Outside Options in the Labor Market

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Motivation

More job opportunities affects wages through:

1. Worker can find a better match (Hsieh et al., 2019)
2. Better outside options (Caldwell & Harmon 2018)

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Availability of job opportunities could **vary across workers**

- Depends on, e.g., local labor market, willingness to commute, transferability of skills
- Could generate lower wages even for equally productive workers
- Ex: Women may have fewer options on average if they are less willing or able to commute

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Challenge: Outside options are typically unobserved

This Paper

1. Which workers have more options?
    - Derive a **sufficient statistic** for outside options:
    - Outside Options Index - **OOI**
    - Learn about outside options from similar workers
    - Example: Men have 25% more relevant options

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   - Identify OOI to wage **elasticity** using two IV strategies
   - 10% more relevant options $\rightarrow$ $\approx$1.7-2.7% higher wages

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   - Identify OOI to wage **elasticity** using two IV strategies
   - 10% more relevant options $\rightarrow$ $\approx$1.7-2.7% higher wages
3. **How do differences in options affect wage inequality?**
   - Combine OOI distribution with elasticity
   - 25% of gender gap
   - **Main mechanism:** willingness to commute/move

Theoretical Framework

Setup - Matching Model

Static matching model (Shapley & Shubik, 1971)

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A worker with characteristics x_i and a job with z_j produce

$$\underbrace{\tau(x_i, z_j) + \varepsilon_{ij}}_{\text{total value}} = \underbrace{y(x_i, z_j)}_{\text{output}} + \underbrace{a(x_i, z_j)}_{\text{amenities}} + \underbrace{\varepsilon_{ij}}_{\text{idiosyncratic}}$$

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Solution details

$$\underbrace{E\left[\omega | x_i\right]}_{\text{E}[compensation]} = \underbrace{E\left[\tau\left(x_i, z^*\right) | x_i\right]}_{\text{Mean Value}} - \underbrace{E\left[\pi\left(z^*\right) | x_i\right]}_{\text{Employer Profits}} + \underbrace{E\left[\varepsilon_{i,j} | x_i\right]}_{\alpha OOI}$$

Workers with more similar options $\rightarrow$ higher $E\left[\varepsilon_{i,j} | x_i\right]$

Outside Options Index (OOI)

Make distributional assumptions on ε to get an analytical expression for $E\left[\varepsilon_{i,j}|x_i\right]$

Details

- Define f_j^i the probability density that i works in job j.

$$OOI_i = -\int_j f_j^i \log f_j^i$$

- Simple case - equally likely to work at measure s of jobs
  $OOI_i = \log s$

OOI Intuition - 1

$$OOI_i = -\int_j f_j^i \log f_j^i$$

OOI is an index of concentration

- Estimated using cross-sectional distribution of similar workers
- On all observable dimensions

OOI is determined by:

1. **Worker flexibility**: Ability to commute/work in more occupation etc.
2. **Job supply** in relevant districts/occupations etc.

OOI Intuition - 2

$$OOI_i = -\int_j f_j^i \log f_j^i$$

Key Features:

- Only <u>relevant</u> options (i.e. those taken in equilibrium) matter
- Common index for unpredictability

OOI Effect:

- Through the model: Sufficient Statistic Theorems
    - Improve match quality
    - Improve compensation through better outside options
- Alternative models:
    - **Easier search:** Higher reservation wage (Black, 1995)

Features and Limitations

The model allows us to understand what is, and what isn't captured in OOI

Main Features:

- Workers allowed to work in all occupation/industry
- Commuting costs vary across workers (not one local labor market)
- Employers within industry are not identical

Main Limitations

- No dynamics: switching costs, specific human-capital, learning
- No firms
    - Data tradeoff

Estimation

German Linked Employer-Employee Data

Main Data: "LIAB Longitudinal" - German linked employer-employee data

- ~1% of employed population
- Sampling Restriction: all workers employed on 06/30/2014

Supplementary Data: BIBB (German O*Net)

Data

Main features:

- Representative sample of establishments
- 22 years of work histories of workers in these establishments
- Combination of administrative data with detailed survey on employer policies
- Flexible wage setting

Main Limitations:

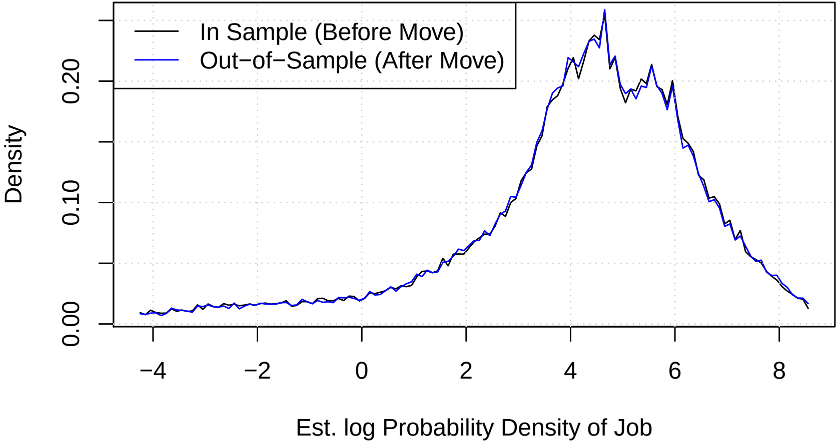
- Does not include self-employed and some civil servants ("Beatre") (18%)
- Does not include non-participants
- Does not include jobs outside of Germany
- Cannot see all potential employers

Estimation

Estimation: Estimate match probabilities f_j^i Details Results

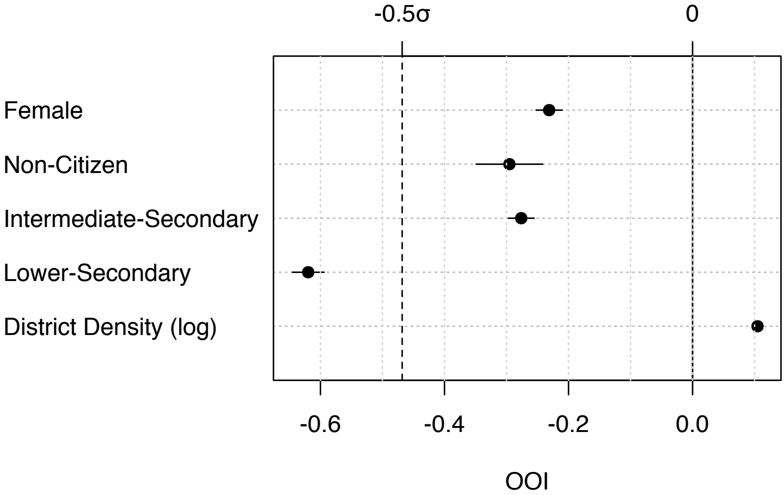
- X_i: demographics, training occupations
- Z_j: Basic job characteristics, occ & industry, establishment characteristics
- Distance: miles between worker's previous residence to establishment
- **Do not include wages**

