This Job Ain't What It Used to Be:

Changes in Occupational Tasks and the Costs of Job Loss

Boris Ivanov
(IAB, ZEW)

EEA ESEM Conference 2024
Labour Market Policies for the Vulnerable
August 27, 2024

Motivation

- **New production technologies**
  - Technological innovation (e.g. Autor et al., 2022)
  - Organizational change (e.g. Battisti et al., 2022)

→ Change job tasks of workers

- 21% of EU workers: “skills very likely outdated in 5 years” (European Skills and Jobs Survey 2014)

→ Speed of technology diffusion (Adao et al., 2023; Lipowski, 2024)

- Is human capital vintage specific?
- Do incumbent workers adjust to task change?

This Paper

- **Measure:** Task change within occupations
  - German Microcensus: large, representative, consistent... yet untapped

- **Estimate:** Effect on worker earnings
  - SIAB: Social security records
  - Plant closure as shock

- **Empirical Strategy:**
  - Compare outcomes of displaced workers: **Low**/**High** vs. **Zero** task change
  - Triple-Diff's to account for unobserved differences

Preview of Results

- **Job loss after high task-change** (Q4 vs. Q1):
  - +75% earnings losses
  - -30% days employed
  - +40% occupation switches

- Not explained by:
  occupation tenure, individual or firm wage premiums

→ HK is vintage-specific

→ Task change: skills mismatch with vacancies (using new tech vintage)

Contributions

- **Technological change and worker outcomes**
  (e.g. Autor et al., 2003, ... , Spitz-Oener, 2006; Janssen & Mohrenweiser, 2018; Horton et al., 2020; Hudomiet & Willis, 2022; Deming & Noray, 2020; Atalay et al., 2020)

  → Within occupations, gradual diffusion of new production tech's

- **Vintage specific human capital**

  (e.g. Chari & Hopenhayn, 1991; Kredler, 2014; Kogan et al., 2022)

  → Empirical support

- **Costs of job displacement**
  (e.g. Jacobsen et al., 1993, ... , Gathmann & Schönberg, 2010; Goos et al., 2020; Blien et al., 2021; Braxton & Taska, 2023)

  → Skill obsolescence and mismatch

Outline

1. Data, Measurement, Descriptives
2. Empirical Strategy
3. Results
4. Summary and Conclusions

1 Data, Measurement, Descriptives

Data

Task data: Microcensus

- Repr. 1% sample of German population, N ≈ 175k to 500k, 1973-2011
- 178 occupations (*KldB*), most important job task (j=1,...,11) (Maier, 2020)

→ Cosine distance: Change in **task composition of jobs <u>within</u> occupation**
(Gathmann & Schönberg, 2010)

Worker data: SIAB

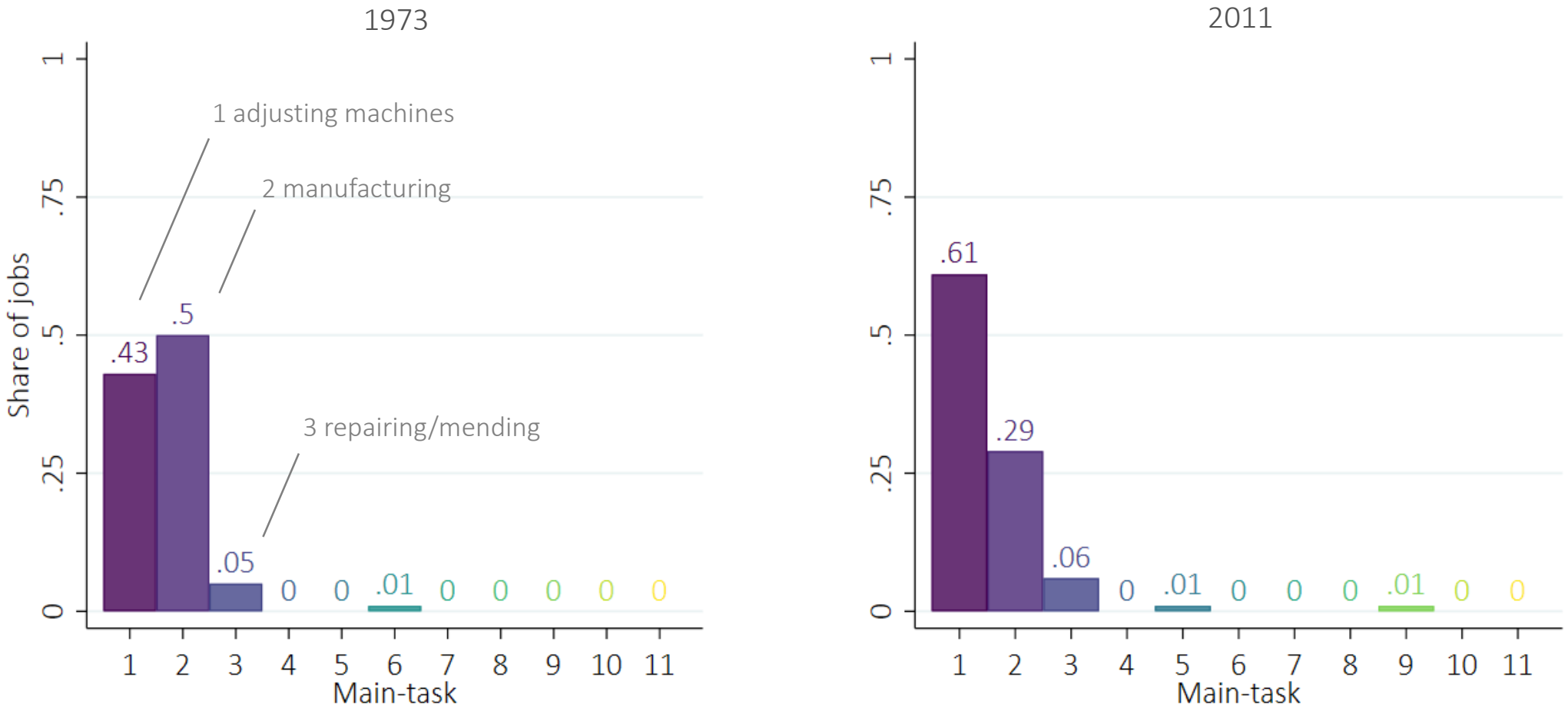
- Rand. 2% sample of German social security records, 1975-2010
- Occupation *o* (*KldB*), year of entry *e*, year of job loss *c,* earnings etc.

→ Plant closures: N_D≈ 14k (200-600 pa) , N_{ND}≈ 630k (Dauth & Eppelsheimer, 2020)

