On The Job Training and Labor Competition

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Extended abstract

In this paper, we provide a new set of stylised facts on firm provision of on-the-job training and local labor market competition by exploiting the language used in job vacancies. We take a supervised machine learning approach to identify training offers in more than 12 million US job vacancies. We show our measure correlates well with established on-the-job training measures at the occupation, industry, and regional level. We find that around 20% of job posts offer on-the-job training, with an upward trend over the last decade. Jobs specifying lower experience and education requirements, and those in lower skill occupations are more likely to advertise on-the-job training. Training offers are positively correlated with local labor market concentration, a finding that is robust to an instrumental variables strategy based on the local differential exposure to national firm-level trends. Moving from the first to the third quartile of labor concentration increases training by 10%. We interpret our results through the lens of a directed search model where training acts to reduce the time to fill a vacancy and training has a greater expected benefit to the employer in less competitive labor markets given the lower separation rates.

Introduction: What?

Key questions,

1. Do job vacancies disclose information on training offers? Why?
2. How labor competition affects the disclosure of training information?

Introduction: Why?

Motivation

- **Training**: crucial for human capital growth
  - Ageing labor force, technological innovation, COVID-19 aftermath
  - **on-the-job training poorly measured** in existing survey data
- Firms compete also in the labour market for workers
  - **labour market very local** [Manning, Petrongolo (2017); Kaplan, Schulhofer-Wohl (2017)]
  - c.d. "Great Resignation"

Introduction: How?

- **Text analysis** on job vacancy text
  - Train a **machine learning algorithm** on a subset of manual tagged vacancies
  - Construct measure of **probability of on-the-job training offer**
- Empirical analysis
  - Proxy labor competition across labor markets with a **concentration** measure
  - Instrument changes in employer concentration with an akin **shift-share Bartik**
- Motivate the results through the lens of a **direct search model**
- Main result: **concentration increases training offers**

Related Literature

Text analysis on job vacancy text

Deming (2017); Deming and Kahn (2018); Hershbein and Kahn (2018); Kuhn et al. (2018); Ziegler (2020); Ash et al. (2020); Adams-Prassl et al. (2020); Lassébie et al. (2021); Alekseeva et al. (2021)

Studies of labor competition on training

Brunello, Gambarotto (2007); Muehlemann, Wolter (2011); Picchio, Van Ours (2013); Rzepka, Tamm (2016); Starr (2019); Bratti et al. (2021); Dietz, Zwick (2021); Brunello, Wruuk (2022)

Studies of labor concentration on wages

Lipsius (2018), Berger et al. (2019), Azar et al. (2020), Marinescu et al. (2020), Arnold (2021), Schubert et al. (2021) Hershbein et al. (2020), Sokolova, Sorensen (2021), Brooks et al. (2021)

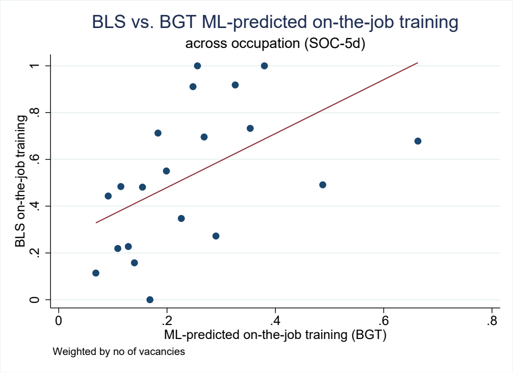
Data

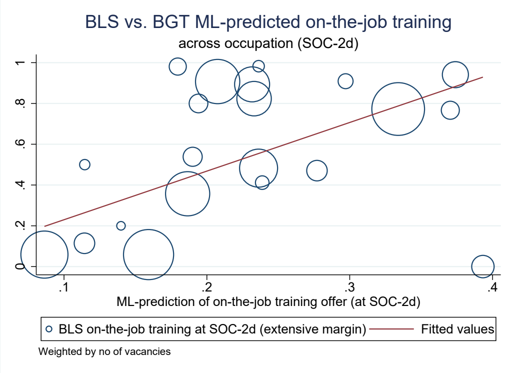
- **Burning Glass Technologies (BGT) vacancies data**
  - provides job postings data covering the near-universe of occupation, industries, and geographic areas in the USA (widely used in academic research)
  - Key elements for this study:
    - Job ad text
    - Location (MSA), time (year), occupation (6-dig SOC)
    - employer identifier
    - education, experience requirements
    - wages (if posted)
  - covers 2013-2019
  - permits construction of employer-based measures of employment concentration within **MSA-by-occupation cells**

Measuring training in job vacancies

- At the moment, no difference between general and specific training
- Training: any program that helps new hires to acquire new skills
- Two-step process
  1. Manual tagging of a sub-sample of job ads
     - detailed guideline for the tagging
     - over 6000 job ads, 12 researchers
     - some job ads assigned to multiple researchers to control for homogeneity
     - Some examples: *"we'll train you"*; *"Paid training"*; *"New employee training"*; *"Practice-paid continuing education opportunities"*; *"8-week comprehensive training program"*; *"No Experience Needed - Paid Training!"*
  2. Estimation of machine-learning models to predict on-the-job training offers
     - decision tree classifier to predicted posting training (70% accuracy)

