14.662, Spring 2018 – Three Perspectives on Neoclassical Labor Market Equilibrium

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Benchmark model used in 14.662 is fully competitive

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- How comfortable should we be with that assumption?

Three recent, first-rate counterexamples

1. Labor market consequences of binding minimum wages
2. Using working sorting to measure firm amenities and rents
3. Implications of labor market ‘fissuring’ for wage structure

Agenda

1. **Labor market consequences of binding minimum wages**
2. **Firm rents, compensating differentials, and worker mobility**
3. **Outsourcing and inequality**

So many minimum wage studies...

Minimum wage research bonanza since Card-Krueger '94

- **Fraught topic**
  1. Strongly help priors
  2. A certain lack of civility
- **Research progress has been incremental since C&K '94**
  1. State-by-year panels have clear weaknesses
  2. Cross-state-border design is good — but not bulletproof
  3. Several novel research designs, but subtle issues
  4. Not much variation in minimum wage laws – until recently

Many good ideas for identification: DiNardo, Fortin, Lemieux '96

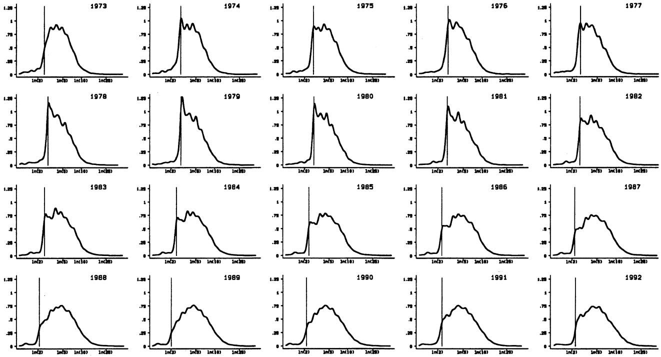
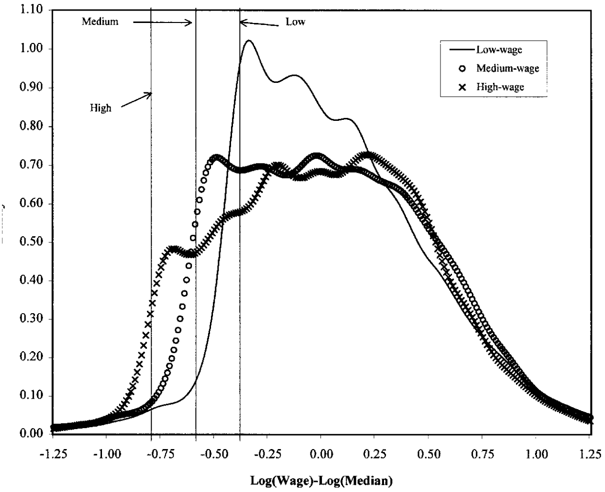


FIGURE 1B—Kernel density estimates of women's real log wages 1973–1992 ($1979).

DiNardo, Fortin, Lemieux '96

Many good ideas for identification: Lee '99



Lee '99

Many good ideas for identification such as Lee '99 – but there are hidden surprises

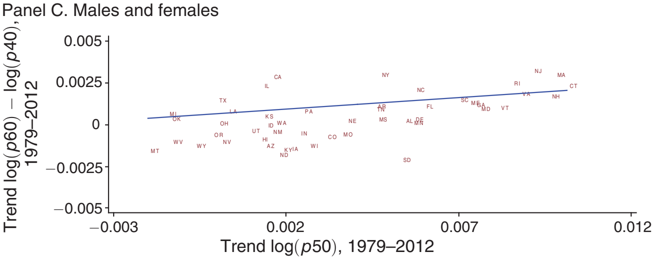
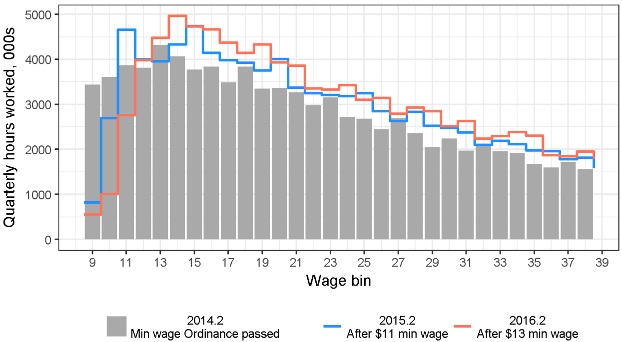