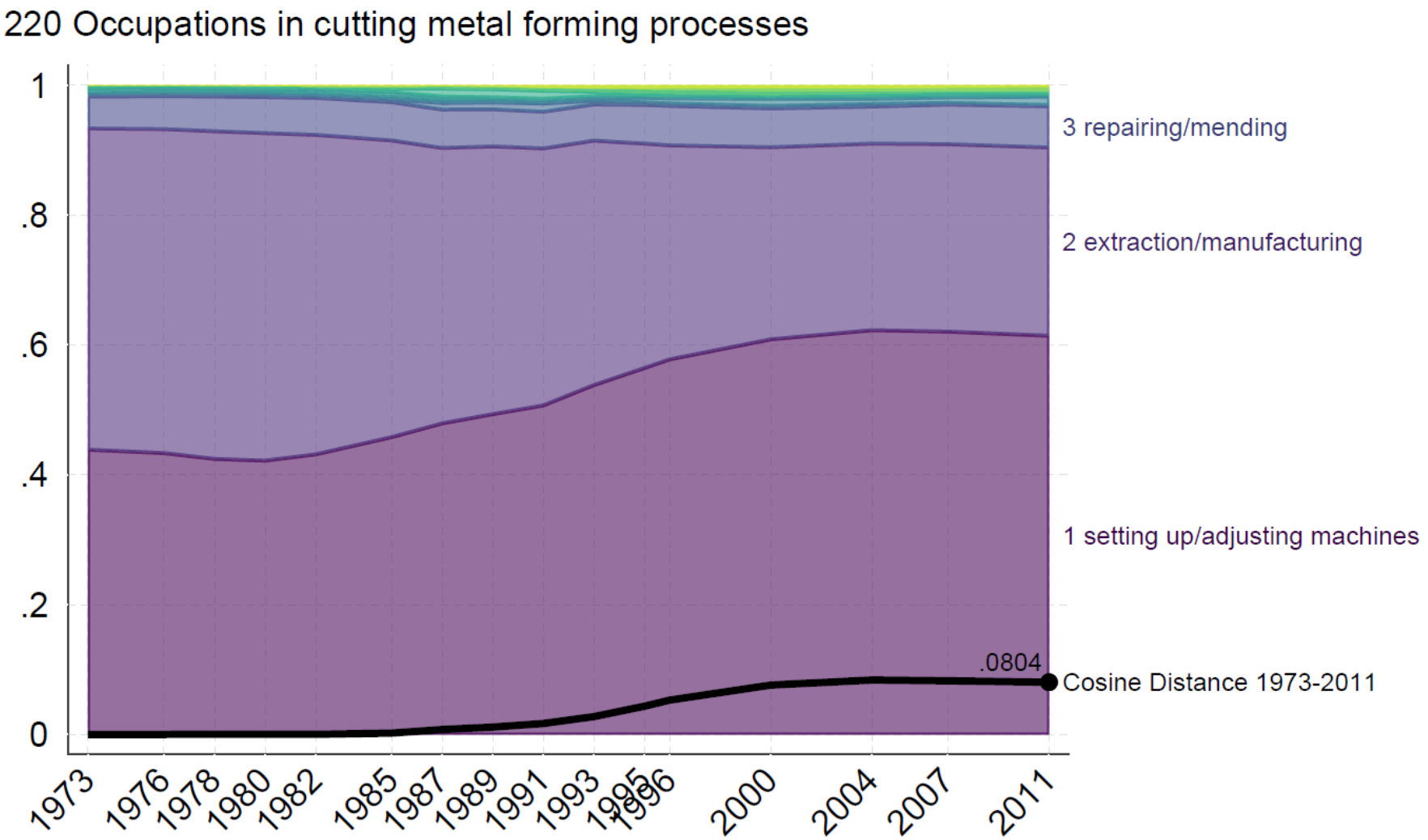
SIAB Microcensus/OPTE

Tasks Data, Example

220 Occupations in cutting metal processing



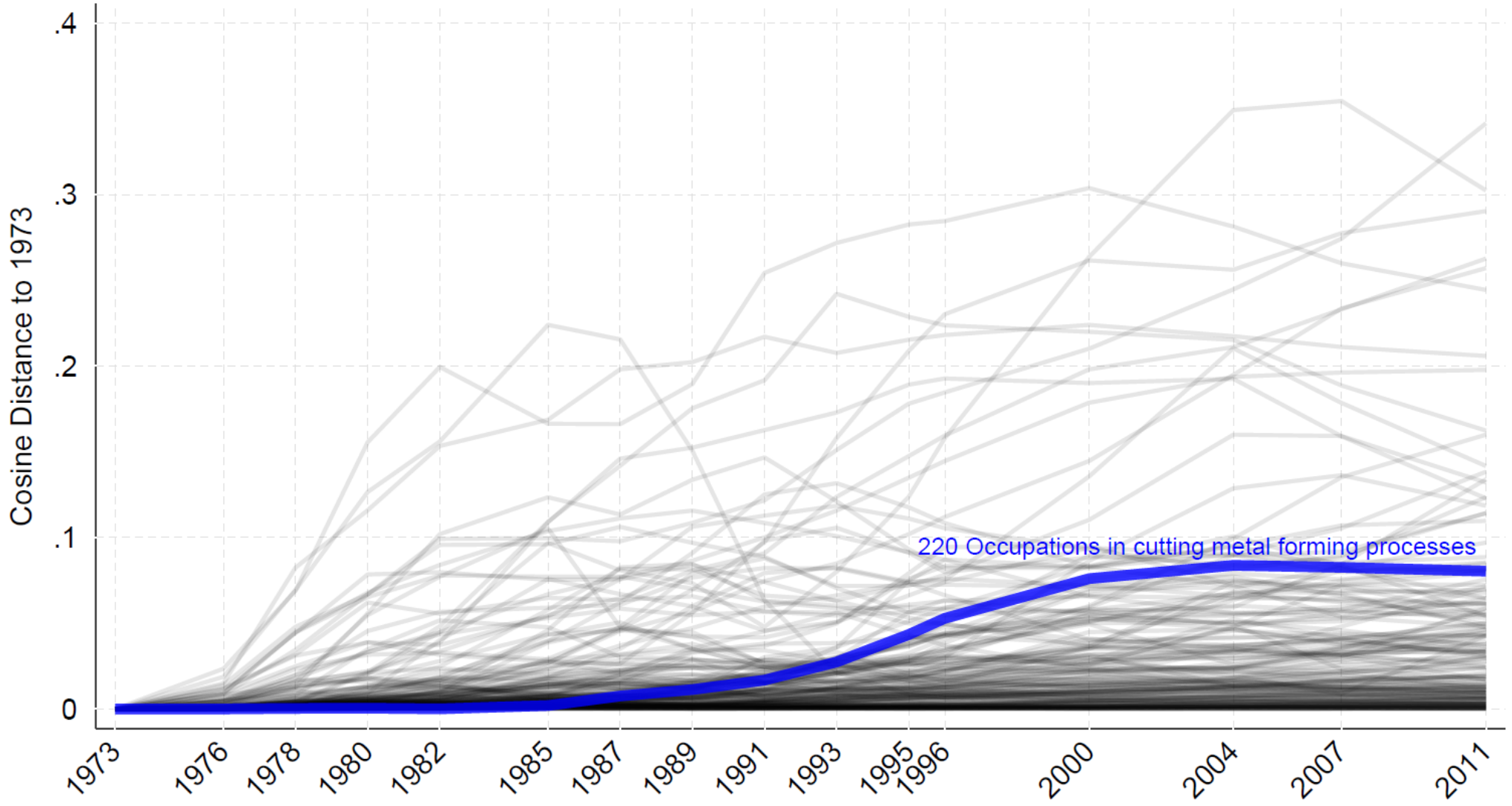
Task Composition Change and Cosine Distance, Example



0.08 ≈ Distance between „220 Cutting metal...“ & „210 Non-cutting metal...“ in 1973

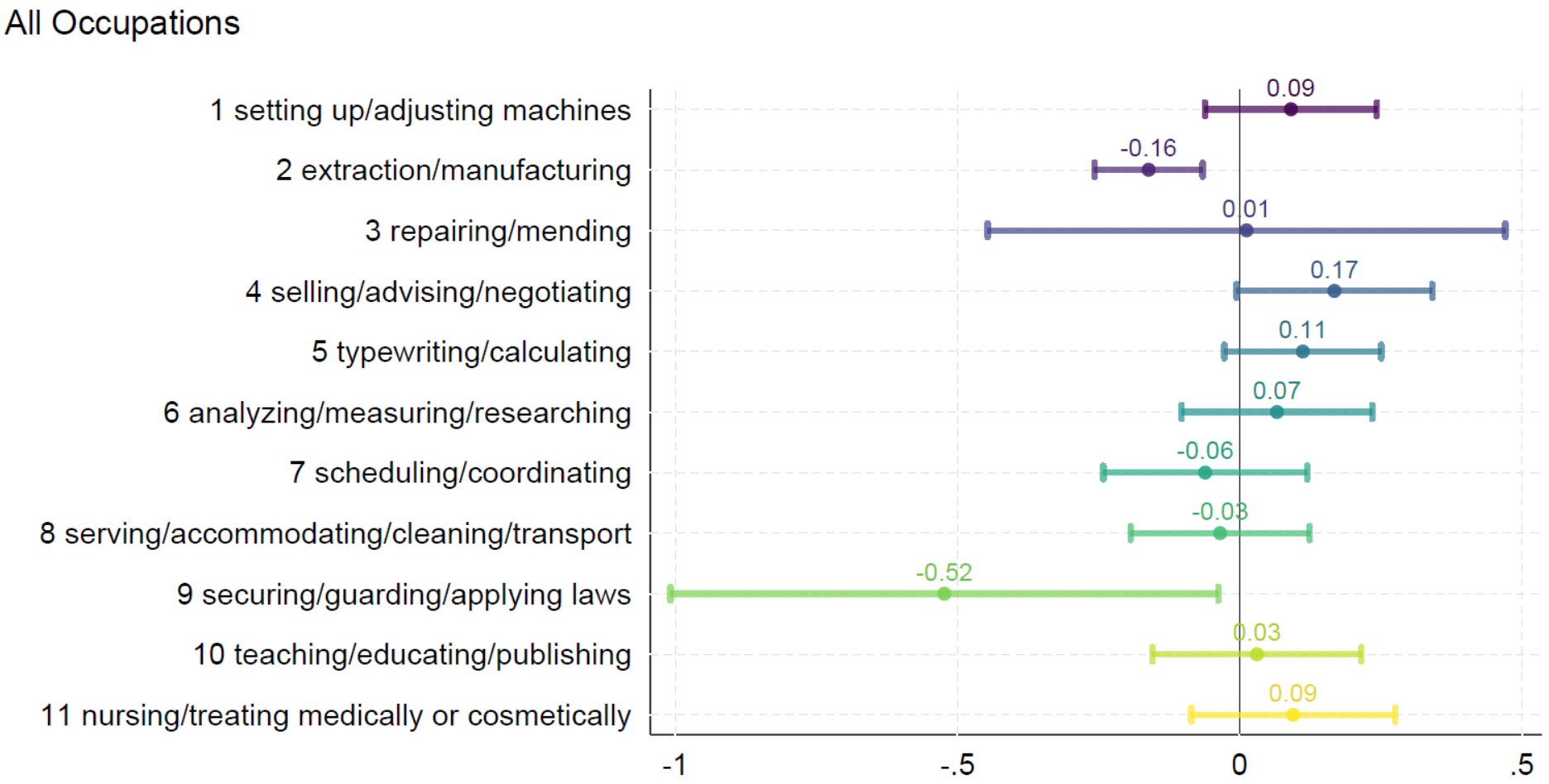
Cosine distance formula Illustration

Task Composition Change Within Occupations



Top/Bottom 5 By occupation categories

Which task shifts are driving changes in composition?

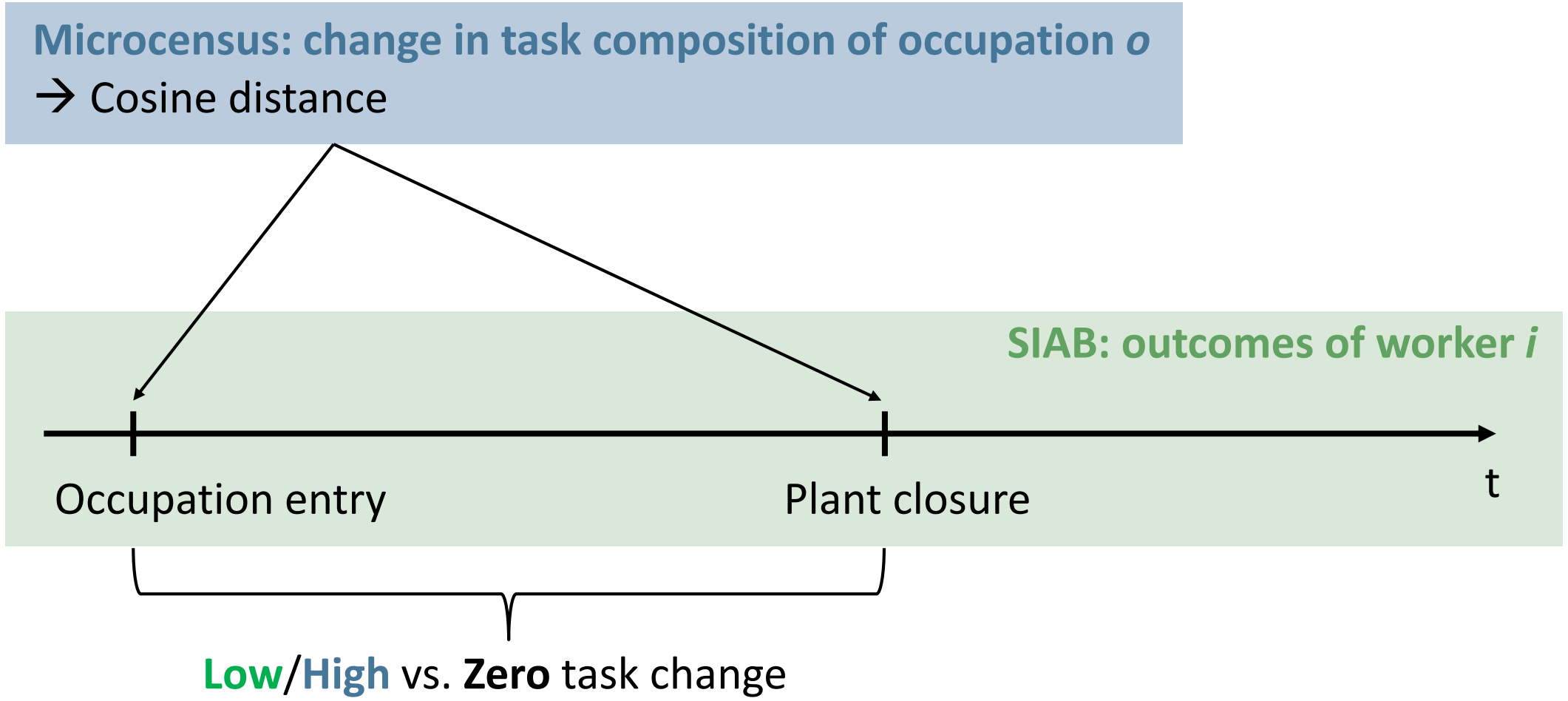


Note: *D* and ΔTS rescaled to [1,100]. Mean Distance = 4.4 , NxT = 2609, controlling for composition changes (age, gender, marital status, formal qualification).

$$CosineDistance_o^{1973,t} = \alpha + \beta_j \, \Delta^{1973,t} \, TaskShare_{jt} + \gamma \mathbf{X}_{ot} + \epsilon_{ot}$$