Out-of-Sample Performance



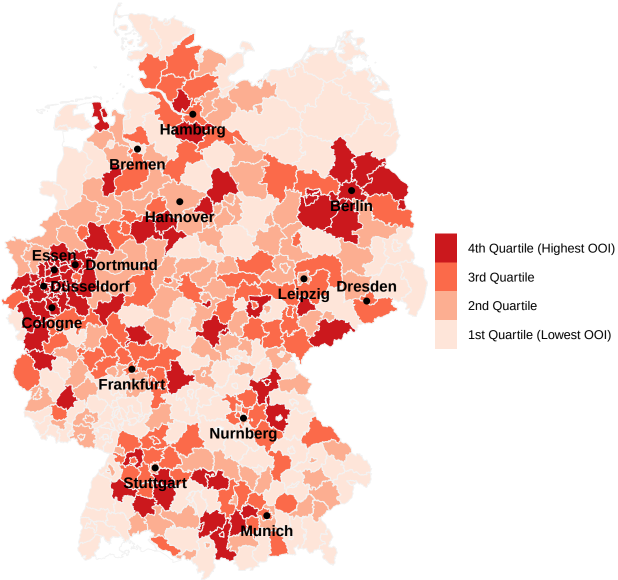
Who Has Better Options?

OOI by Demographics

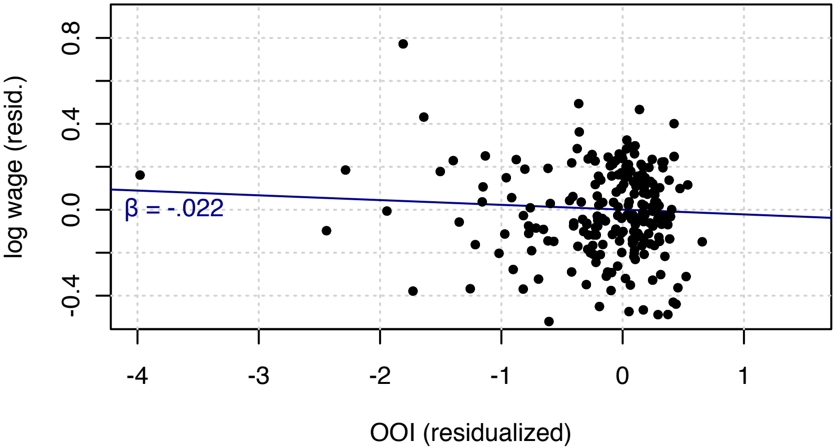


Coefficients from a single regression of *OOI* on all variables + quadratic age variable

OOI is Higher in Big Cities

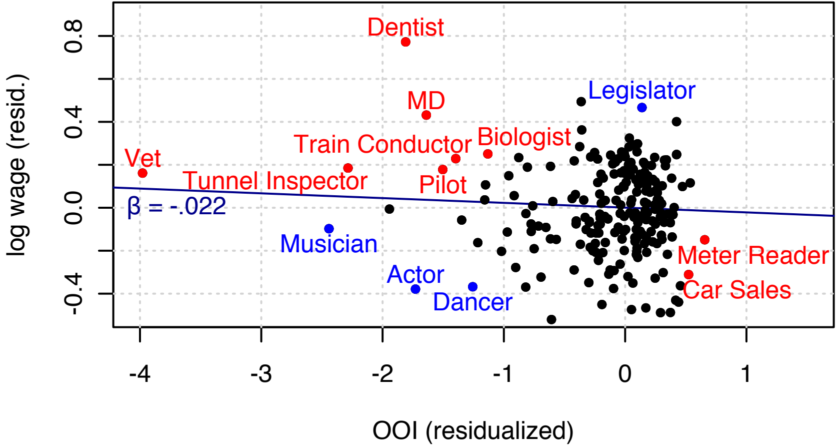


Training Occupations



Residualized *OOI* and log *wage* are taken from a regression on gender, age, education, citizenship status and district.

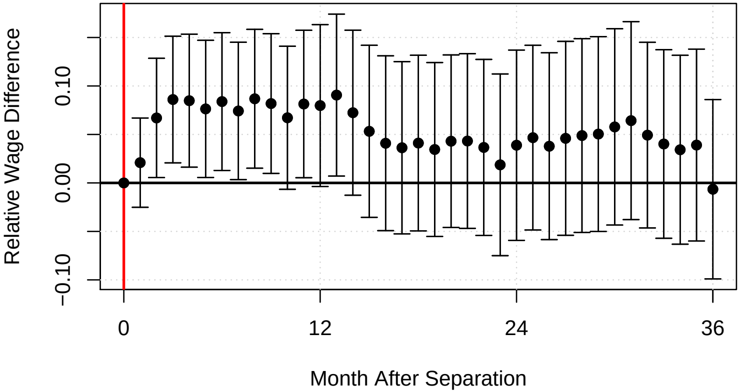
Training Occupations



Residualized *OOI* and log *wage* are taken from a regression on gender, age, education, citizenship status and district, weighted by occupation employment share

Mass-Layoffs

- Construct sample following Jacobson et al. (1993) Details
- Compare workers **above/below establishment median OOI**
- **Outcome variable**: Daily wage divided by baseline $\frac{w_t}{w_0}$



Additional Results

- Full distribution Details
- CDF by Gender Details
- Different functional form (HHI) yields similar results ($\rho = .62$) Details
- OOI gaps similar with different controls Details
- Results for age Details
- Mass-Layoff
  - Relative Income trend Details
  - Effect on Search Details
  - Controls Details

How Do Differences in Options Translate into Wages?

