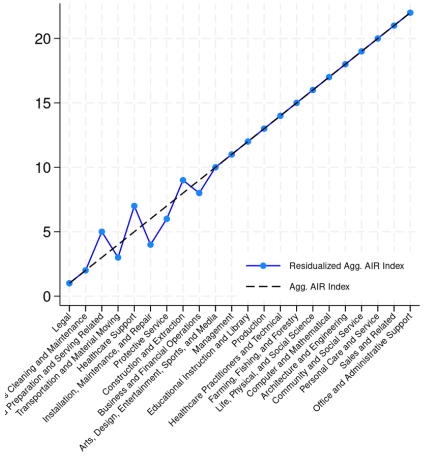
6-Digit Deep Dive for Low Ranked Occupations

- Office & Admin Support (AIR rank 23/23) by main 6-digit occupation

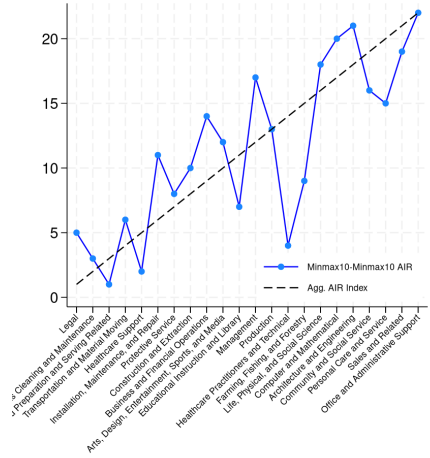


Robustness to Index Functional Form

(a) Residualized Index



(b) Alt. Functional Form

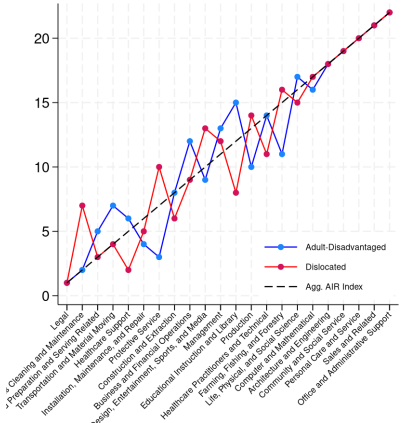


Heterogeneity by Program Type

(a) Baseline Earnings by WIA Program



(b) WIA Program Heterogeneity

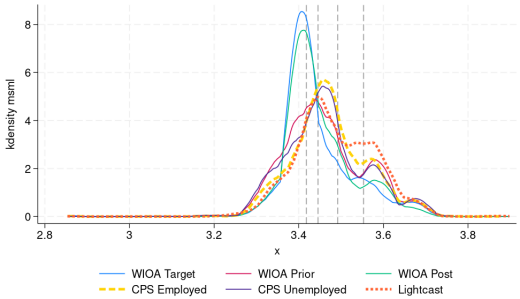


2017+

Overtraining or Undertraining for AI work?

Suggestive Evidence of Successful AI Retraining, but is it Enough?

- Need efficient benchmark to ask whether supply of AI skills matches skills demanded: social planner problem
- We build on Sahin et al. (2014) to think about "job training mismatch", where AI mismatch is a special case
- Our model adds heterogeneity in trainee skills and vacancy skill requirements
  - New hires can apply skills in the "wrong" job, negatively impacting output
  - Skill types can crowd out matches



Set-Up

Consider what a planner would do if given some set of vacancies $\{v(y)\}$, needed to **decide which markets** different skill types (x) **should search in** subject to crowd out effects

- $x = (x_m, x_c)$ stands for the worker's skill in manual and cognitive ($\approx$ AI) tasks
- $y = (y_m, y_c)$ is the demand for each task by jobs defined by y
- $u(x)$ is the measure of unemployed with skill bundle x, $e(x, y)$ the measure of employed with skill bundles x in jobs with bundle y
- $v(y)$ represents the measure of openings of jobs characterized by y
- Output for a job y when filled by a worker x is $z(x, y) = \gamma_{mm} x_m y_m + \gamma_{mc} x_m y_c + \gamma_{cm} x_c y_m + \gamma_{cc} x_c y_c$