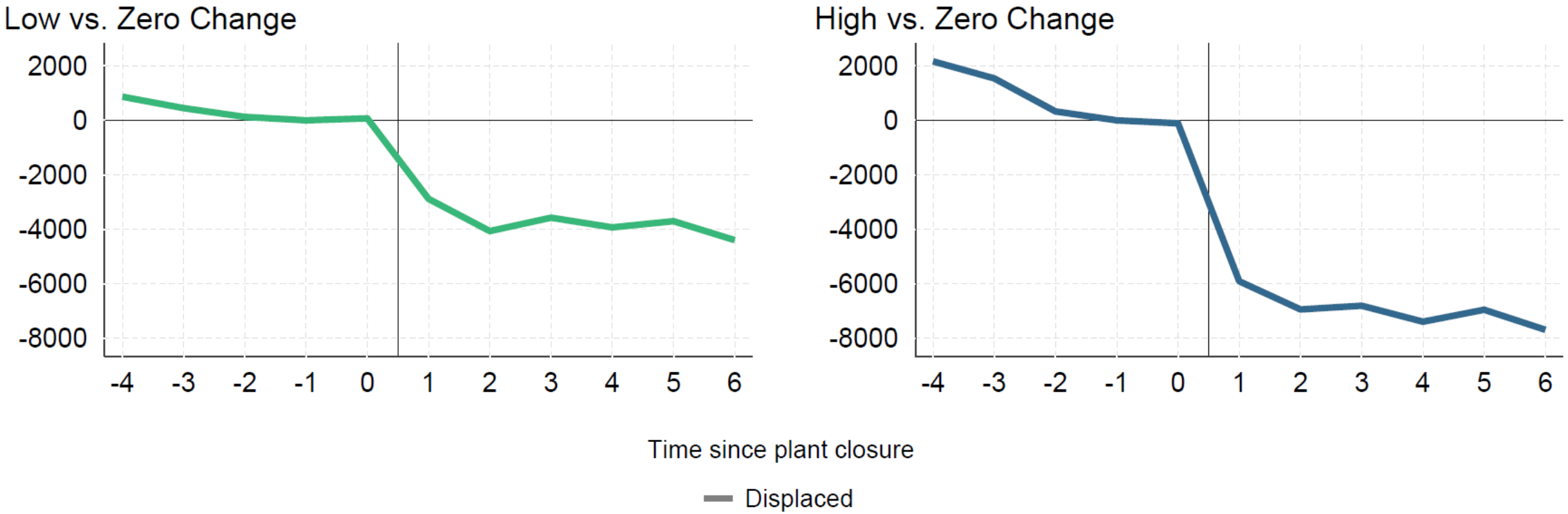
2 Empirical Strategy

Setup


Microcensus: change in task composition of occupation *o*
→ Cosine distance
SIAB: outcomes of worker *i*
Occupation entry
Plant closure
t
Low/High vs. Zero task change

Identification

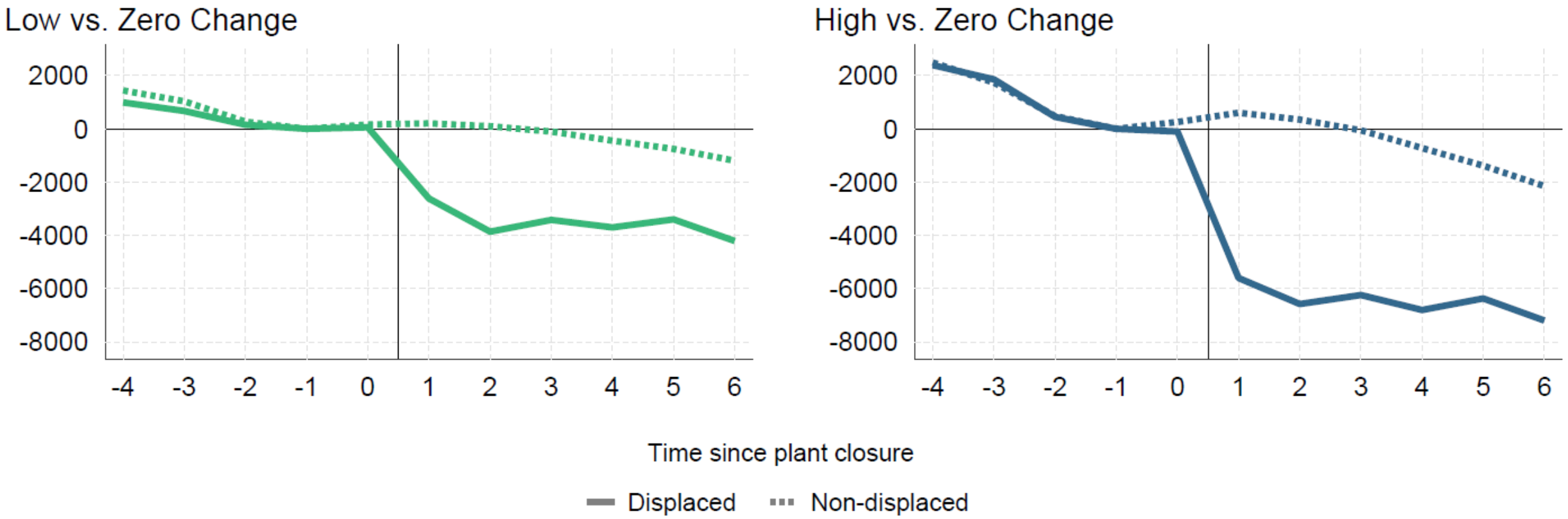
Labor Earnings per Year



- **Diff-in-Diff's:** Low/High vs. **Zero**
- **Assumption:** Parallel trends ? → Probably **no**