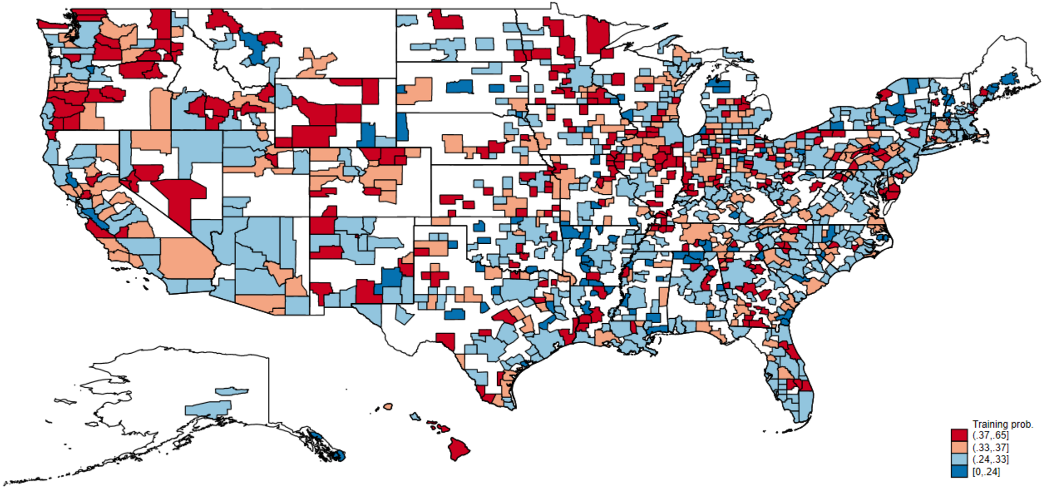
Comparison with other training data



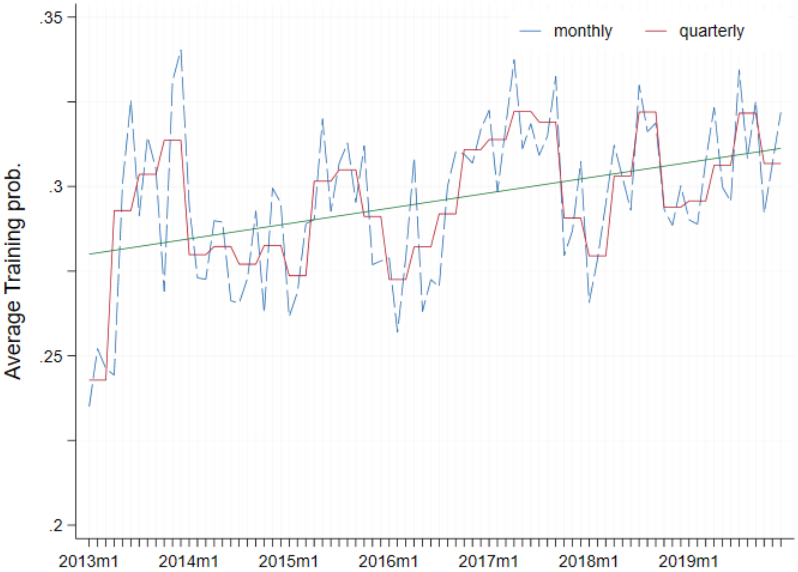


SIPP

Training offers: Across MSA



Training offers: Trend over Time



Measuring labor market competition

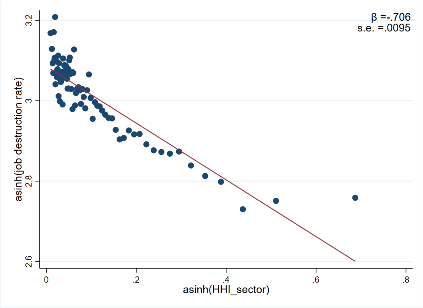
Two main issues:

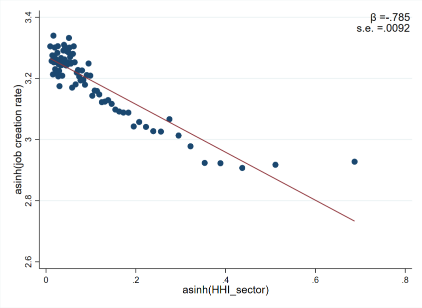
1. How to measure labor competition?
   - Herfindahl-Hirschman Index: $HHI_{imt} = \sum_{j=1}^{J} s_{jimt}^2$
     - s_{jitz} share of vacancies posted by employer j in occupation i, MSA m, and year t
   - Consistent with a Cournot model
   - Finest dimension and correlated with other labor market competition measures