Intercity Express

- High-speed (200 mph) commuter rail introduced in two waves (Heuermann & Schmieder, 2018)
    1. Pre 1999: all big cities are connected
    2. Post 1999: only cities en route + further periphery

- Only used for commute

- Match workers from second wave, to similar workers who never received

Details Map

Main ICE Results

2SLS (1)	First-Stage (2)	Reduced-Form (3)	OLS (4)
.272***	.084***	.024***	.002
(.034)	(.009)	(.004)	(.008)
Number of observations:			143,313
Number of treated observations:			37,695

Table: Effect of OOI on log w using ICE IV

Standard errors are calculated with Abadie-Imbens (2006) extended for 2SLS

Shift-Share Procedure

Idea: (BGS, 2012) Compare workers within the same industry with outside options in different industries

- Variation from local industry composition
- Local industry trends instrumented with national trends

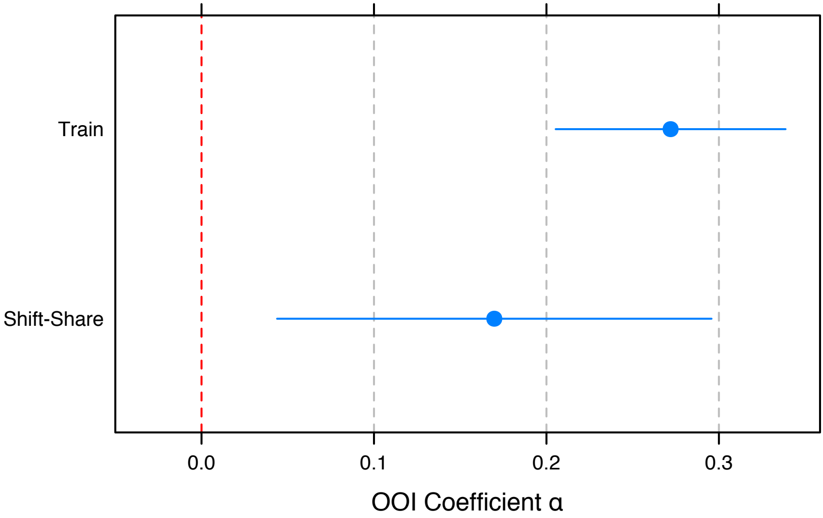
Specification: Look at change in wages 2004-2014 within industries

$$\Delta_{04}^{14} \log w_{ijr} = \alpha \Delta_{04}^{14} OOI_{ijr} + \beta \Delta_{04}^{14} X_{ijr} + Ind_j^{04} + \varepsilon_{ijr}$$
$$\Delta_{04}^{14} OOI_{ijr} = \gamma B_r + \delta \Delta_{04}^{14} X_{ijr} + Ind_j^{04} + \epsilon_{ijr}$$

i - worker, j - industry, r - region ("Regierungsbezirk")

Instrument Construction

Train and Shift-Share

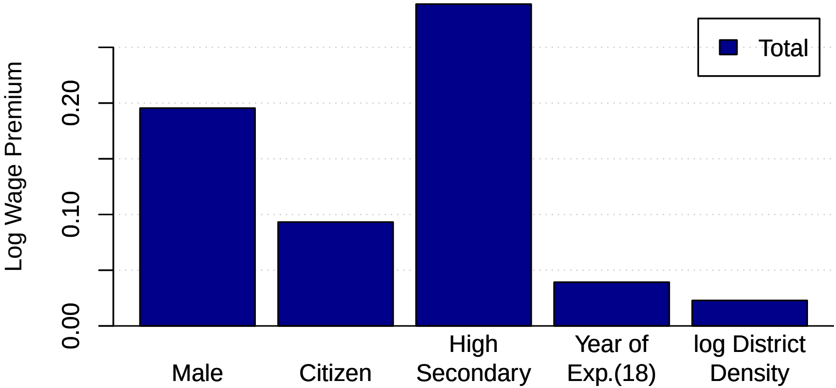


Additional Results

- Effect is similar by gender and education Details
- Decomposing the effect on stayers and movers:
  Stayers get about 50% the overall effect Details
- Local demand shock? Similar effect on exporters Details

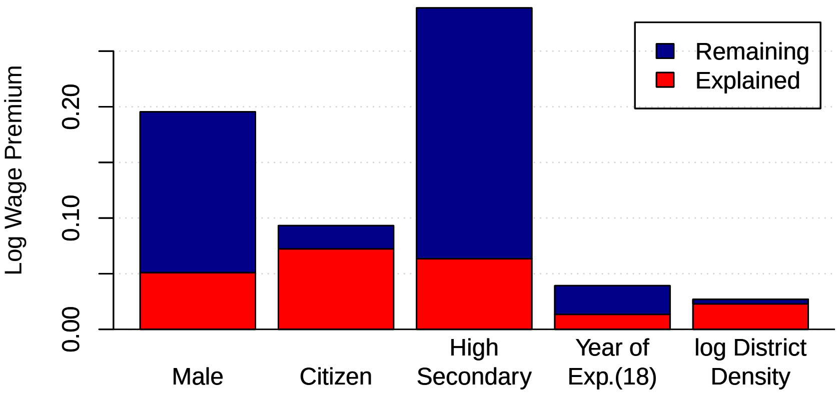
How Do Differences in Options Affect Wage Inequality?

Effect on Wage Gaps



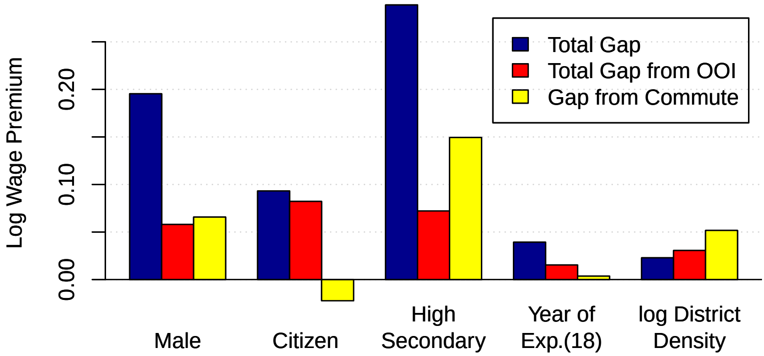
Coefficients from a single regression of log *wage* on these demographics, quadratic in age, and part-time indicator.