FIGURE 6B. OLS ESTIMATES OF THE RELATIONSHIP BETWEEN TREND LOG($p60$) – LOG($p40$) AND TREND LOG($p50$), 1979–2012

Autor, Manning, Smith '16

Many good ideas for identification: Seattle minimum wage study (Jardim et al. '17)

Figure 2: Changes in the Wage Distribution in Seattle



Jardim et al. '17

Not much variation in minimum wage laws – until recently

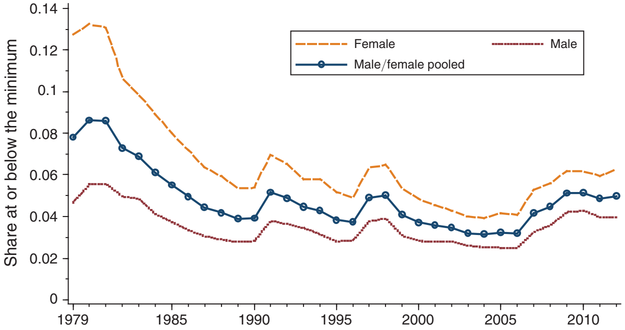


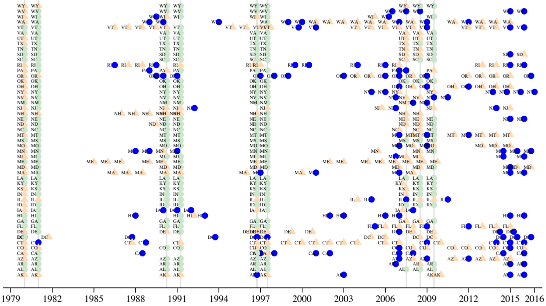
FIGURE 2. SHARE OF HOURS AT OR BELOW THE MINIMUM WAGE

Notes: The figure plots estimates of the share of hours worked for reported wages equal to or less than the applicable state or federal minimum wage, corresponding with data from columns 4 and 8 of Tables 1A and 1B.

Autor, Manning, Smith '16

516 minimum wage increases between 1979 and 2016

Figure A.2: Minimum Wage Increases between 1979 and 2016



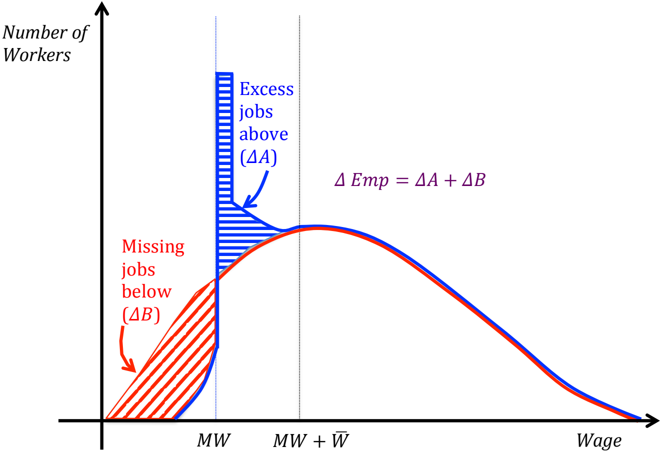
Notes: The figure shows all minimum wage increases between 1979 and 2016. There are a total of 516 minimum wage increases. The blue circles show the primary minimum wage events used in estimating equation 4; the light orange triangles highlight small minimum wage changes where minimum wage increased less than \$0.25 (the size of our wage bins) or where less than 2 percent of the workforce earned between the new and the old minimum wage. The green circles indicate federal changes, which we exclude from our primary sample of treatments because only the change in missing number of jobs, Δb, is identified from time-series variation for these events as there are no "control states" with wage floors lower than the new minimum wage (see the text for details).