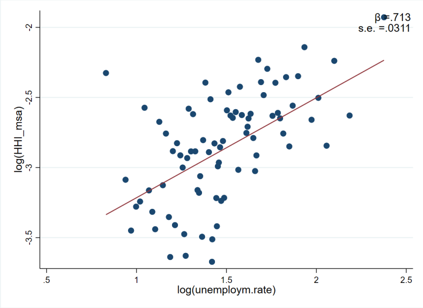
2. What is a local labor market?
   - Combination of geography, occupation, and time
     - MSA $\times$ occupation (6d-SOC) $\times$ year

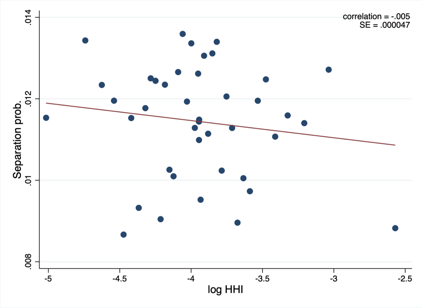
HHI distrib. HHI map

Comparison HHI with other labor competition measures









Empirical strategy

Empirical Strategy

Baseline specification:

$$y_{zjimt} = \beta log(HHI_{imt}) + \gamma X_{zjimt} + \mu_t + \mu_s + \mu_m + \mu_j + \varepsilon_{zjimt}$$

- y_{zjimt}: **predicted probability of offering training** for vacancy z, employer j, occupation i, MSA m, and year t
- X_{zjimt} are vacancy level controls, like: **experience and education requirements**
- the μs are **fixed effects** at year, occupation, MSA, and employer level
- unit of observation: **vacancy**
- clustered standard error at labor market level (MSA $\times$ occupation $\times$ year)
- Tractability: sample restricted to a random sample of 10% employers

Instrumental Variable Approach

- Endogeneity threat: **time-varying market-specific** shocks
- **Shift-share Bartik IV strategy**, as in [Schumbert, Stansbury, Taska (2021)]
  - instrument the change in concentration in a local labor market as the **predicted growth rate of hiring in the occupation**.

$$log(HHI^{instr.}_{imt}) = log\left[\sum_j s^2_{jim,t-1}\left(\frac{(1+\tilde{g}_{jit})^2}{(1+\sum_k s_{kimt}\tilde{g}_{kit})^2} - 1\right)\right]$$

    - where $\tilde{g}_{jit}$ is the national growth in vacancy for occupation i and year t leaving out employer j
- Conceptually, this identifies the effects of HHI on training using **only non-local (national) variations**

Baseline: Effect on Training

	Training	Training	Training	Training	Training	Training
log(HHI)	0.0228***	0.0099***	0.0041***	0.0154***	0.0084***	0.0035***
	(0.0009)	(0.0007)	(0.0005)	(0.0008)	(0.0006)	(0.0004)
Controls				✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓	✓	✓
NAICS_2d FE	✓	✓	✓	✓	✓	✓
SOC_6d FE		✓	✓		✓	✓
Employer_FE			✓			✓
MDV	0.302	0.302	0.302	0.302	0.302	0.302
mean(HHI)	0.085	0.085	0.086	0.085	0.085	0.086
std(log(HHI))	1.406	1.406	1.406	1.406	1.406	1.406
R^2	0.078	0.221	0.471	0.131	0.243	0.477
no employers	96,865	96,864	63,968	96,865	96,864	63,968
N	11,150,235	11,150,233	11,117,337	11,150,235	11,150,233	11,117,337

Notes: standard error in parenthesis, clustered at occupation × MSA × year level.

Different FE Binscatter

IV: Effect on Training

	Training	Training	Training	Training	Training	Training
log(HHI)	0.0193***	0.0173***	0.0071***	0.0130***	0.0151***	0.0064***
	(0.0012)	(0.0011)	(0.0009)	(0.0011)	(0.0011)	(0.0008)
Controls				✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓	✓	✓
NAICS_2d FE	✓	✓	✓	✓	✓	✓
SOC_6d FE		✓	✓		✓	✓
Employer_FE			✓			✓
MDV	0.303	0.303	0.303	0.303	0.303	0.303
mean(HHI)	0.070	0.070	0.070	0.070	0.070	0.070
std(log(HHI))	1.351	1.351	1.350	1.351	1.351	1.350
F	19,580	6,998	7,197	19,740	7,003	7,200
no employers	95,620	95,619	62,637	95,620	95,619	62,637
N	9,785,719	9,785,712	9,752,730	9,785,719	9,785,712	9,752,730

Notes: standard error in parenthesis, clustered at occupation × MSA × year level.

First Stage

IV: Effect on Training

	Training	Training	Training	Training	Training	Training
log(HHI)	0.0193***	0.0173***	0.0071***	0.0130***	0.0151***	0.0064***
	(0.0012)	(0.0011)	(0.0009)	(0.0011)	(0.0011)	(0.0008)
Controls				✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓	✓	✓
NAICS_2d FE	✓	✓	✓	✓	✓	✓
SOC_6d FE		✓	✓		✓	✓
Employer_FE			✓			✓
MDV	0.303	0.303	0.303	0.303	0.303	0.303
mean(HHI)	0.070	0.070	0.070	0.070	0.070	0.070
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no employers	95,620	95,619	62,637	95,620	95,619	62,637
N	9,785,719	9,785,712	9,752,730	9,785,719	9,785,712	9,752,730

HHI ↑of a IQ
Training +3%

Notes: standard error in parenthesis, clustered at occupation × MSA × year level.