Effect on Wage Gaps

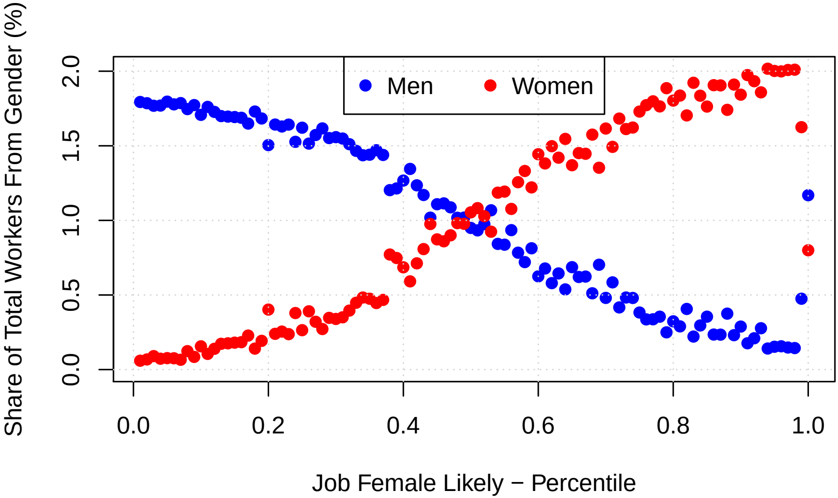


Mechanisms

Gap From Willingness to Commute/Move

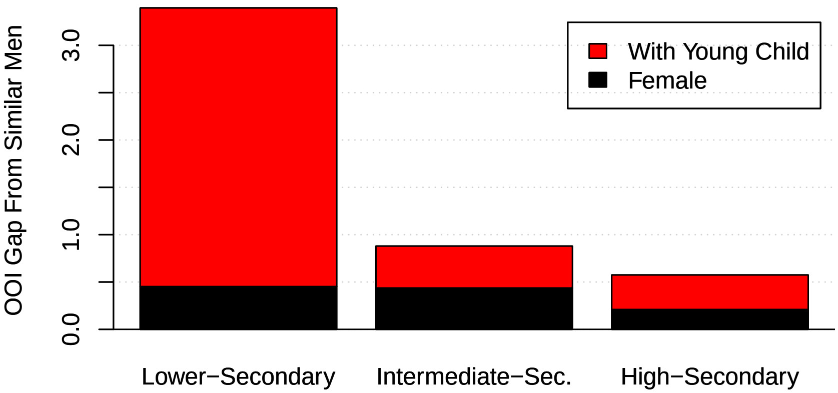


Segregation



Jobs are ranked by the estimated odds ratio of hiring a woman vs a men

Children



OOI Gap From Similar Men
0.0
1.0
2.0
3.0
With Young Child
Female
Lower−Secondary
Intermediate−Sec.
High−Secondary

Summary

Results Summary

1. Which workers have better outside options?
    - Males, German citizens, urban residents
    - Low skill occupations
2. How do differences in options translate into wages?
    - 10% more options yields 2.5% higher income
3. **How do differences in outside options affect wage inequality?**
    - Differences in options tend to increase inequality
    - 25% of gender gap
    - 21% of return to higher education
    - Decrease gaps between occupations

Discussion

- Policy implication:
  - Many policies could have a direct effect on the OOI
  - Ex: Transportation, working hours regulation, mandated benefits
  - Potential tool to close wage gaps
  - Ex: Mandatory maternal leave could increase women options

Thank You

Theory Extended

Payoff

Payoffs are

$$\underbrace{\omega(x,z)}_{\text{compensation}} = \underbrace{a(x,z)}_{\text{amenities}} + \underbrace{w(x,z)}_{\text{wages}}$$

$$\underbrace{\pi(x,z)}_{\text{profit}} = \underbrace{y(x,z)}_{\text{output}} - \underbrace{w(x,z)}_{\text{wages}}$$

and their sum is total value produced

$$\tau(x,z) = \omega(x,z) + \pi(x,z) = a(x,z) + y(x,z)$$

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$$\tau(x,z) = \omega(x,z) + \pi(x,z) = a(x,z) + y(x,z)$$

Q: How is $\tau(x,z)$ divided to $\omega(x,z), \pi(x,z)$?

Equilibrium

Solve as a cooperative game (Shapley Shubik 1971).

- Static framework
- Perfect information

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Equilibrium if everyone gets more than outside option

$$\max_{z'} \omega\left(x, z'\right) \leq \omega\left(x, z\right) \leq \tau\left(x, z\right) - \max_{x'} \pi\left(x', z\right)$$

Details

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Details

Example - if Nash split:

$$\omega\left(x, z\right) = \frac{1}{2} \max_{z'} \omega\left(x, z'\right) + \frac{1}{2}\left(\tau\left(x, z\right) - \max_{x'} \pi\left(x', z\right)\right)$$

Empirical Assumptions

$\max_{z'} \omega(x, z')$ depends on several factors:

- Options availability, but also productivity etc.
- To separate these effect and take to data, we will make simplifying assumptions

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Assumptions: (Choo & Siow, 2006, Dupuy & Galichon, 2014)

1. Continuum of workers and jobs
2. Total value produced is

$$\tau_{ij} = \tau(x_i, z_j) + \varepsilon_{i,z_j} + \varepsilon_{j,x_i}$$

- $\varepsilon \sim$ continuous logits with scale α Details
- $\varepsilon_{i,z_j} \perp \varepsilon_{j,x_i}$

Quasi-Nash Solution

Corollary:

1. Workers (employers) get "their" ε_{i,z_j} (ε_{j,x_i})

Quasi-Nash Solution

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1. Workers (employers) get "their" ε_{i,z_j} (ε_{j,x_i})
2. $\tau(x,z)$ splits into $\omega(x,z) + \pi(x,z)$ by

$$\omega(x,z) = \frac{1}{2} E[\omega|x] + \frac{1}{2}\left(\tau(x,z) - E[\pi|z]\right)$$

- Workers get exactly half of expected surplus
- Proof
- Return

Solution: Equilibrium

Stable equilibrium (core allocation) includes:

1. Allocation of workers and jobs $m : \mathcal{I} \to \mathcal{J}$
2. Transfer w_{ij} that sets ω_{ij} and π_{ij}

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1. Allocation of workers and jobs $m : \mathcal{I} \to \mathcal{J}$
2. Transfer w_{ij} that sets ω_{ij} and π_{ij}

Which satisfies the following conditions:

1. No profitable deviations $\forall i \in \mathcal{I}, \forall j \in \mathcal{J}$:

$$\underbrace{\omega_{i,m(i)}}_{\substack{i \text{ Equilibrium} \\ \text{compensation}}} + \underbrace{\pi_{m^{-1}(j),j}}_{\substack{j \text{ Equilibrium} \\ \text{profit}}} \geq \underbrace{\tau_{ij}}_{\substack{i,j \text{ potential} \\ \text{value produced}}}$$