Identification

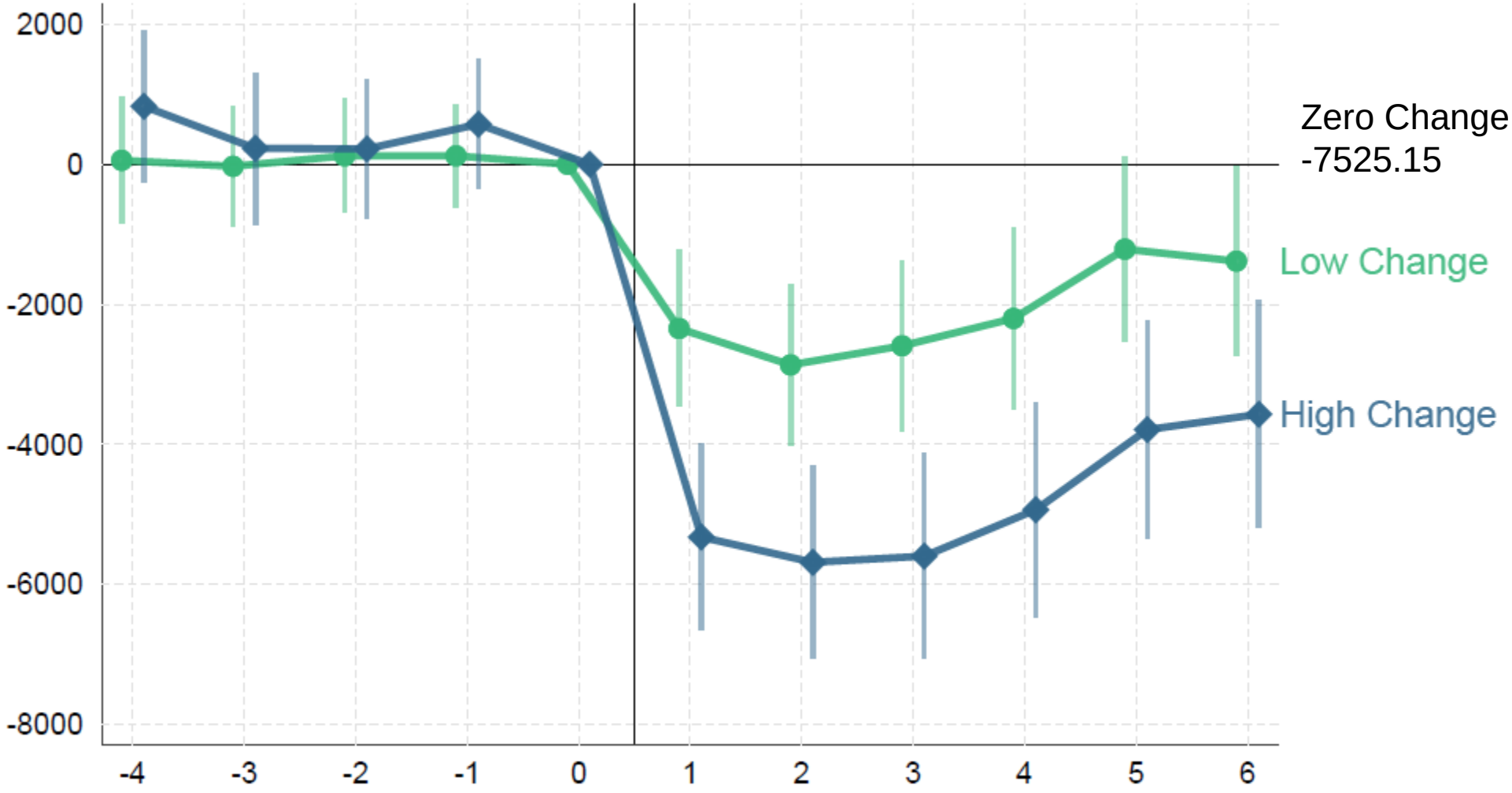
Labor Earnings per Year



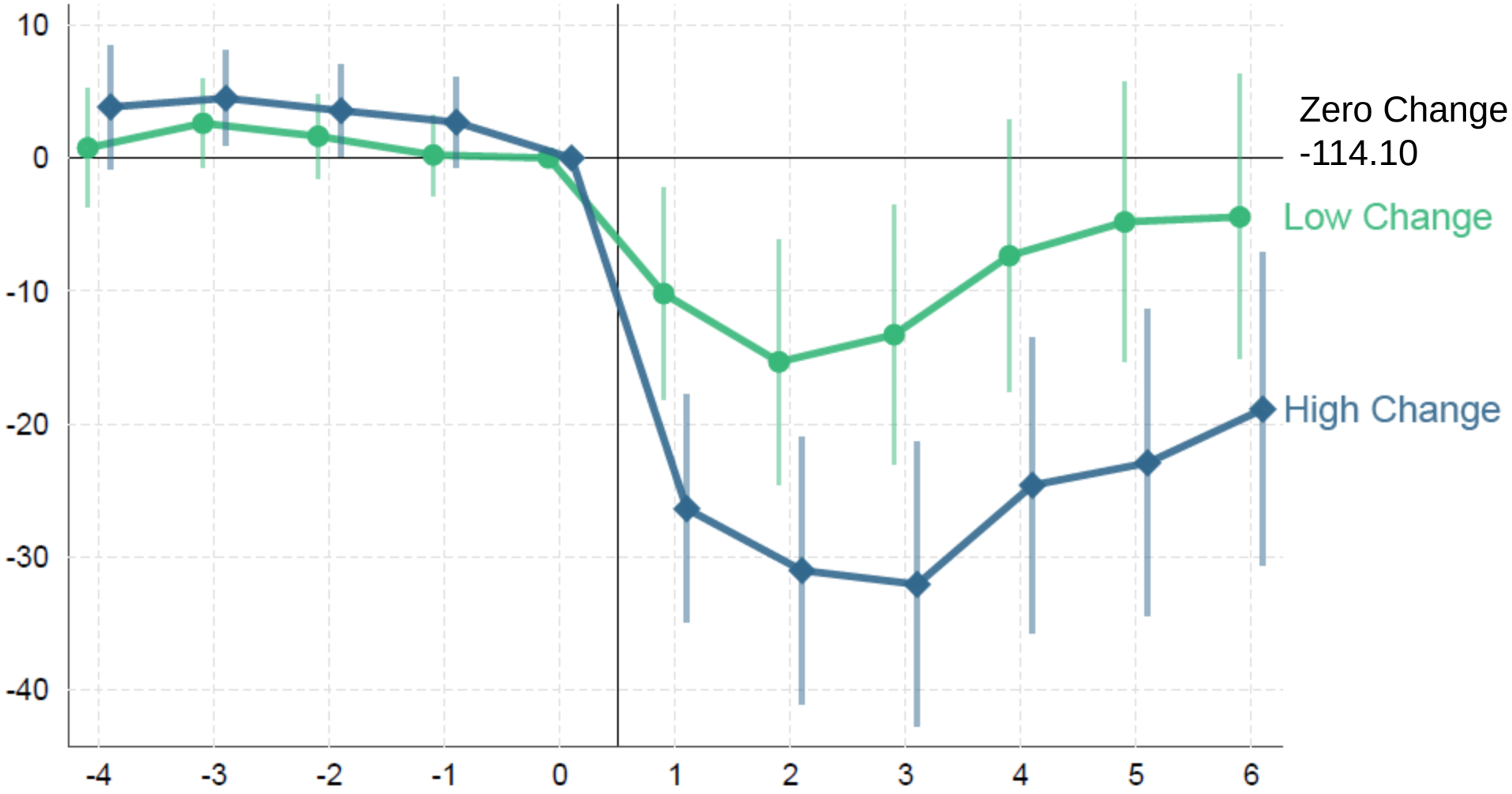
- **Triple-Diff's:** **(Low/High** vs. **Zero)** vs. Non-displaced
- **Assumption:** Bias displaced = bias non-displaced → Probably **yes** (Olden & Møen, 2022)

3 Results

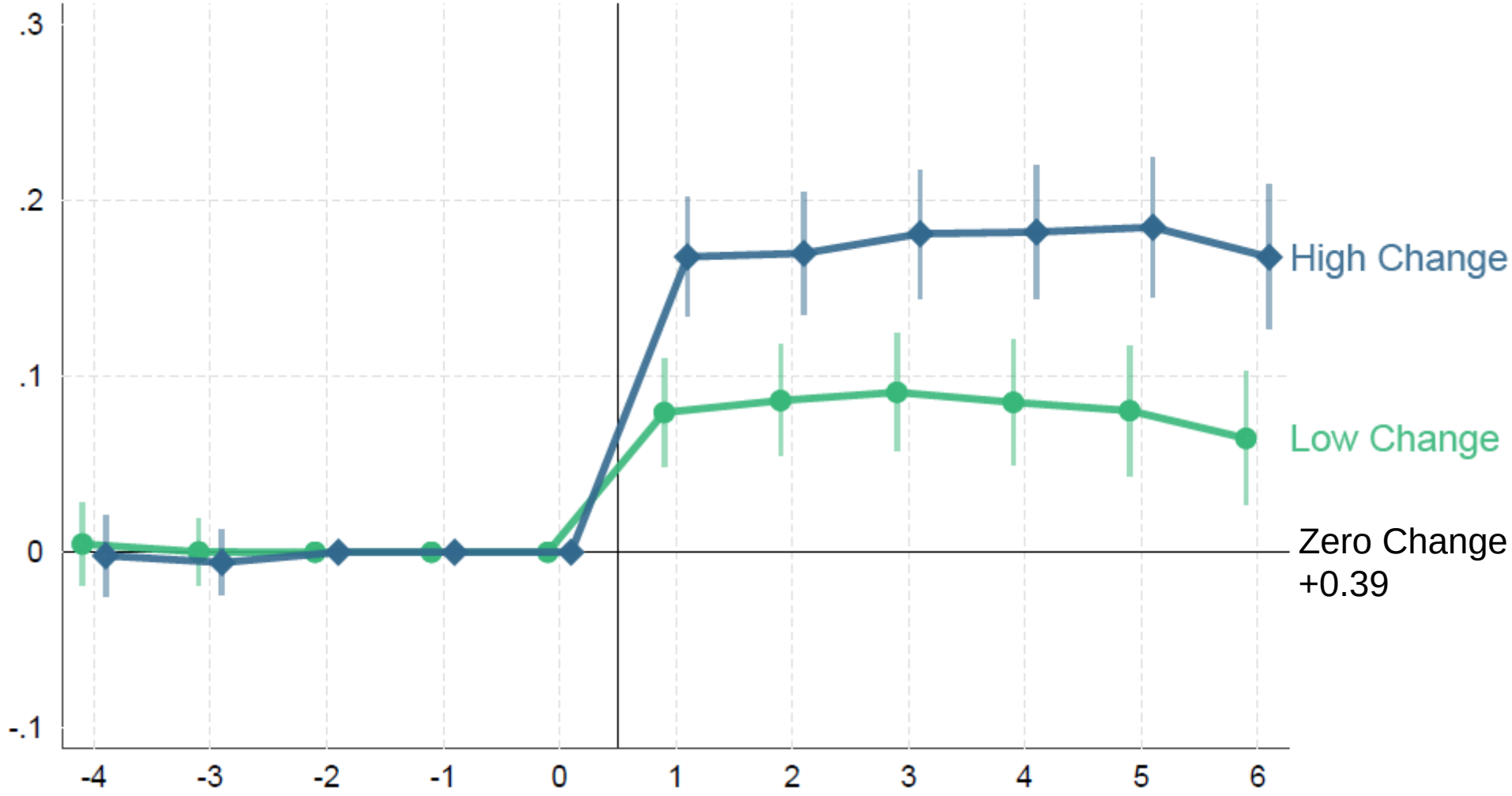
Labor Earnings per Year



Days Employed per Year



Switching out of Baseyear Occupation



Average Effect on Earnings Losses

Labor Earnings per Year		Conditional on	
	All	**Re-Employed**	**Same Occupation**
Zero Change	ref.	ref.	ref.
Low Change	**-2,152.7*** **	**-1,490.6*** **	**-352.2**
	(491.5)	(450.4)	(604.2)
High Change	**-5,183.8*** **	**-2,711.8*** **	**1,681.0***
	(578.5)	(526.4)	(772.6)
Matched sample	✓	✓	✓
N	310,068	256,888	212,907
Adj. R^2	0.069	0.032	0.041

Alternative Mechanism: Task Change vs. Occupation Tenure

Labor Earnings per Year	Occupation Tenure		
	Low	**Medium**	**High**
Zero Change	ref.	ref.	ref.
Low Change	**-987.0**	**-1,623.8***	**-1,089.2**
	(812.9)	(732.6)	(1,178.2)
High Change	**-517.6**	**-3,560.8*****	**-4,344.7*****
	(1,308.2)	(830.0)	(1,245.8)
Matched sample	✓	✓	✓
Mean occupation tenure	3.3	10.2	21.4
N	89,793	150,084	67,837
Adj. R^2	0.040	0.063	0.130

4 Summary and Conclusions

Summary and Conclusions

- **Effect of changes in occupational job tasks on costs of job loss:**
  - +75% earnings losses
  - -30% days employed
  - +40% occupation switches

  } Main drivers of earnings losses

- Task change → skills obsolescence, mismatch
- Supports vintage specific HK theory

- Policy:
  - Incentivize training → worker welfare + tech diffusion (Adao et al., 2023; Lipowski, 2024)
  - Foster beneficial switches (Belot, Kircher & Muller, 2019; Altmann et al., 2023)

✉ Boris.Ivanov2@iab.de

Thank you!

Appendix

Task Data

- Microcensus, 1973-2011, N ≥ 173,000

- Aggregated to occupation level: (Maier, 2020)
  - 178 occupations, N ≥ 30
  - 11 main tasks → share of workers
  - West Germany, >1h work per week, s.t. SSC

- **Pro:** Long time + consistent + large N
- **Con:** Only Main task → underestimates task change → Lower bound

Back

Sample Restrictions SIAB

Plant closures:

- No more than 30% of workers move to same new plant ID

Workers:

- FT SSC workers
- Age 24-59
- n-spell or spell in East Germany since $c - 4$
- Agriculture, mining and “peculiar” occupations
- Establishment with <500 employees (very few plant closures)

→ -4 to +6 year panel around baseyear c

Back

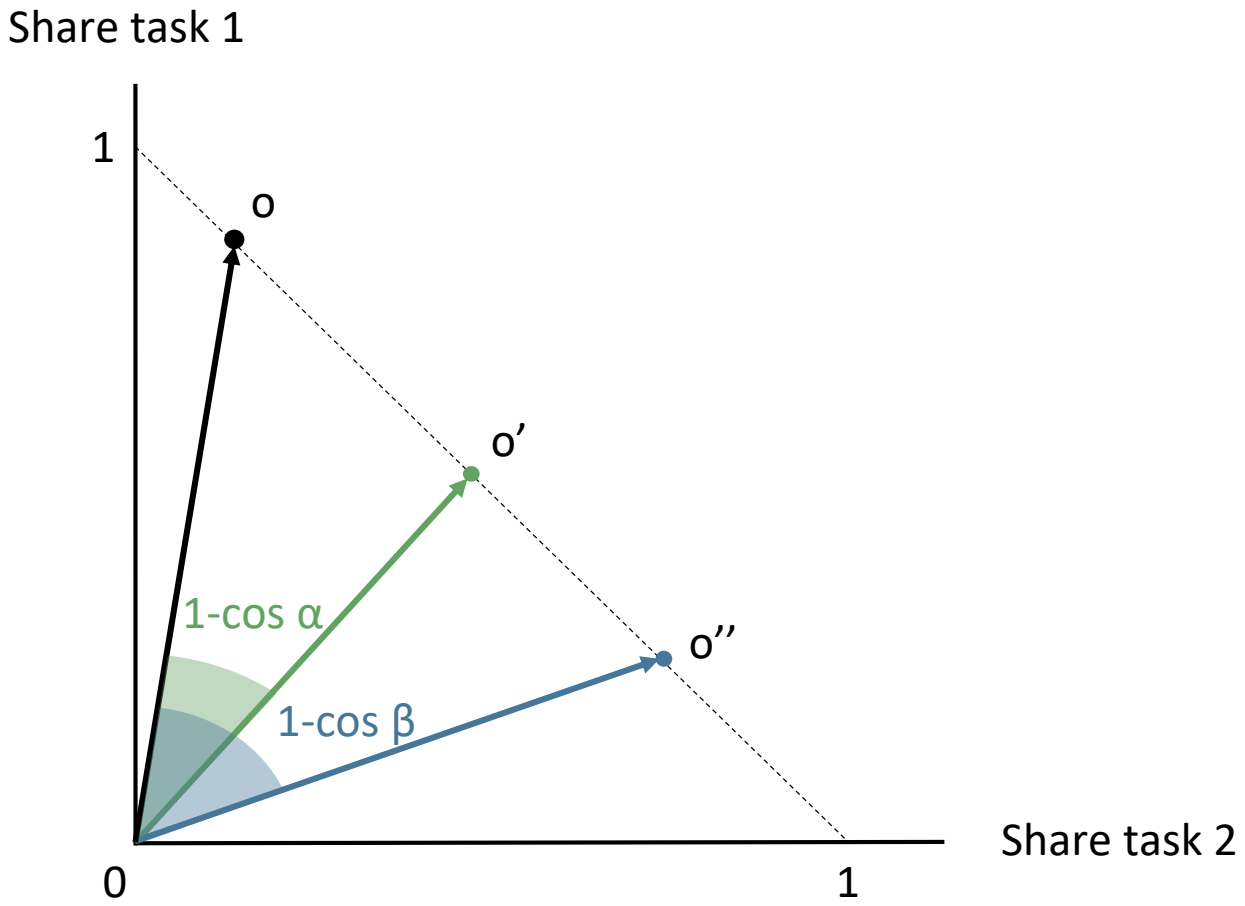
Cosine Distance

$$\mathcal{D}_{ott'} = 1 - \frac{\sum_{j=1}^{11} q_{jot} \times q_{jot'}}{\sqrt{\sum_{j=1}^{11} q_{jot}^2 \times q_{jot'}^2}}$$