Cengiz, Dube, Lindner, Zipperer '18

A phalanx of state minimum wage laws since mid-2000's

- **But should we just hit this variation with another state-by-year FE model?**
  - And if not, what provides the counterfactual for treated locations?
- **New idea: Harasztosi and Lindner '16**
  - Use distribution of employment *prior to new minimum wage* as a measure of treated group
  - Compare to distribution of employment *above new minimum wage* as a measure of effect of treatment on employment

The idea: Contrast employment losses below MW with employment gains above MW



Cengiz, Dube, Lindner, Zipperer '18

How does this differ from Diff-in-Diff?

Need a comparison group, so it's like Diff-in-Diff, but...

1. Localized comparisons: considering *local* (to MW) regions of wage distribution
2. Using info about employment dist'n btwn MW_{old} and MW_{new}
   - This variation not used in prior work (perhaps Autor-Manning-Smith '16, but for a different objective)
3. Above/below MW comparison provides a sanity check
   - If *net effects* on employment are large and positive: a concern
   - If large effects at top of wage distribution: a concern

Hey, where did that spike come from?

In a conventional market-clearing setting, why would you have a spike at minimum wage?

- Should just truncate wage distribution
- But there *is* a spike!

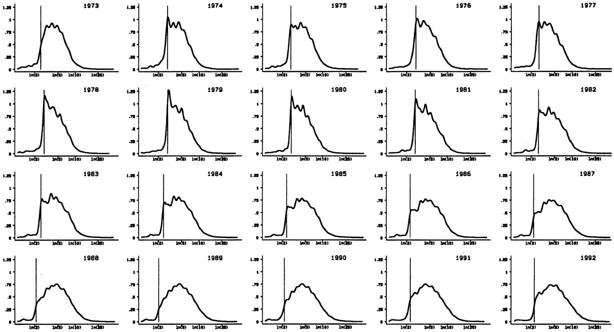


FIGURE 1B—Kernel density estimates of women's real log wages 1973–1992 ($1979).

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CES prod f'n: worker types j differ by reservation wage ω_j

$$Y = \left(\int_{\underline{\omega}}^{\bar{\omega}} \phi_j l_j^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}}$$

- Conditional on ω_j, labor supply of worker type j is perfectly elastic

Where did that spike come from?

CES prod f'n: worker types j differ by reservation wage ω_j

$$Y = \left(\int_{\underline{\omega}}^{\bar{\omega}} \phi_j l_j^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}}$$

- Conditional on ω_j, labor supply of worker type j is perfectly elastic

This gives intuitive explanation for 'bunching'

- Sub-*MW* workers *pushed up* to new *MW* because other groups imperfect substitutes
- It does not explain spillovers b/c all groups equally substitutable
- Need distance-dependent-elasticities for that

Rationalizing (and learning from) the spike

CES production function where workers types j are differentiated by their reservation wage ω_j

$$Y = \left(\int_{\underline{\omega}}^{\bar{\omega}} \phi_j l_j^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}}$$

- Where l_j is the quantity of labor type j used in production, ϕ_j is its efficiency, σ is elasticity of substitution
- [Why do employers' care about workers' reservation wages as an index of their productivity?]
- Assume (for now) that labor supply of each worker type is perfectly elastic