2. Participation constraint

$$\begin{aligned} \forall i \in I &: \quad \omega_{i,m(i)} \geq u_i \\ \forall j \in J &: \quad \pi_{m^{-1}(j),j} \geq v_j \end{aligned}$$

where u_i, v_j value of unemployment or vacancy Return

Continuous Logit Assumptions

Assume

$$\tau_{ij} = \tau\left(x_i, z_j\right) + \varepsilon_{i,z_j} + \varepsilon_{j,x_i}$$

$$\text{s.t.} \qquad \begin{aligned} \varepsilon_{i,z_j} &\perp \varepsilon_{j,x_i} \\ \varepsilon_{i,z_j}, \varepsilon_{j,x_i} &\sim CL\left(\alpha\right) \end{aligned}$$

Continuous logit draws ε from a Poisson Process on $\mathcal{Z} \times \mathbb{R}$ with intensity

$$f\left(z\right) dz \times e^{-\varepsilon} d\varepsilon$$

so the maximum value on each Borel measurable subset is EV_1 with scale α

Return

Continuous Logit Choice

$Q_{z_j|x_i}$ is the measure of x_i times their share that chooses z_j.

$$Q_{z_j|x_i} = f(x_i)\, f(z_j|x_i)$$

In continuous logit the share to choose z_j is

$$\frac{\exp \omega(x_i, z_j)\, f(z_j)}{\int_{z'} \exp \omega(x_i, z')\, f(z')\, dz'} = \frac{\exp \omega(x_i, z_j)\, f(z_j)}{\exp E[\omega_i|x_i]}$$

Market clears when

$$Q_{z_j|x_i} = \frac{\exp \omega(x_i, z_j)\, f(z_j)\, f(x_i)}{\exp E[\omega_i|x_i]} = \frac{\exp \pi(x_i, z_j)\, f(z_j)\, f(x_i)}{\exp E[\pi_j|z_j]} = Q_{x_i|z_j}$$

$$\omega(x_i, z_j) - \pi(x_i, z_j) = E[\omega_i|x_i] - E[\pi_j|z_j]$$

By definition

$$\omega(x_i, z_j) + \pi(x_i, z_j) = \tau(x_i, z_j)$$

And the sum gives the Quasi-Nash solution

Return

Sufficient Statistic

An increase in options gives a worker access to more similar jobs. Formally:

Definition

We define λ_x to be the measure of a random set of jobs that are accessible to workers with observables x. All jobs that are not accessible have $\tau_{ij} = -\infty$ and are therefore never chosen in equilibrium. We model an increase in access to more jobs would be an increase to this λ_x.

Results would also hold also if λ_x is the slope of linear commuting costs

Sufficient Statistic Theorems

Theorem

Let j be $i's$ equilibrium match. Access to outside options λ_{x_i} has the following effect on the maximum offer j is willing to make in the new equilibrium:

$$\frac{d\omega_{i,j}}{d\lambda_{x_i}} = \alpha \frac{dOOI}{d\lambda_{x_i}}$$

Theorem

Access to options λ_{x_i} has the following overall effect on expected worker compensation in equilibrium

$$\frac{dE\left[\omega_{i,j}\right]}{d\lambda_{x_i}} = 2\alpha \frac{dOOI}{d\lambda_{x_i}}$$

Return

More Results

Summary Statistics - Workers (X)

	Mean	SD
Female	.46	(.50)
Age	45.05	(12.49)
German Citizen	0.97	(.17)
Education: Higher Secondary	.29	(.45)
Education: Intermediate Secondary	.31	(.46)
Education: Lower Secondary	.22	(.41)
Education: Intermediate/Lower	.19	(.39)
N	450,929	

Table: Summary Stats - Workers

Distribution

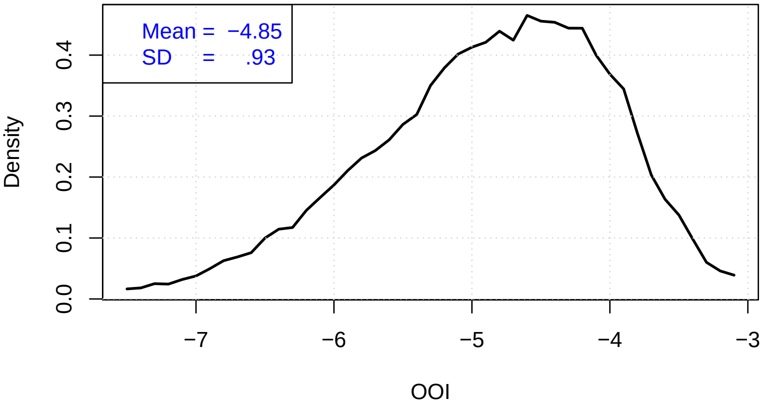
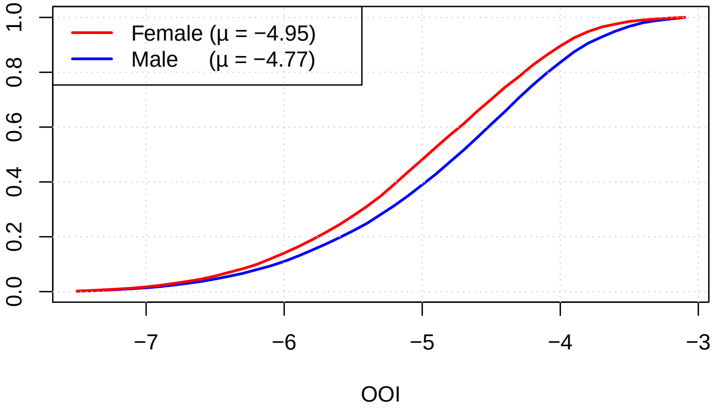


Figure: Outside Option Index Distribution

CDF by Gender

Male's OOI distribution first-order stochastically dominates female's distribution



Summary Statistics - Jobs (Z)

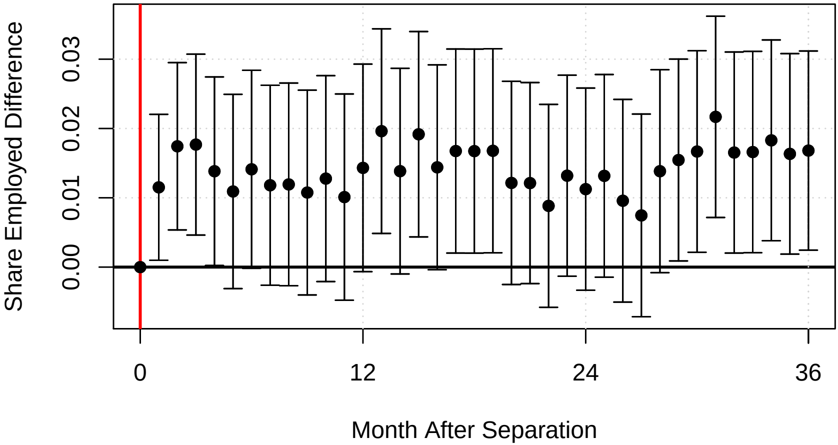
Name	Mean	SD
Part - Time	.31	(.46)
Fixed Contract	.11	(.31)
Temporary Agency	.02	(.12)
Establishment Size	1,552.8	(7679)
Sales per worker (Euro)	163,286.7	(185,651)
%Female in Management	.26	(.31)
Complexity	2.22	(.84)
N	450,929	
N Establishments	8,792	