- Cosine Distance of task vector *o* at *t* and *t'* (Gathmann & Schönberg, 2010)
- Change in the task composition of jobs in occupation *o* between *t* and *t'*
- Scaled 0 to 1

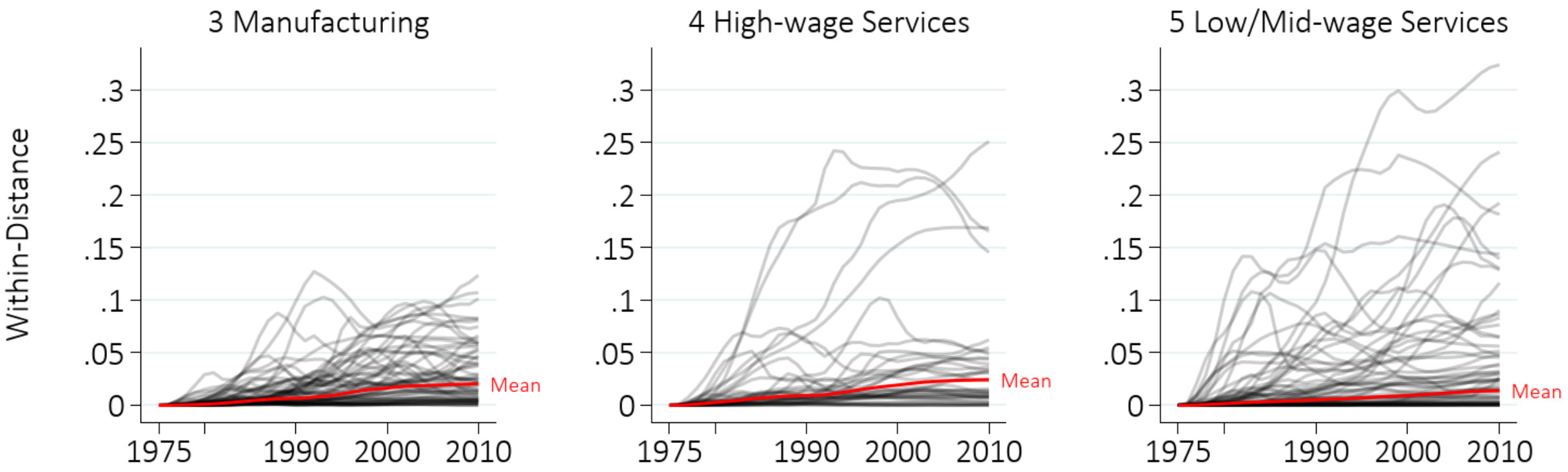
Back

Cosine Distance, Illustration



Back

Within Distance by Occupation Category



Back

Top/Bottom 5: Cosine Distance 1973-2011

Rank	Occupation	Cosine Distance 1973-2011	Most Important Main Task 1973	Share	Most Important Main Task 2011	Share
167	936 Occupations in vehicle cleaning and vehicle care	29.04	3 repairing/mending	38.53	8 serving/accommodating/ cleaning/transport	79.84
166	627 Other production technicians	26.27	7 scheduling/coordinating	26.03	6 analyzing/measuring/researching	28.61
165	793 Janitors, gatekeepers	25.71	9 securing/guarding/applying laws	32.87	3 repairing/mending	44.86
164	704 Commercial brokers, real estate agents	24.44	1 setting up/adjusting machines	20.13	4 selling/advising/negotiating	33.21
163	631 Specialised biological-technical workers	20.59	2 extraction/manufacturing	34.47	6 analyzing/measuring/ researching	69.96
162	752 Marketeers, advert. professionals, controllers, organisers, business consult.	19.78	7 scheduling/coordinating	34.33	7 scheduling/coordinating	32.62
...						
5	841 Medical doctors	0.02	11 nursing/treating medically or cosmetically	95.61	11 nursing/treating medically or cosmetically	94.11
4	851 Healers, masseuses, balneotherapists, therapeutic occupations	0.02	11 nursing/treating medically or cosmetically	95.09	11 nursing/treating medically or cosmetically	97.19
3	481 Construction finishers	0.01	2 extraction/manufacturing	72.27	2 extraction/manufacturing	70.37
2	842 Dentists	0.01	11 nursing/treating medically or cosmetically	96.29	11 nursing/treating medically or cosmetically	96.71
1	872 Upper secondary school teacher	0.00	10 teaching/educating/publishing	95.63	10 teaching/educating/ publishing	94.38

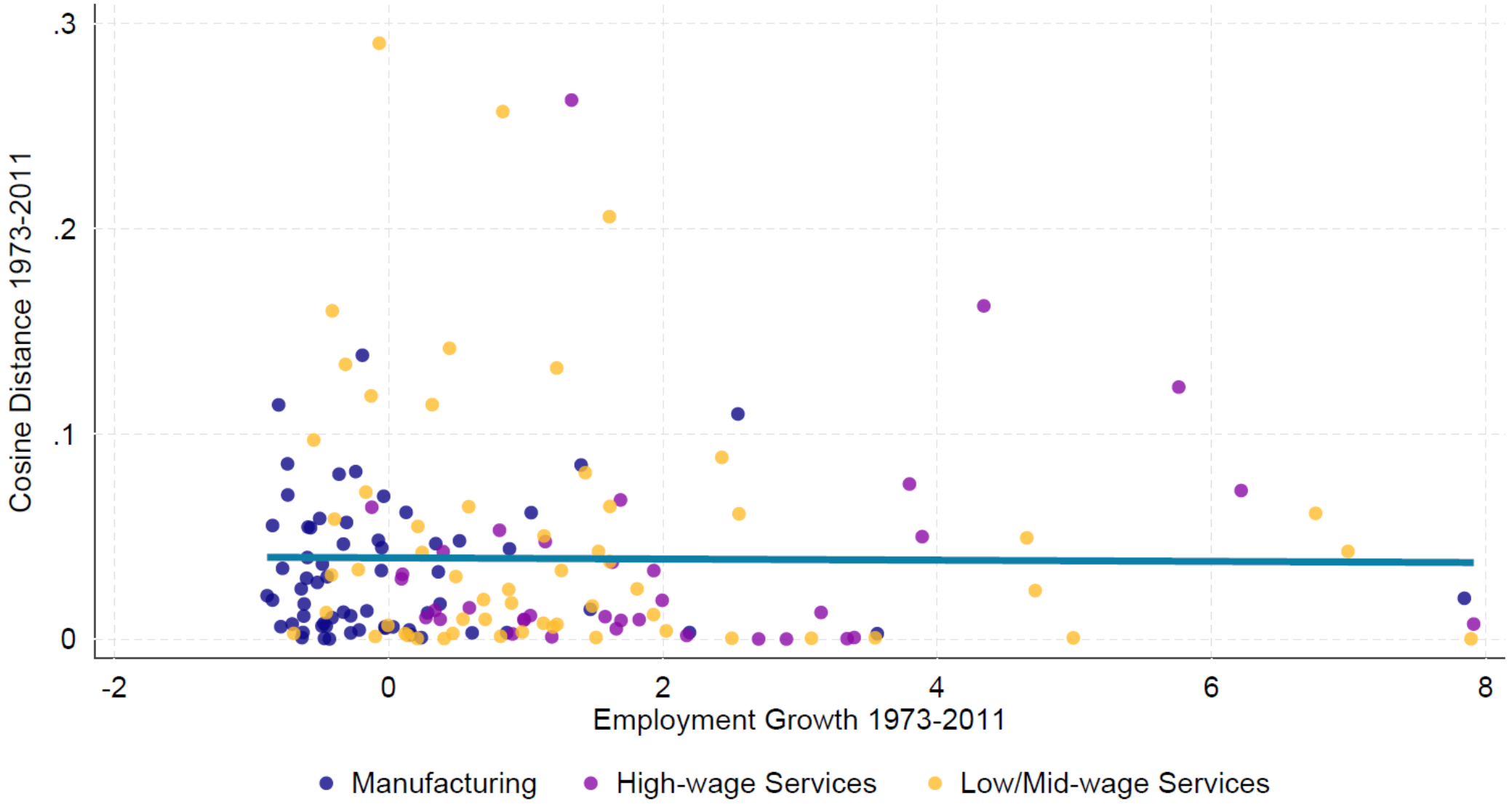
Back

Triple Differences Specification

$$
\begin{aligned}
Y_{ioect} = & \sum_{k=1}^{2} \beta_{1k} E_k \cdot Post_t \cdot Disp_{ic} \\
& + \sum_{k=1}^{2} \beta_{2k} E_k \cdot Post_t + \sum_{k=1}^{2} \beta_{3k} Disp_i \cdot E_k + \beta_4 Disp_{ic} \cdot Post_t \\
& + \sum_{k=1}^{2} \beta_{5k} E_k + \beta_6 Post_t + \beta_7 Disp_{ic} \\
& + \alpha + \epsilon_{ioect}
\end{aligned}
$$