First Stage

Conceptual Framework

- **Direct search model** as in [Shimer, (2005)]
- Firms post vacancies, workers observe vacancies and decide where to apply
- Consider the most stylized version:
  - Firms and workers are homogeneous and eternally living (no entry and exit)
  - Symmetric equilibrium: each agent behaves the same
- Expected number of applications (**queue length**) for a firm depends on the relative number of potential applicants in the economy

Conceptual Framework – Two markets

- Consider economy divided in two disjoint markets (A,B)
  - workers matched with a firm in their same market are more productive
  - capturing the idea of different occupations, which require different skills
- Firm can decide to post or not wages
  - wages are not type dependent and are binding
  - risk-averse workers: prefer vacancies with wages posted
- Concentration: proxy for relative number of suitable workers
  - a suitable candidate capture the idea of a skilled/experienced worker
  - job transitions are mostly on-the-job transitions
  - if most workers in an occupation are employed by the same employer, few other suitable candidates are left
- Vacancies can offer training by paying a fixed cost
  - training reduces the productivity gap due to mismatch

Conceptual Framework – Empirical predictions

- The **queue length** will depend on
  - relative number of suitable applicants
  - difference in productivity between occupation
- Vacancies in market with fewer suitable candidates (high concentration)
  - Train more, because it reduces probability the vacancy remain unfilled
  - Post less wages: hiring less productive workers are better than no match
- If productivity difference is small,
  - as we can expect in low-skilled occupations,
  - lower incentive to offer training
  - higher incentive to not posting wages

Baseline: Effect on Wage Posting

	Wage	Wage	Wage	Wage	Wage	Wage
log(HHI)	-0.0046***	-0.0151***	-0.0066***	-0.0081***	-0.0155***	-0.0068***
	(0.0005)	(0.0008)	(0.0006)	(0.0005)	(0.0008)	(0.0006)
Controls				✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓	✓	✓
NAICS_2d FE	✓	✓	✓	✓	✓	✓
SOC_6d FE		✓	✓		✓	✓
Employer FE			✓			✓
MDV	0.135	0.135	0.134	0.135	0.135	0.134
mean(HHI)	0.085	0.085	0.086	0.085	0.085	0.086
std(log(HHI))	1.406	1.406	1.406	1.406	1.406	1.406
R^2	0.165	0.201	0.423	0.172	0.202	0.423
no employers	96,865	96,864	63,968	96,865	96,864	63,968
N	11,150,961	11,150,959	11,118,063	11,150,961	11,150,959	11,118,063

Notes: standard error in parenthesis, clustered at occupation × MSA × year level.

Binscatter

IV: Effect on Wage Posting

	Wage	Wage	Wage	Wage	Wage	Wage
log(HHI)	-0.0019**	-0.0185***	-0.0094***	-0.0054***	-0.0193***	-0.0096***
	(0.0007)	(0.0013)	(0.0010)	(0.0007)	(0.0013)	(0.0010)
Controls				✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓	✓	✓
NAICS_2d FE	✓	✓	✓	✓	✓	✓
SOC_6d FE		✓	✓		✓	✓
Employer_FE			✓			✓
MDV	0.141	0.141	0.140	0.141	0.141	0.140
mean(HHI)	0.070	0.070	0.070	0.070	0.070	0.070
std(log(HHI))	1.351	1.351	1.350	1.351	1.351	1.350
F	6.71	213	94.7	638	256	78.5
no employers	95,620	95,619	62,637	95,620	95,619	62,637
N	9,786,427	9,786,420	9,753,438	9,786,427	9,786,420	9,753,438

↑

Notes: standard error in parenthesis, clustered at occupation × MSA × year level.

IV: Effect on Wage Posting

	Wage	Wage	Wage	Wage	Wage	Wage
log(HHI)	-0.0019**	-0.0185***	-0.0094***	-0.0054***	-0.0193***	$\boxed{\text{-0.0096***}}$
	(0.0007)	(0.0013)	(0.0010)	(0.0007)	(0.0013)	$\boxed{\text{(0.0010)}}$
Controls				✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓	✓	✓
NAICS_2d FE	✓	✓	✓	✓	✓	✓
SOC_6d FE		✓	✓		✓	✓
Employer_FE			✓			✓
MDV	0.141	0.141	0.140	0.141	0.141	0.140
mean(HHI)	0.070	0.070	0.070	0.070	0.070	0.070
std(log(HHI))	1.351	1.351	1.350	1.351	1.351	1.350
F	6.71	213	94.7	638	256	78.5
no employers	95,620	95,619	62,637	95,620	95,619	62,637
N	9,786,427	9,786,420	9,753,438	9,786,427	9,786,420	9,753,438

HHI ↑of a IQ
Wages -7.5%

Notes: standard error in parenthesis, clustered at occupation × MSA × year level.