Cost minimization

Cost minimization with fixed Y

$$\min_{l_j} \int_{\underline{\omega}}^{\bar{\omega}} l_j w_j d_j \ s.t. \quad Y = \left(\int_{\underline{\omega}}^{\bar{\omega}} \phi_j l_j^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}}$$

$$F.O.C. \ w_j = \lambda \left(\int_{\underline{\omega}}^{\bar{\omega}} \phi_j l_j^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}-1} \left(\phi l_j^{\frac{\sigma-1}{\sigma}-1} \right)$$

- where λ is the multiplier on the constraint
- Take the ratio of FOCs for types i and j

$$\phi l_j^{\frac{\sigma-1}{\sigma}} = l_j w_j \frac{\phi}{w_i} l_i^{\frac{\sigma-1}{\sigma}-1}$$

- Integrating between two wage levels

$$\int_{\underline{\omega}}^{\bar{\omega}} \phi_j l_j^{\frac{\sigma-1}{\sigma}} dj = \frac{\phi}{w_i} l_i^{\frac{\sigma-1}{\sigma}-1} \int_{\underline{\omega}}^{\bar{\omega}} l_j w_j dj \Rightarrow Y^{\frac{\sigma-1}{\sigma}} = \frac{\phi}{w_i} l_i^{\frac{\sigma-1}{\sigma}-1} \mathbb{C}(Y, w)$$

where $\mathbb{C}(Y, w) = \int_{\underline{\omega}}^{\bar{\omega}} l_j^* w_j dj$ is the cost function

Cost minimization

After a lot of algebra

$$l_i = Yc\left(w\right)^{\sigma}\left(\frac{\phi_i}{w_i}\right)^{\sigma} \text{ with } c\left(w\right) = \left(\int_{\underline{\omega}}^{\bar{\omega}} \phi_j^{\sigma} l_j^{\sigma-1} dj\right)^{\frac{1}{1-\sigma}}$$

Introducing a binding minimum wage

$$l_j = \begin{cases} Y\left(\frac{\phi_j}{MW}\right)^{\sigma} c\left(MW, w\right)^{\sigma} & \textbf{if } w_j < MW \\ Y\left(\frac{\phi_j}{w_j}\right)^{\sigma} c\left(MW, w\right)^{\sigma} & \textbf{if } w_j > MW \end{cases}$$

- Where $c\left(MW, w\right) = \left(\int_{\underline{\omega}}^{MW} \phi_j^{\sigma} MW^{1-\sigma} dj + \int_{MW}^{\bar{\omega}} \phi_j^{\sigma} w_j^{1-\sigma} dj\right)$
- Thus $c\left(MW, w\right)$ is the unit cost of prod'n given MW

The spike

The size of the spike is

- $a = \int_{\underline{\omega}}^{MW} Y \left(\frac{\phi_j}{MW}\right)^{\sigma} c\left(MW, w\right)^{\sigma} dj$
- where $c\left(MW, w\right) = \left(\int_{\underline{\omega}}^{MW} \phi_j^{\sigma} MW^{1-\sigma} dj + \int_{MW}^{\bar{\omega}} \phi_j^{\sigma} w_j^{1-\sigma} dj\right)$

1. If σ is small, spike is large because it's harder to substitute away from types j who would otherwise earn below MW
2. If $\sigma = \infty$, then spike must be zero
3. Spike is also larger if area below MW is larger

Employment change and the spike

Employment change

$$\frac{d \ln \text{Emp}}{d \ln MW} = -\sigma \left(1 - s_{MW}\right) \text{ where } s_{MW} = \frac{\int_{\underline{\omega}}^{MW} \phi_j^{\sigma} MW^{1-\sigma} dj}{\int_{\underline{\omega}}^{MW} \phi_j^{\sigma} MW^{1-\sigma} dj + \int_{MW}^{\bar{\omega}} \phi_j^{\sigma} w_j^{1-\sigma} dj}$$

Follows from Hicks-Marshall laws of demand

1. Larger response if σ is greater
2. Smaller employment response if a larger number of workers affected (holding elasticity constant, limits substitution possibilities)
3. Labor demand increases for workers who are above MW (this is 'labor-labor substitution')