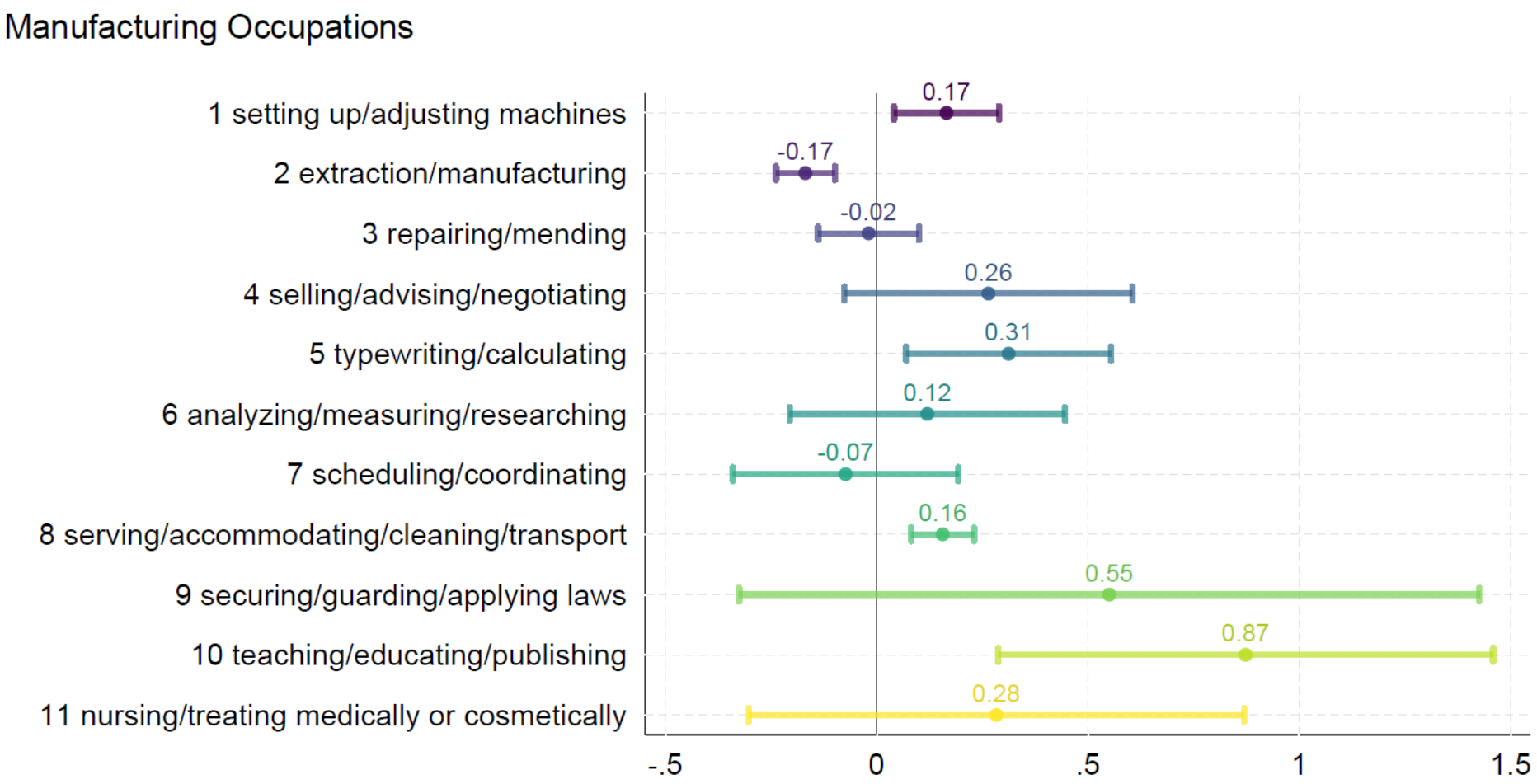
Back

Task-Change and Job Growth



back

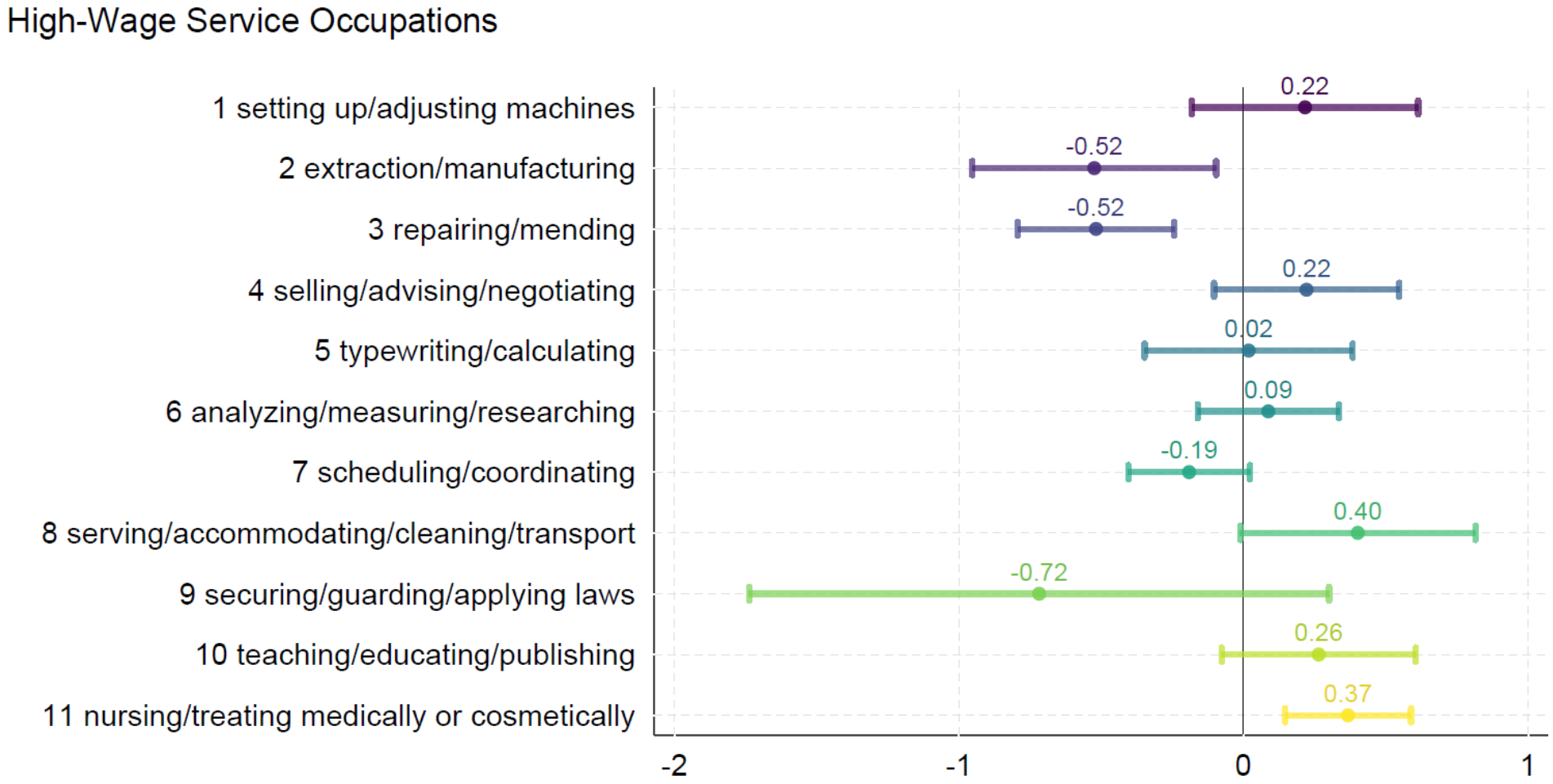
Which task shifts are driving changes in composition?



Note: *D* and ΔTS rescaled to [1,100]. Mean Distance = 3.23 , NxT = 960, controlling for composition changes (age, gender, marital status, formal qualification).

back

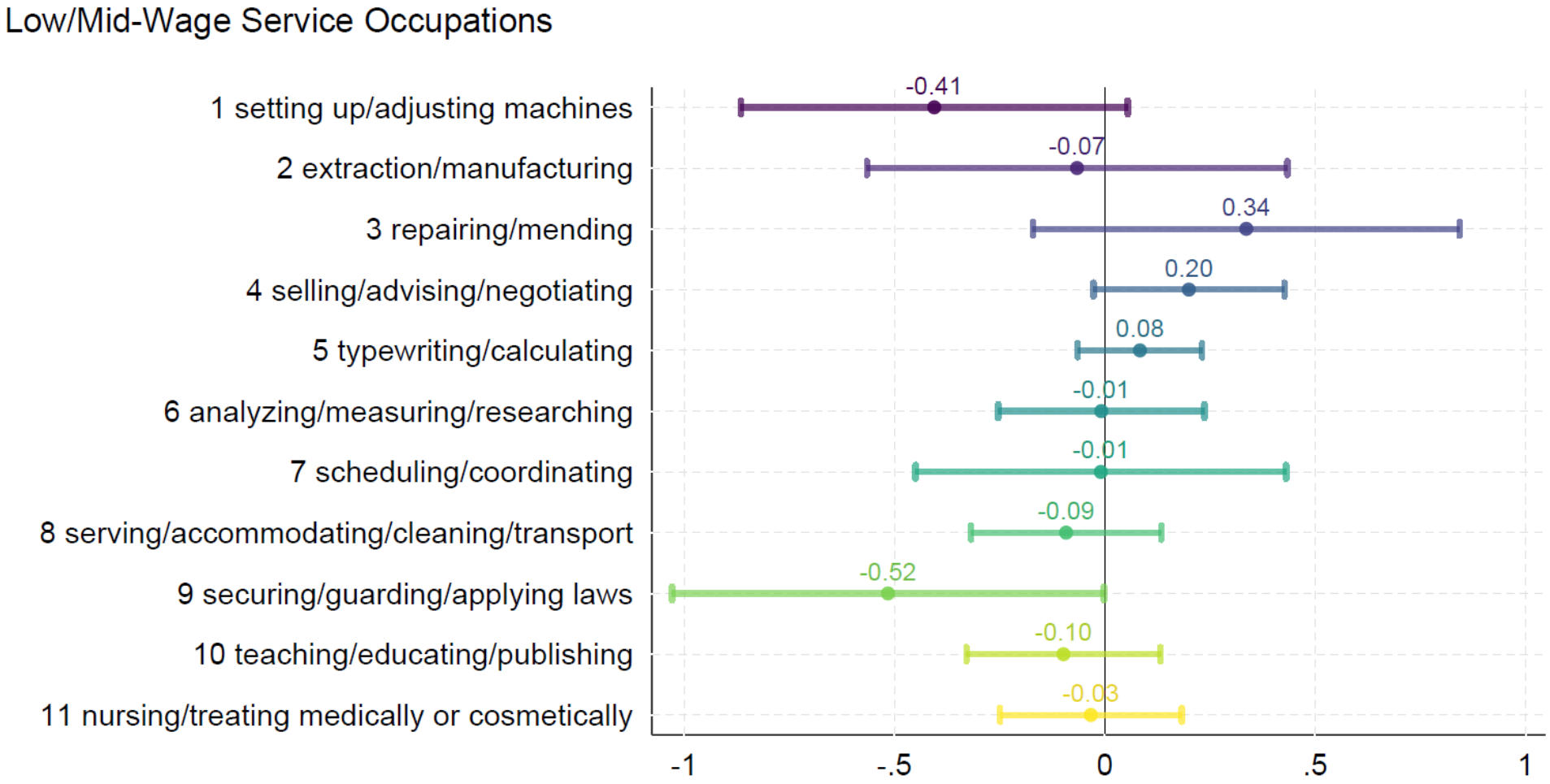
Which task shifts are driving changes in composition?



Note: *D* and ΔTS rescaled to [1,100]. Mean Distance = 3.92 , NxT = 584, controlling for composition changes (age, gender, marital status, formal qualification).

back

Which task shifts are driving changes in composition?