Heterogeneity on Training: Low/High skill occupations

	High Skill		Low Skill	
	OLS	IV	OLS	IV
log(HHI)	0.0032***	0.0096***	0.0021***	-0.0007
	(0.0001)	(0.0003)	(0.0002)	(0.0004)
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
SOC_6d FE	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓
NAICS_2d FE	✓	✓	✓	✓
Employer_FE	✓	✓	✓	✓
MDV	0.252	0.253	0.358	0.358
mean(HHI)	0.095	0.081	0.075	0.059
std(log(HHI))	1.434	1.385	1.365	1.300
N	5,815,416	5,060,700	5,286,584	4,676,846
R^2	0.532	.	0.420	.
F	.	1,206,364	.	991,087

Notes: standard error in parenthesis, clustered at occupation × MSA × year level.

Heterogeneity on Wage Posting: Low/High skill occupations

	High Skill		Low Skill	
	OLS	IV	OLS	IV
log(HHI)	-0.0060***	-0.0041***	-0.0072***	-0.0154***
	(0.0002)	(0.0004)	(0.0002)	(0.0006)
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
SOC_6d FE	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓
NAICS_2d FE	✓	✓	✓	✓
Employer_FE	✓	✓	✓	✓
MDV	0.113	0.117	0.156	0.164
mean(HHI)	0.095	0.081	0.075	0.059
std(log(HHI))	1.434	1.385	1.365	1.300
N	5,815,738	5,061,013	5,286,988	4,677,241
R^2	0.447	.	0.421	.
F	.	1,206,489	.	991,232

Notes: standard error in parenthesis, clustered at occupation × MSA × year level.

Effect on Education and Experience

Dependent Variable:	Experience		Education		Graduate	
	OLS	IV	OLS	IV	OLS	IV
log(HHI)	-0.0264***	-0.0387***	-0.0210***	-0.0389***	-0.0070***	-0.0122***
	(0.0025)	(0.0045)	(0.0020)	(0.0036)	(0.0009)	(0.0015)
MDV	1.357	1.354	1.193	1.185	0.264	0.262
mean(HHI)	0.086	0.070	0.086	0.070	0.086	0.070
std(log(HHI))	1.406	1.350	1.406	1.350	1.406	1.350
R^2	0.367	.	0.455	.	0.456	.
F	.	7,198	.	7,198	.	7,198
no employers	63,968	62,637	63,968	62,637	63,968	62,637
N	11,118,063	9,753,438	11,118,063	9,753,438	11,118,063	9,753,438

Notes: standard error in parenthesis, clustered at occupation × MSA × year level.
Experience = years of exp.; Education index (0-5).

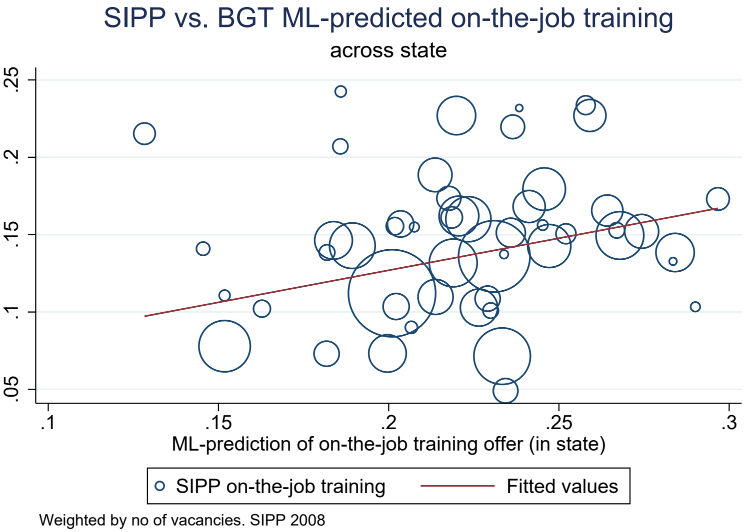
other vars exp. by skill grad. by skill

Conclusion

- Develop a **novel measure of on-the-job training** through a supervised machine learning technique
- Found a **positive effect of concentration on training**
  - An IQ increase of the concentration increases training offers by 3%
- Found a **negative effect of concentration on wage posting decisions**
  - An IQ increase of the concentration decreases wage posting by 7.5%
- **Heterogeneous results across** high and low skill **occupations**
  - Training effect is stronger in high-skill occupation
  - Wage disclosure effect is stronger in low-skill occupations
- Reduction of education and experience requirements with concentration