Frictional Matching within Markets

$$V\left(\{v(y)\},\{e(x,y)\},\{u(x)\}\right)=\max_{\{u(x,y)\}}\sum_{x}\sum_{y}\underbrace{z(x,y)\left(e(x,y)+h(x,y)\right)}_{\text{output in } y \text{ with employed and new hires}}$$
$$+\underbrace{\Big(u(x,y)-h(x,y)\Big)b}_{\text{value of unemployed}}+\beta V\left(\{v(y)'\},\{e(x,y)'\},\{u(x)\}'\right)$$

subject to:

$$\sum_{y}u(x,y)=u(x)\quad\text{(adding up constraint on workers of a certain skill level)}$$

$$h(x,y)=\frac{u(x,y)}{u(y)}\underbrace{\phi_y\Big(\sum_{k}u(k,y)\Big)^{\alpha_y}v(y)^{1-\alpha_y}}_{M^y()}\quad\text{(matching function technology in market } y)$$

$$e(x,y)'=(1-\Delta)\left(e(x,y)+h(x,y)\right)\quad\text{(flow equation for employment)}$$

FOCs

FOC produces measure that is equated across skill markets y. In Sahin et al. (2014) w/ Cobb-Douglas $M^y()$, productivity-weighted $\theta = \frac{v}{u}$ ratios should be equated:

$$h(y) = \Phi\phi_y u(y)^{\alpha_y} v(y)^{1-\alpha_y} \quad \Longrightarrow \quad \text{FOC: } \alpha_y \phi_y \theta(y)^{1-\alpha_y} z(y) = 0$$

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Our model's FOC:

$$\underbrace{\phi_y \theta(y)^{1-\alpha_y} \left(z(x,y) - \sum_k \left[\frac{u(k,y)}{u(y)} z(k,y) \right] \right)}_{\text{conditional on same probability of matching, gain from hiring type } x \text{ over expected output without them}} +$$

$$\underbrace{\alpha_y \phi_y \theta(y)^{1-\alpha_y} \sum_k \left[\frac{u(k,y)}{u(y)} z(k,y) \right]}_{\text{expected decline in output from crowding out in matching function}} = 0$$

Discussion

- 3 Facts:
  1. Majority of workers are able to transition into more AI-intensive occupations after training, yet the share doing so has remained flat over time
  2. About 25% to 35% of workers and initial occupations are "AI-retrainable"
  3. The share of AI-retrainable workers receiving a positive return from AI upskilling has increased from just over 50% in 2012 to 75% in 2022

$\Longrightarrow$ training may play role in mediating future labor market disruptions from AI

- Key empirical question will be whether "AI retraining" measured here: i.e. mostly cognitive skill retraining, is a good proxy for restructuring that will occur moving forward

Appendix

Survey Details

"AI and the Labor Market: Will Firms Hire, Fire, or Retrain?" Jaison Abel, Rich Deitz, Natalia Emanuel, and Ben Hyman, *Liberty Street Economics*, September, 2024.

- 264 respondents. 25% of service firms reported using AI, as did 16% of manufacturers.
- Among AI users, 80% were using generative AI services. 50% of service firms using AI and 75% of manufacturers using AI were engaging a free service such as ChatGPT.
- "*Examples of AI include the use of virtual agents or chatbots, machine learning, natural language processing, large language models, text or data analytics using AI, neural networks, ChatGPT, augmented reality, deep learning, image/pattern recognition, speech/voice recognition, machine/computer vision, robotics process automation, biometrics.*"

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Eloundou, Manning, Mishkin, and Rock (2024) GenAI Measure

- Modify a ChatGPT prompt that targets human annotator responses to human prompt, facilitating machine scoring of *all* 18,156 O*NET task, not just 2,069 work activities. Preferred measure = E1 + 0.5 * E2

- *"Consider the most powerful OpenAI large language model (LLM). This model can complete many tasks that can be formulated as having text input and text output where the context for the input can be captured in 2000 words... You have access to the LLM as well as any other existing software or computer hard-ware tools... and commonly available technical tools. Please label the given task according to the taxonomy below".*

Summary of exposure rubric

No exposure (E0) if:
- using the described LLM results in no or minimal reduction in the time required to complete the activity or task while maintaining equivalent quality[a] or
- using the described LLM results in a decrease in the quality of the activity/task output.