Table: Summary Stats - Jobs

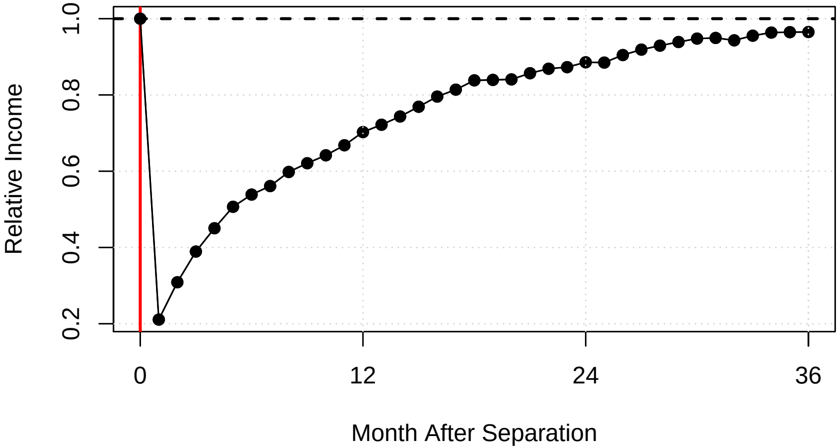
Return

Mass Layoffs - Job Search

Return



Trend in Relative Income



Income divided by income before layoff ($t = 0$) Return

Mass Layoff - Table

Table: Relative Income by OOI After Mass Layoff

OOI_i coefficient	(1)	(2)	(3)
3 months (λ_3)	.061**	.062**	.068**
	(.029)	(.029)	(.031)
6 months (λ_6)	.068**	.069**	.082**
	(.030)	(.030)	(.033)
12 months (λ_{12})	.061*	.064*	.079**
	(.034)	(.034)	(.038)
24 months (λ_{24})	.033	.039	.064
	(.042)	(.042)	(.048)
Mass-Layoff×Month FE	Y	Y	Y
Tenure		Y	Y
Age, Education, Gender			Y
No. of Observations	558,686	558,686	558,686

Return

Heuermann Schmieder

Table VI: Travel Times and Commuter Numbers (Long-Run Equilibrium)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Dependent Variable:				log(*Commuter Numbers*)			
Direct ICE	6.236	0.050					
	(0.100)**	(0.006)**					
log(*Duration*)			-1.136	-0.046	-1.296	-0.520	-0.602
			(0.008)**	(0.007)**	(0.056)**	(0.069)**	(0.121)**
log(*Pop Orig*)		0.195	0.333	0.169	0.430	0.257	0.398
		(0.023)**	(0.003)**	(0.023)**	(0.006)**	(0.028)**	(0.121)**
log(*Pop Dest*)		0.876	0.543	0.908	0.614	0.941	0.861
		(0.019)**	(0.003)**	(0.019)**	(0.006)**	(0.021)**	(0.097)**
log(*Distance*)			-0.466		-0.321		
			(0.007)**		(0.043)**		
Year 2009		0.033	0.031	0.034	0.030	0.022	0.038
		(0.002)**	(0.005)**	(0.002)**	(0.006)**	(0.002)**	(0.009)**
R^2	0.03	0.13	0.74	0.13	0.58	0.05	0.20
N	124,284	124,250	123,680	123,680	123,680	89,440	2,068
Method	OLS	FE	OLS	FE	IV	FE, IV	PSM, IV, FE

* $p < 0.05$; ** $p < 0.01$

Table: Direct ICE Impact on Number of Commuters (HS,2014)

A - Largest Values

Variable (X)	Variable (Z)	A_{xz}
-	Distance	-4.15
Train Occ - Physical Cond. 1	Occ - Physical Cond. 1	1.477
Train Occ - Task Type 2	Occ - Task Type 2	1.077
⋮	⋮	⋮

Table: Top Standardized Values of A

Return

A - Heterogeneity in Distance

Variable (X)	Variable (Z)	A_{xz}
-	Distance	-.049
Female	Distance	-.009
German	Distance	-.005
Lower Secondary	Distance	-.021
Intermediate	Distance	-.015
Age	Distance	.002
Age^2	Distance	-.000

Baseline category - Male with higher secondary education

Table: A Values for Distance (Miles)

Return

Correlation with Demographics

	Dep Var: Outside Option Index			
	(1)	(2)	(3)	(4)
Female	-.237***	-.231***	-.227***	-.167***
	(0.009)	(0.011)	(0.008)	(0.008)
School Lower-Secondary	-.660***	-.620***	-.596***	-.617***
	(0.013)	(0.013)	(0.009)	(0.010)
School Intermediate	-.279***	-.277***	-.211***	-.216***
	(0.011)	(0.011)	(0.007)	(0.008)
Non-Citizen	-.307***	-.295***	-.459***	-.501***
	(0.031)	(0.027)	(0.021)	(0.019)
Age	.099***	.107***	.107***	.099***
	(0.004)	(0.003)	(0.002)	(0.002)
Age^2	-.001***	-.001***	-.001***	-.001***
	(4e-05)	(4e-05)	(3e-05)	(2e-05)
District Density	.112***	.104***		
	(0.004)	(0.005)		
Training Occ FE		X	X	
District FE			X	
Establishment FE				X
R^2	0.13	0.29	0.66	0.56
N	380,109	380,109	380,109	380,109

Table: OOI by Demographics Return

PCA Over BIBB (X and Z)

Name	N	Comp 1	Comp 2
Hours	11,021	Sundays and public holidays	hours per week like to work
Type of Task	15,035	responsibility for other people	Cleaning, waste, recycling
Requirements	10,904	Acute pressure & deadlines	Highly specific Regulations
Physical	20,036	Oil, dirt, grease, grime	pathogens, bacteria
Mental	17,790	Support from colleagues	Often missing information

Table: Most Weighted Question in PCA - BIBB

- Used to project training occupations (X) and current occupations and industries (Z) into characteristic space Return