Note: *D* and ΔTS rescaled to [1,100]. Mean Distance = 5.01 , NxT = 945, controlling for composition changes (age, gender, marital status, formal qualification).

back

Matching

2-step matching:

1. **Estimate propensity of displacement on full sample**
   - Gender, German, medium/high skilled
   - No of benefit receipt spells, no of n-spells
   - Experience (+sq.), occupation tenure (+sq.) job tenure (+sq.)
   - Log real daily wage (c-1, c-2, c-3)
   - Industry FE‘s, establishment size
2. **Match on propensity score within cells:**
   - Baseyear
   - Zero/Medium/High exposure to task change
   - Establishment size class

back

Balancing Displaced vs. Non-Displaced, before/after matching

		Non-displaced (ND)		Diff (D - ND)	
	Displaced (D)	All	Matched	All	Matched
Task Change since occupation entry					
Cosine distance [0,100]	0.43	0.36	0.45	0.07	-0.01
Person characteristics					
Female	0.39	0.44	0.39	-0.05 +	0.00
Age	42.83	41.33	43.08	1.50 +	-0.23
Academic degree	0.05	0.10	0.05	-0.05 +	0.00
Experience	13.57	10.97	13.45	2.60 ++	0.22
Occupation tenure	11.73	9.53	11.78	2.20 ++	0.05
AKM Person FE (not in matching)	4.31	4.40	4.33	-0.09 +	-0.02
Establishment					
Manufacturing/energy/construction	0.53	0.41	0.53	0.12 +	0.00
Establishment size	78.79	1,437.94	77.12	-1,359.15 ++	1.59
Baseyear outcomes (*c*-1)					
Labor earnings per year	34,336.83	37,903.78	34,046.32	-3,566.96 +	512.94
Observations	14,094	630,609	14,094		

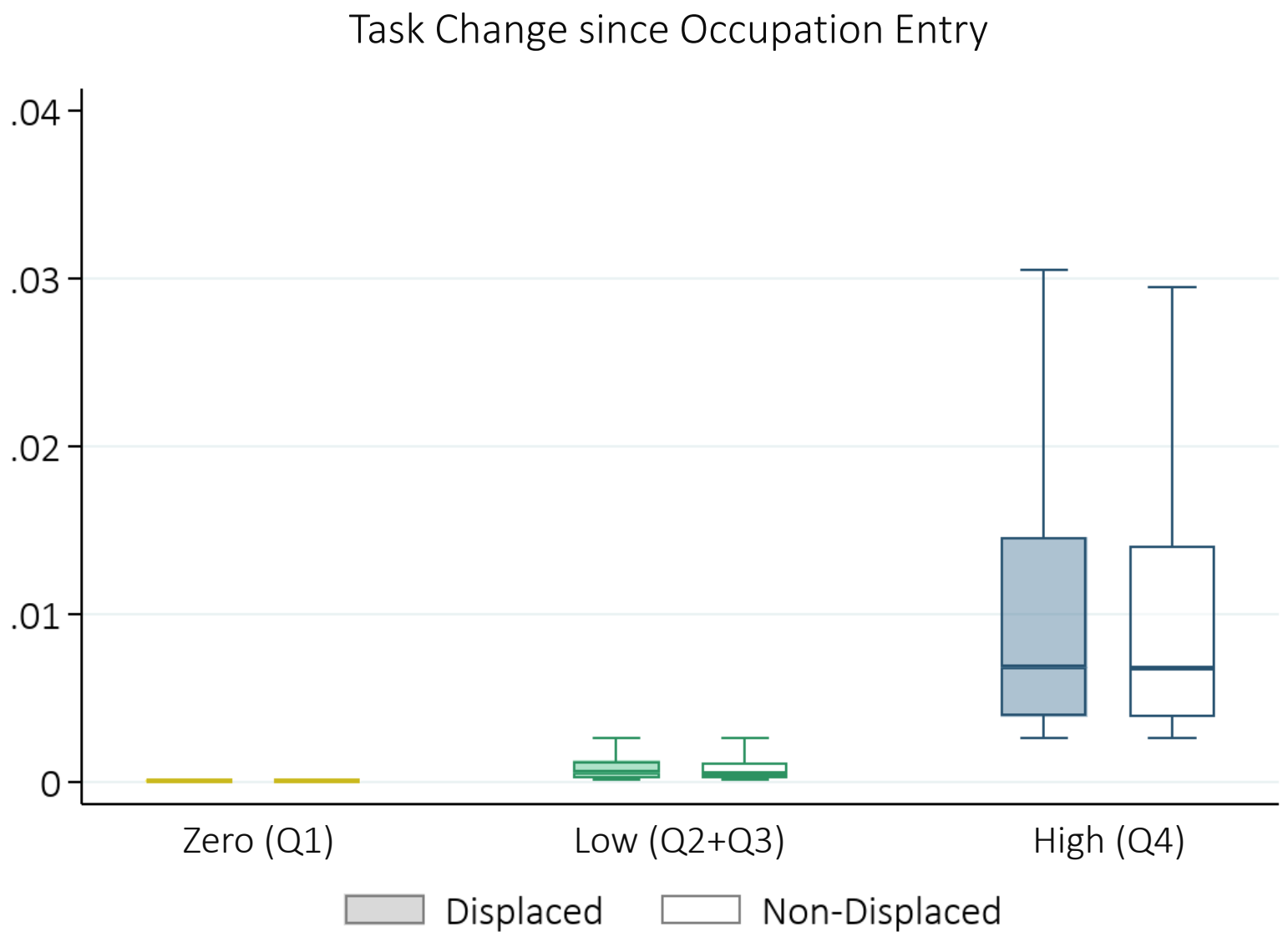
Back

Baseyear Characteristics Displaced Workers by Task-Change

	(1)	(2)	(3)
	Zero Change	**Low Change**	**High Change**
Person:			
Age	39.262	41.781	43.678
No professional training	.107	.144	.193
Experience	10.084	12.197	15.145
Job tenure	5.258	7.318	9.368
AKM person FE*	4.181	4.284	4.347
Occupation:			
Within-distance since entry	0	.001	.013
Occupation tenure	7.226	10.462	13.816
Establishment:			
Establishment size	43.567	53.511	64.064
Median daily wage	62.781	65.647	72.609
AKM establishment FE*	.064	.114	.145
Outcomes:			
Labor earnings per Year	28,417.624	34,124.762	37,530.723
min(N)*	1,618	3,702	2,801
max(N)	2,868	7,033	4,192