Thank you
for your attention

Training measure comparison across states



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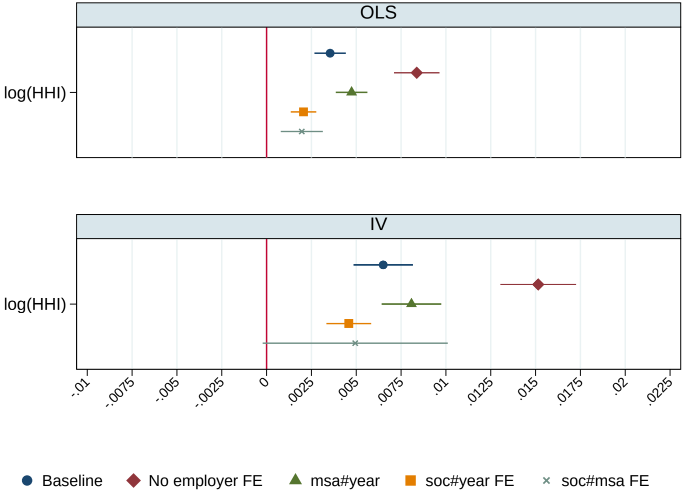
Different FE combinations



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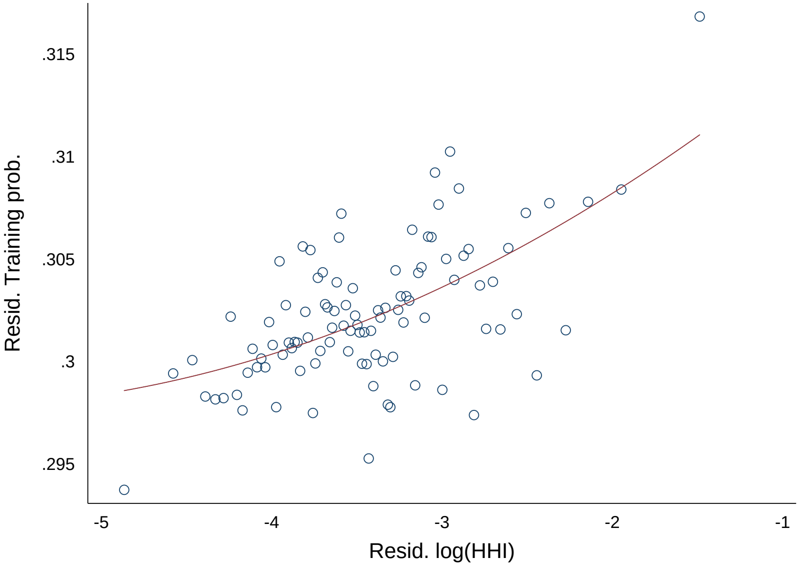
Binned scatter plot on Training



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First Stage

	log(HHI)	log(HHI)	log(HHI)	log(HHI)	log(HHI)	log(HHI)
log(HHI$^{\text{instr.}}$)	0.6737***	0.3929***	0.3713***	0.4019***	0.3927***	0.3713***
	(0.0048)	(0.0047)	(0.0044)	(0.0047)	(0.0047)	(0.0044)
Controls				✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓	✓	✓
NAICS (2d) FE	✓	✓	✓		✓	✓
SOC (6d) FE		✓	✓	✓	✓	✓
Employer FE			✓			✓
R^2	0.709	0.846	0.857	0.850	0.846	0.857
N	9,786,427	9,786,420	9,753,438	11,167,895	9,786,420	9,753,438

Notes: standard error in parenthesis, clustered at occupation × MSA × year level.

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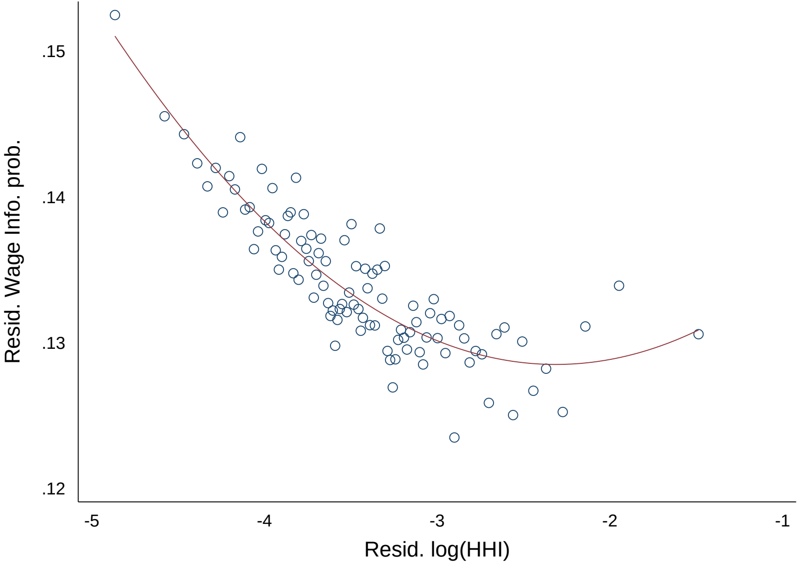
Binned scatter plot on Wage Information



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IV: Other variables

	No. Words	Average Syllables	Openness	Other 3
log(HHI)	1.1109	-0.0028***	0.0077***	0.0010
	(0.6824)	(0.0005)	(0.0015)	(0.0016)
MDV	349.772	2.134	0.288	0.410
mean(HHI)	0.070	0.070	0.070	0.070
std(log(HHI))	1.350	1.350	1.350	1.350
F	7,200	7,197	7,201	7,201
no employers	62,637	62,637	62,637	62,637
N	9,752,730	9,750,133	9,753,438	9,753,438

Notes: standard error in parenthesis, clustered at occupation $\times$ MSA $\times$ year level.