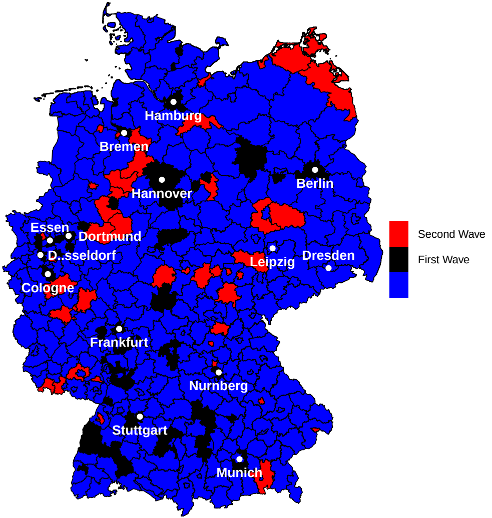
Survey PCA (Z)

Name	N	Comp 1	Comp 2
Business Performance	8,792	chamber of Industry	profit category
Investment & Innovation	8,792	IT investment	total investment
Hours	8,792	long leaves policy	flextime
In-Company Training	8,792	internal courses	share in training
Vocational Training	8,792	offer apprenticeship	ability to fill
General	8,792	family managed	staff representation

Table: Most Weighted Question in PCA - Establishment 2014 Survey

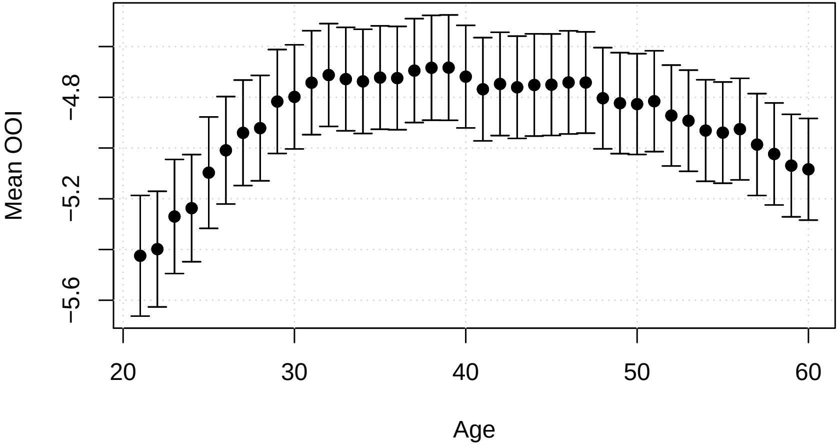
Return

Intercity Express



ICE Stations Before/After 1999 Return

OOI by Age



Return

Functional Form

- We estimated

$$OOI_i = -\int_j f_j^i \log f_j^i$$

- Try instead

$$\widetilde{OOI}_i = -\int \left(f_j^i\right)^2$$

- We get that

$$\rho_{OOI,\widetilde{OOI}} = .62$$

- Distribution by demographics remains similar

Return

Functional Form

	Treatment		Control	
	Mean	SD	Mean	Sd
log *wage* (1993)	3.26	2.49	3.27	2.49
log *wage* (1999)	4.25	.62	4.27	.58
Female	.356	.479	.356	.479
Age	36.4	6.8	36.4	6.7
Citizen	.995	.073	.995	.073
Low-Secondary	.257	.437	.257	.437
Intermediate-Secondary	.508	.500	.508	.500
High-Secondary	.235	.424	.235	.424
N	37,695		26,963	

Return

Estimation - Details

Estimation Assumptions

Lemma:

$$f_j^i = \frac{f\left(X_i, Z_j\right)}{f\left(X_i\right) f\left(Z_j\right)} \cdot const$$

Proof

Estimation Assumptions

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Proof

Assumption: Parameterization (Dupuy & Galichon, 2014)

$$\log f_j^i = \log \frac{f\left(X_i, Z_j\right)}{f\left(X_i\right) f\left(Z_j\right)} = X_i A Z_j + a\left(X_i\right) + b\left(Z_j\right)$$

where $a\left(X_i\right), b\left(Z_j\right)$ are fixing the marginal distribution

Estimation - Method

Estimation of OOI in 6 steps:

1. Simulate N observations from $f(X_i)\,f(Z_j)$ (˜.5 Million)
2. Append N simulated to N real observations (Total $= 2N$)
3. Define a new variable

$$Y = \begin{cases} 1 & \textit{Real Match} \\ 0 & \textit{Simulated Match} \end{cases}$$

Estimation - Method

4. Estimate a Logit model

$$\log \frac{P\left(Y=1|X=x,Z=z\right)}{P\left(Y=0|X=x,Z=z\right)} = xAz + a\left(x\right) + b\left(z\right)$$

This gives f_j^i for every (x_i, z_j) pair since

$$\frac{P\left(Y=1|X=x_i,Z=z_j\right)}{P\left(Y=0|X=x_i,Z=z_j\right)} =$$

$$\frac{f\left(x_i,z_j|Y=1\right)}{f\left(x_i,z_j|Y=0\right)}\frac{P\left(Y=0\right)}{P\left(Y=1\right)} = \frac{f\left(x_i,z_j\right)}{f\left(x_i\right)f\left(z_i\right)} = f_j^i \cdot c$$

Estimation - Method

5. Calculate $\widehat{f_j^i}$ for every possible worker-job combination
6. Plug in the OOI formula

$$\widehat{OOI_i} = \sum_j \widehat{f_j^i} \log \widehat{f_j^i}$$

Return

Estimation Details

- Simulate data from independent distribution $P(x)P(z)$
- Define $y = \textit{real}$ for data from $P(x,z)$ and $y = \textit{simulated}$ for data from $P(x)P(z)$
- Predict whether y_i is *real* or *simulated* given x_i, z_i using logit

$$\log \frac{P(y = \textit{real}|x,z)}{P(y = \textit{simulated}|x,z)} = \log \frac{P(x,z)}{P(x)P(z)} = xAz + a(x) + b(z)$$

with $a(x) = \widetilde{a}(x) - \log P(x)$

- We linearly approximate a and b Return

Proof

$$f_j^i = f\left(j|i\right) = f\left(j|X = x_i\right) =$$

$$= f\left(j|Z = z_j, X = x_i\right) f\left(Z = z_j|X = x_i\right) =$$

$$= f\left(j|Z = z_j\right) \frac{f\left(X = x_i, Z = z_j\right)}{f\left(X = x_i\right)} =$$

$$= \frac{|J|^{-1}}{f\left(Z = z_j\right)} \frac{f\left(X = x_i, Z = z_j\right)}{f\left(X = x_i\right)}$$