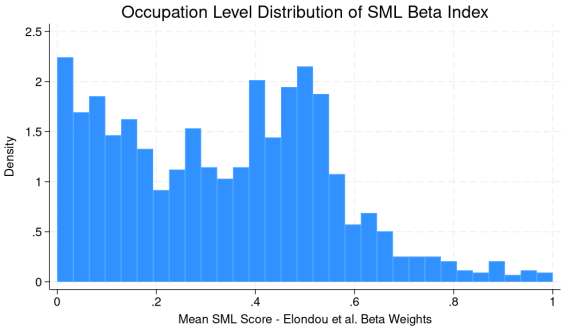
Direct exposure (E1) if:
- using the described LLM via ChatGPT or the OpenAI playground can decrease the time required to complete the DWA or task by at least half (50%).

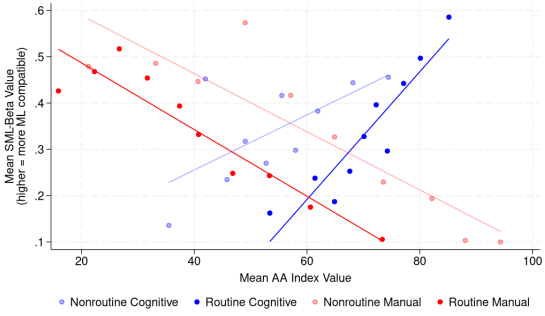
LLM+ Exposed (E2) if:
- access to the described LLM alone would not reduce the time required to complete the activity/task by at least half, but
- additional software could be developed on top of the LLM that could reduce the time it takes to complete the specific activity/task with quality by at least half. Among these systems, we count access to image generation systems.[b]

[a] Equivalent quality means that a third party, typically the recipient of the output, would not notice or care about LLM assistance.

[b] In practice, as can be seen in the full rubric in Appendix A.1, we categorize access to image capabilities separately (E3) to facilitate annotation, though we combine E2 and E3 for all analyses.

GenAI (SML-"Beta") Measure Validations



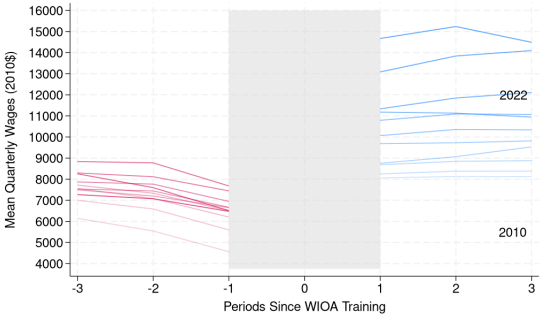


- Consistent with Brynjolfsson et al. (2018) finding that occupations contain "packages" of SML-compatible tasks which are more or less easy to repackage. Cognitive part of the package might be what drives SML compatibility.

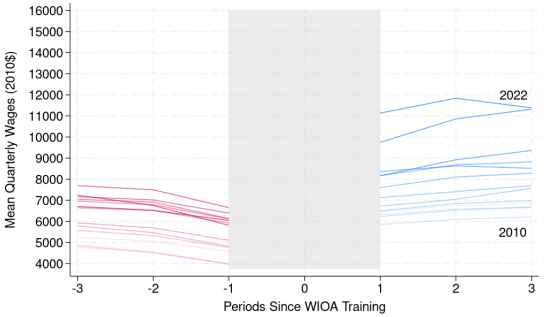
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Returns to WIA/WIOA by Program Year, Including Zeros

(a) Including Observed Zeros



(b) Including Zeros & Missing Occ Codes

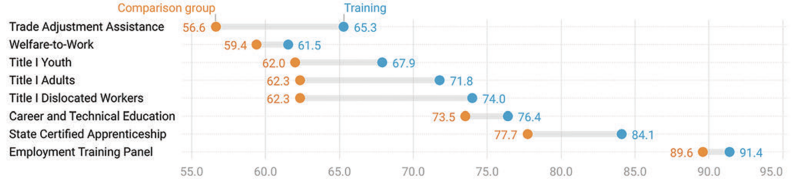


- Correlation between zero earnings and missing occupation codes, suggesting zero earnings are miscoded and should perhaps be missing