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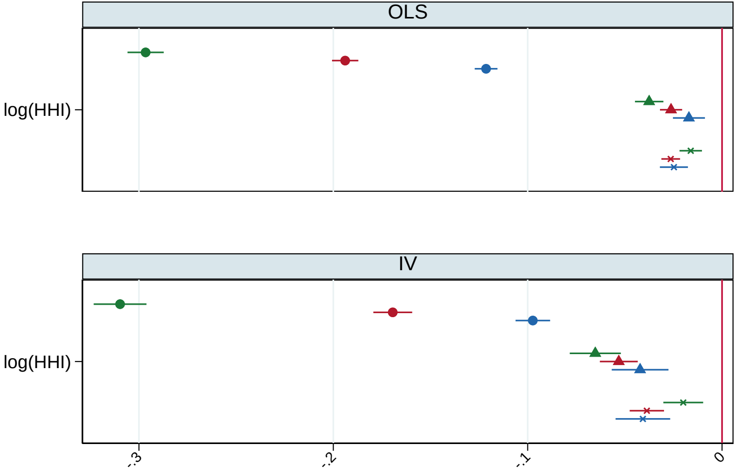
based on Big 5 personality traits:

Openness to Experience: {'intellectual', 'creative', 'complex', 'imaginative', 'bright', 'innovative', 'introspective'}

Other 3: Extraversion, Agreeableness, Conscientiousness; (Neuroticism excluded)

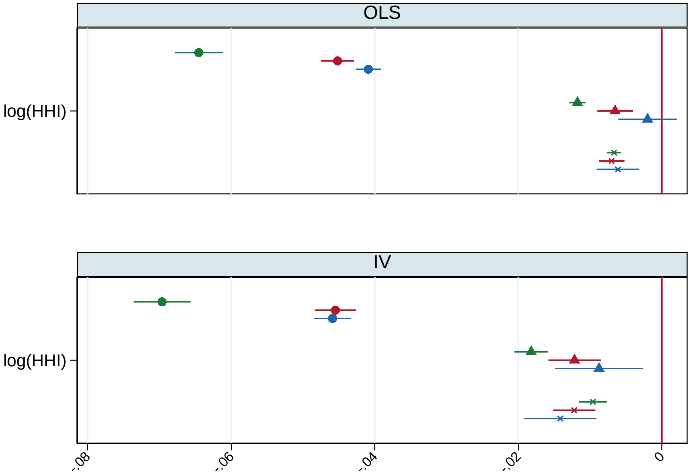
Coefplot. Experience by skill



back

Low skill, High skill, Pooled. Circles: Year, MSA, Naics FE. Triangles +SOC. Crosses +employer