Return

IV

ICE - Empirical Strategy

1. We estimate OOI, adding direct ICE line (interacted with X's) in our probability estimation

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   - Treated: district got a station between 1999 and 2012
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ICE - Empirical Strategy

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   - Control: district never got a station

3. Match workers on state, training occupation, school level, age, gender, lagged income

$$
\begin{aligned}
\Delta_{1999}^{2012} \log w_{im} &= \alpha \Delta_{1999}^{2012} OOI_i + \mu_m + \varepsilon_{im} \\
\Delta_{1999}^{2012} OOI_{im} &= \delta Treat_i + \lambda_m + \nu_{im}
\end{aligned}
$$

Identification assumption: $E\left[\varepsilon_{im} Treat_i | m\right] = 0$

Map Balance Table

Return

Main ICE Results

2SLS (1)	First-Stage (2)	Reduced-Form (3)	OLS (4)
.324***	.073***	.024***	.004
(.048)	(.003)	(.004)	(.007)
Number of observations:			143,313
Number of treated observations:			37,695

Table: Effect of OOI on log w using ICE IV

Standard errors are calculated with Abadie-Imbens (2006) extended for 2SLS

Return

Shift-Share Procedure

Idea: (BGS, 2012) Compare workers within the same industry with outside options in different industries

- Variation from local industry composition
- Local industry trends instrumented with national trends

Specification: Look at change in wages 2004-2014 within industries

$$\Delta_{04}^{14} \log w_{ijr} = \alpha \Delta_{04}^{14} OOI_{ijr} + \beta \Delta_{04}^{14} X_{ijr} + Ind_j^{04} + \varepsilon_{ijr}$$
$$\Delta_{04}^{14} OOI_{ijr} = \gamma B_r + \delta \Delta_{04}^{14} X_{ijr} + Ind_j^{04} + \epsilon_{ijr}$$

i - worker, j - industry, r - region ("Regierungsbezirk")

Instrument Construction

$$E\left[\varepsilon_{ijr} B_r | Ind_j^{04}, \Delta_{04}^{14} X_{ijr}\right] = 0$$

Shift-Share Results

	2SLS (1)	First-Stage (2)	Reduced-Form (3)
	.170***	.622***	.106***
	(.064)	(.241)	(.056)
N	408,792	408,792	408,792
Number of Clusters	38	38	38

Table: Effect of OOI on $\log w$ using Shift-Share IV

Each regression controls for industry fixed effects. Standard errors are clustered by region.

Instrument Construction

The instrument is a weighted average with initial industry shares

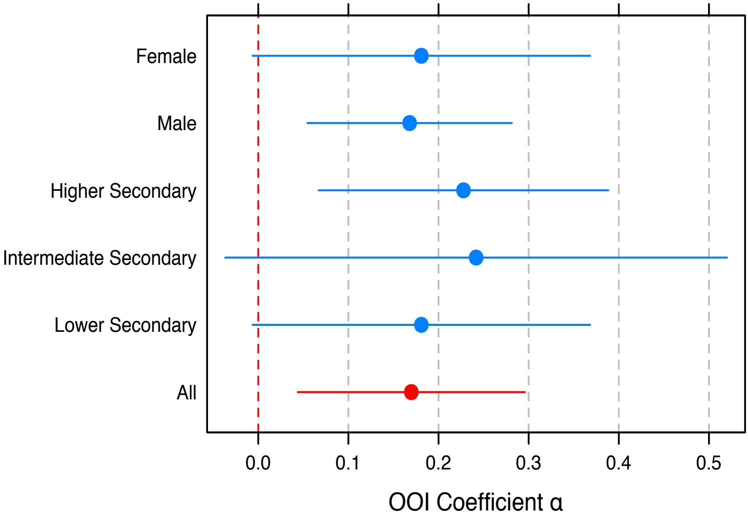
$$B_r = \sum_j \underbrace{s_{jr}^{04}}_{\text{initial shares}} \times \underbrace{g_j}_{\text{national trends}}$$

Calculate g_j by regressing changes in employment on industry & region dummies:

$$\Delta_{04}^{14} \log E_{jr} = \underbrace{g_j}_{industry} + \underbrace{g_r}_{region} + \varepsilon_{jr}$$

Return

Shift-Share Results: Heterogeneity



Return

Shift-Share Results: Stayers

	(1)	
OOI	.170***	.257***
	(.064)	(.092)
OOI × *Stay*		-.159***
		(.062)
N	408,792	408,792
Industry FE	X	X

Table: Effect of OOI on log w by stayer/mover

Stayers are workers who haven't switched establishment between 2004-2014. Standard errors are clustered by region.

Return

Shift-Share Results: Exporters

	Export>33% (1)	33%≥Export≥1% (2)	1%>Export (3)
OOI	.105**	.593**	.132
	(.052)	(.266)	(.141)
N	119,645	146,217	142,930
Industry FE	X	X	X

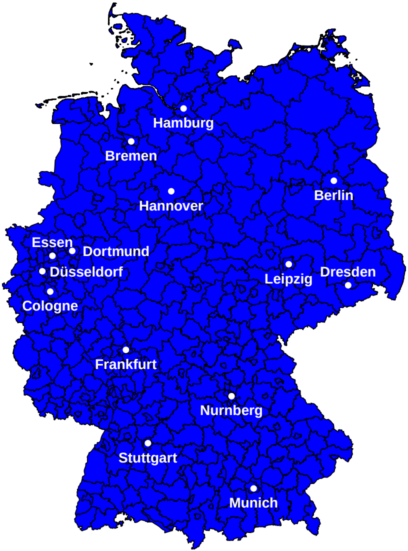
Table: Effect of OOI by Export Status

Export is share of sales from export. Calculated at the industry level, based on survey information on establishments in 2014. SE are clustered at the region level

Return

Other

402 German Districts



60% of workers work outside their district Return

Mass Layoff Sample

- Mass layoff sample definition follows Jacobson, Lalonde & Sullivan (1993)
- Workers who
  - Separated between 1993-2014
  - At establishments with at least 50 workers
  - At establishments whose workforce declined 30% over the year
  - With at least 3 years of tenure pre mass-layoff
  - Below age 55
  - $N = 13,681$

Return

Reasons for Differences in Outside Options

Commuting Costs

We find significant differences in commuting/moving costs across workers.
Want to test its impact on overall OOI differences.

Counterfactual exercise:
For every worker, estimate their wage gain, if they had the minimal commuting cost

- Commute cost of 40 year old, high-educated, male citizen
- All other workers/employers don't change
- Compare the differential wage gain between workers