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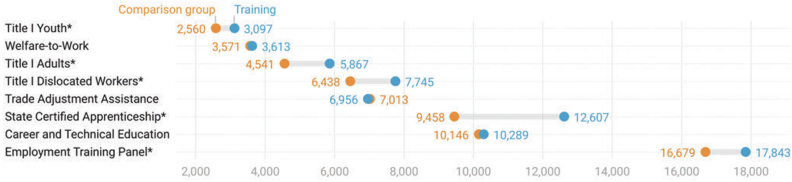
Rothstein et al. (2022) Evaluation of WIOA in California

FIGURE 1: Average quarterly employment rates from the research design, by training program



All differences are statistically significant at a 95% level of confidence.

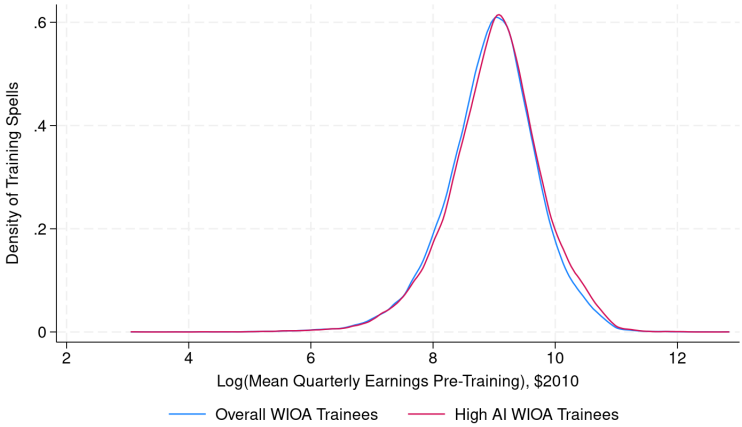
FIGURE 2: Average quarterly earnings from the research design, by training program



** = statistically significant difference at a 95% level of confidence. All figures are in 2016 dollars.*

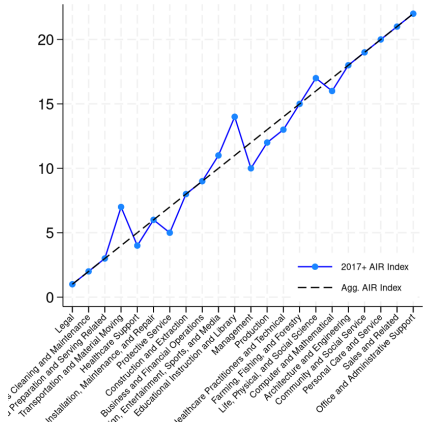
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Baseline Earnings, Full Sample vs. High Initial AI Exposure



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Restricting Index to 2017+

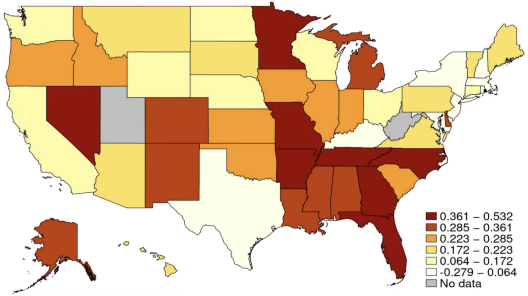


σ-Minmax AIR Ranking

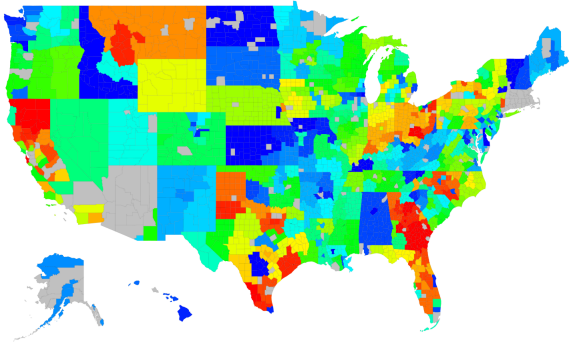
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Geographic Heterogeneity

(a) Change in Log Wages by State



(b) Workforce Development Board (WDB) Coverage



- Local WDBs have discretion over Federal funding allocation across activities, worker eligibility, and training program accreditation requirements