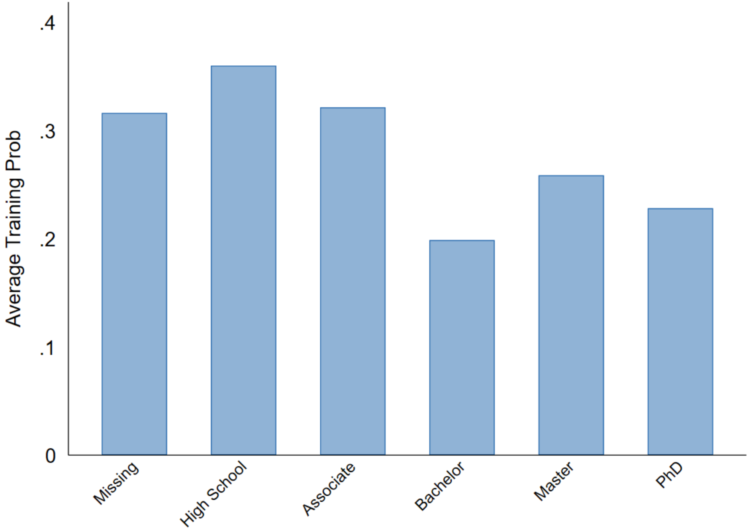
Coefplot. Graduate by skill



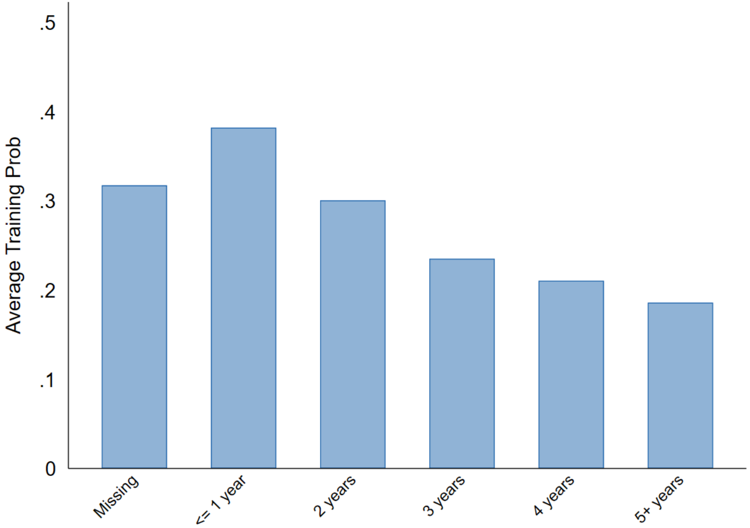
back

Low skill, High skill, Pooled. Circles: Year, MSA, Naics FE. Triangles +SOC. Crosses +employer

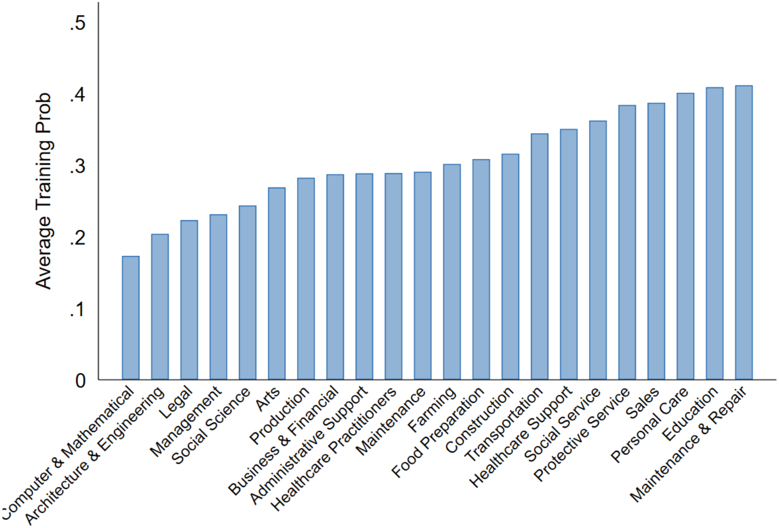
Training prob. by education req.



Training prob. by experience req.

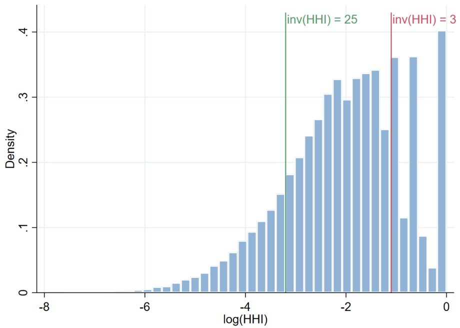


Training prob. by occupation

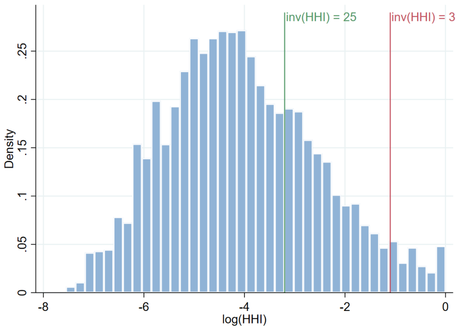


HHI distribution

(a) across markets



(b) across vacancies



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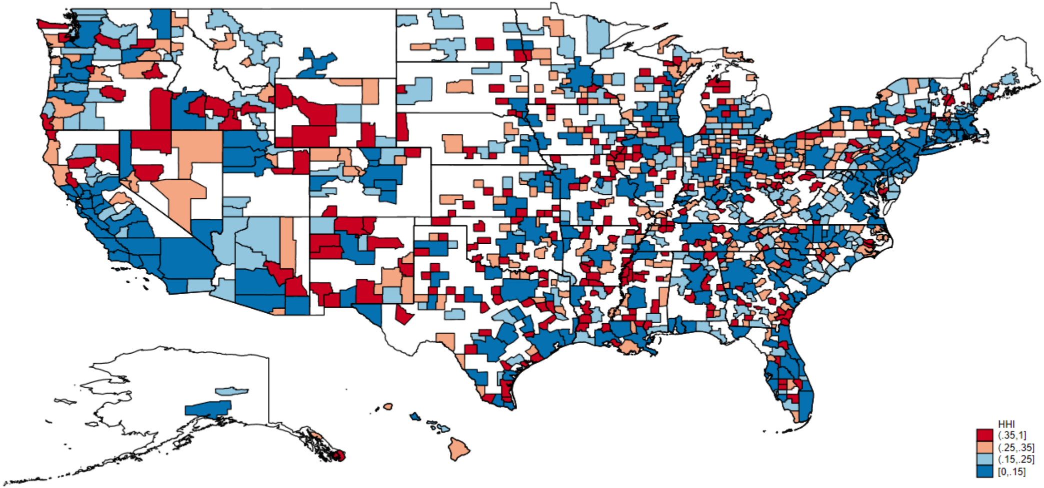
HHI map



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