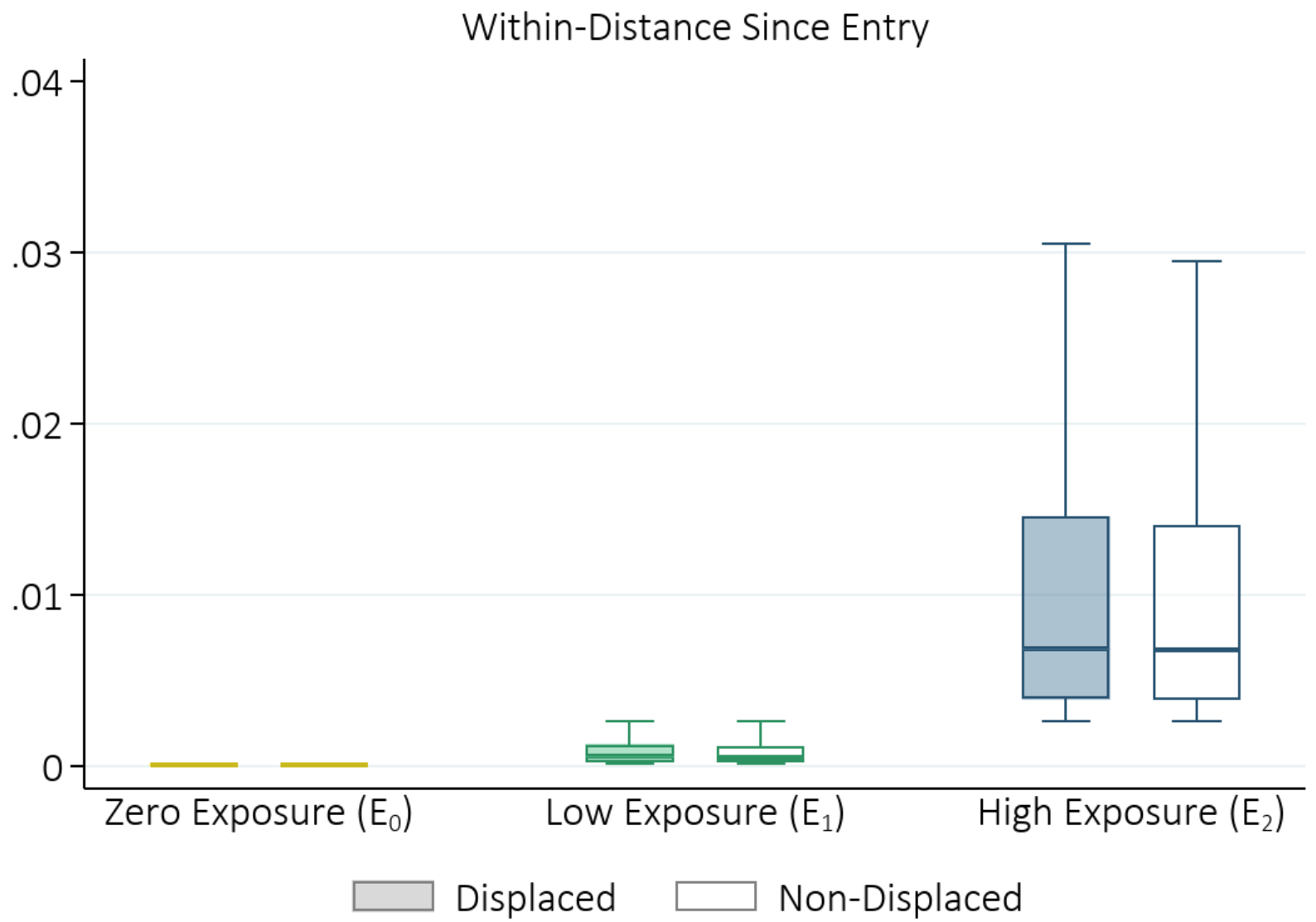
Back

Box Plots: Exposure



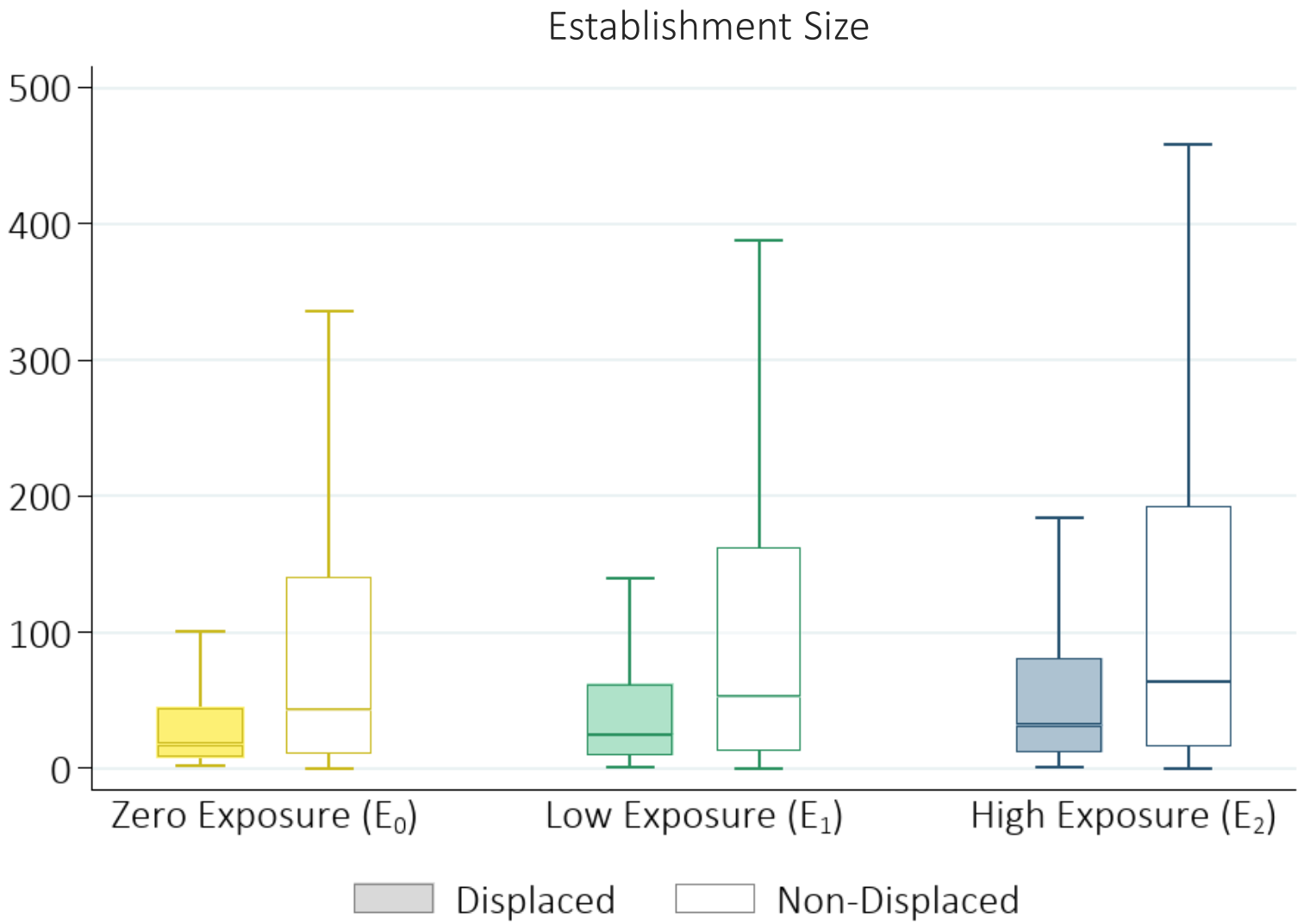
Back

Box Plots: Within-Distance Exposure Groups



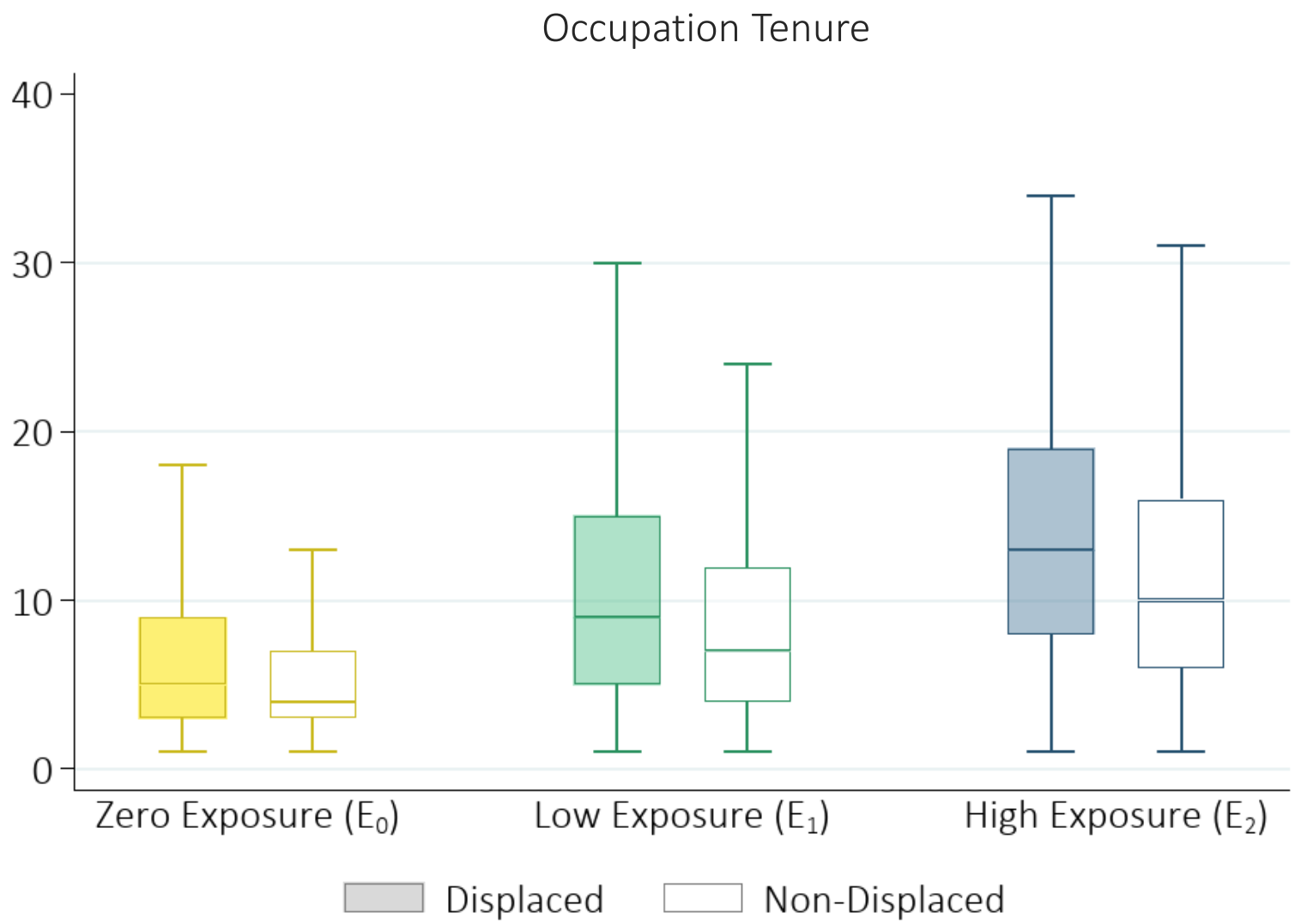
Back

Box Plots: Establishment Size



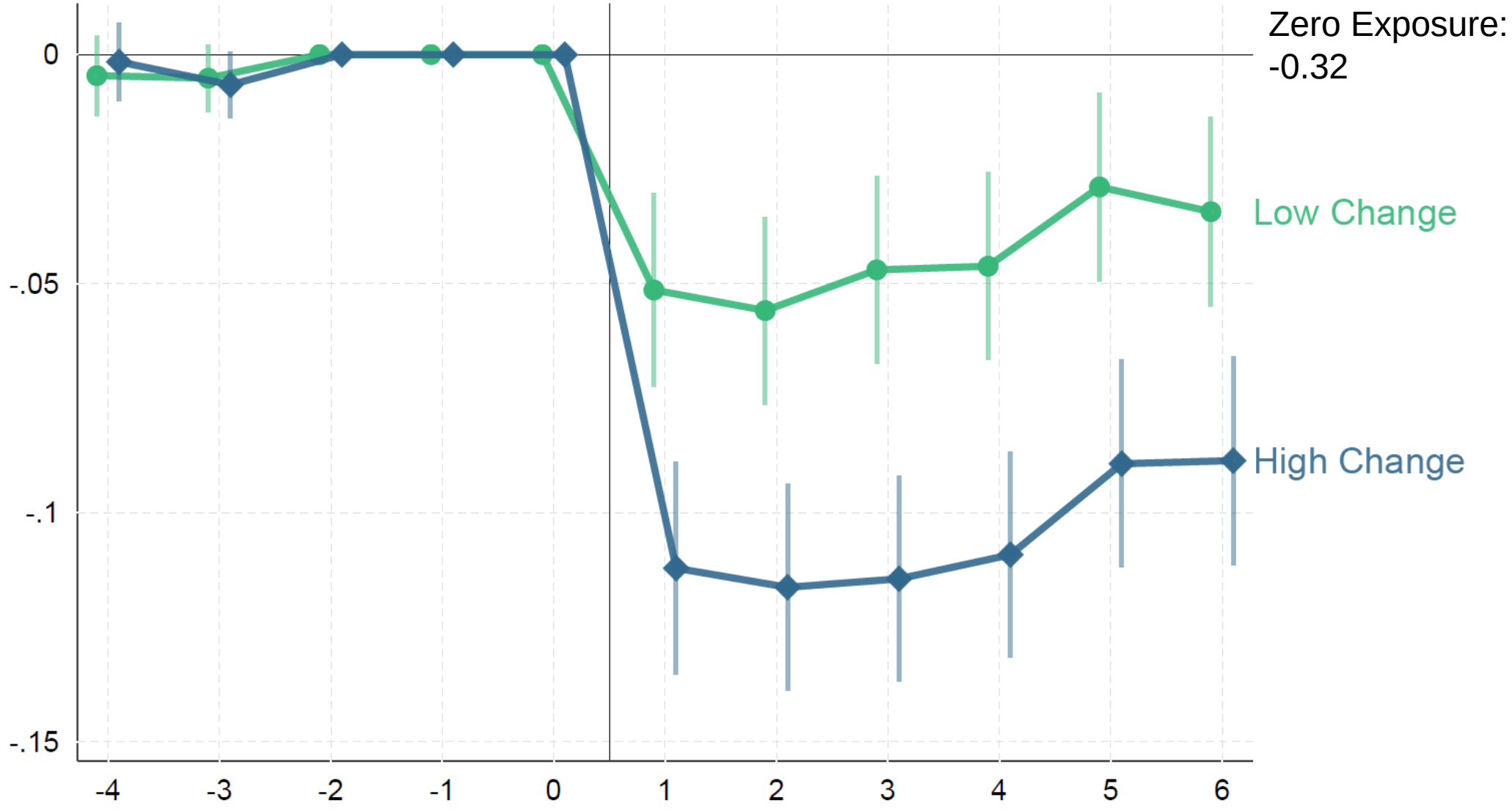
Back

Box Plots: Occupation Tenure



Back

Employment Probability on June 30



Back

Alterantie Mechanism: Task-Change vs. Individual Skills

Labor Earnings per Year	AKM Person FE		
	Low	**Medium**	**High**
Zero Change	ref.	ref.	ref.
Low Change	-270.8	-321.2	-5363.1*
	(897.5)	(905.2)	(2496.2)
High Change	-2275.2*	-2785.1**	-7432.7**
	(1033.9)	(954.6)	(2490.8)
Matched sample	✓	✓	✓
Mean AKM person FE	3.92	4.31	4.67
N	42,735	85,470	42,724
Adj. R^2	0.098	0.092	0.086

Back

Alterantie Mechanism: Task Change vs. Firm Wage Premiums

Labor Earnings per Year	AKM Establishment FE		
	Low	**Medium**	**High**
Zero Change	ref.	ref.	ref.
Low Change	-1,566.0	-846.7	-6,125.1***
	(940.1)	(927.5)	(1,837.3)
High Change	-2,202.4	-3,949.3***	-9,024.1***
	(1,125.7)	(1,007.2)	(1,930.1)
Matched sample	✓	✓	✓
Mean AKM person FE	3.92	4.31	4.67
N	44,715	89,419	44,704
Adj. R^2	0.081	0.084	0.077

Back