Employment response versus spike

- If spike a is large, σ must be small, so $d \ln \text{Emp}$ small
- If spike a is small, σ must be large, so so $d \ln \text{Emp}$ large
- So, spike is a measure of bindingness scaled by elasticity

More realistic setting: Labor supply elasticity $< \infty$

Labor supply

$$l_j^w = k_j w_j^{\lambda}$$

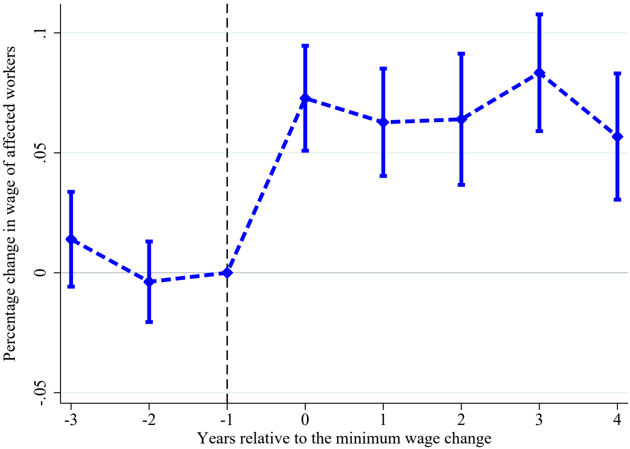
Then

$$\frac{d \ln \textbf{Emp}}{d \ln MW} = \underbrace{-\sigma \left(\frac{\lambda - s_{MW}\lambda}{\lambda + s_{MW}\sigma} \right)}_{\textbf{Substitution effect}} - \underbrace{\eta^w MW}_{\textbf{Scale effect}}$$

Follows from Hicks-Marshall laws of demand

1. Larger response if σ is greater
2. Small response if labor supply is more elastic, λ larger, b/c supply response buffers wage changes at top
3. Larger response if output demand more elastic η larger

Wage effects: Pooled event study

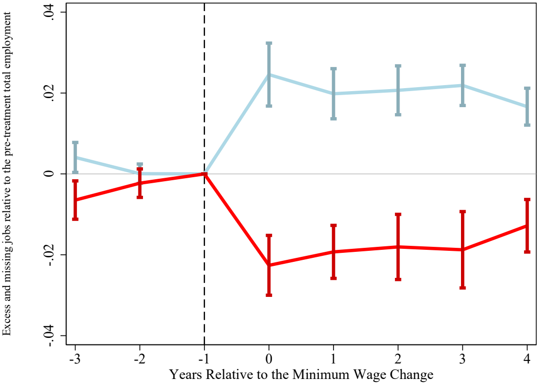


(a) Evolution of the average wage of the affected workers

Cengiz, Dube, Lindner, Zipperer '18

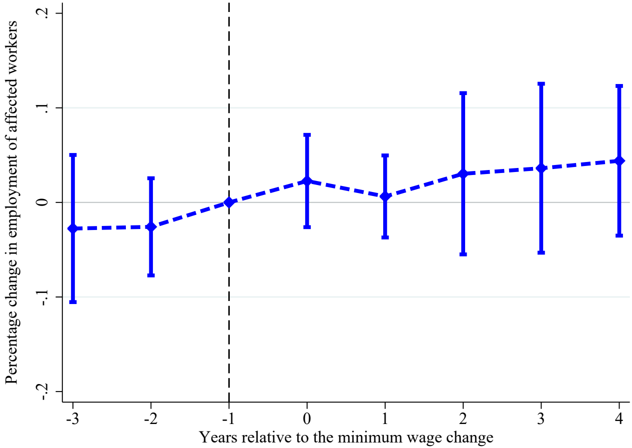
Employment effects: Pooled event study

Figure 4: Impact of Minimum Wages on the Missing and Excess Jobs Over Time (Pooled Event Study Analysis)



Cengiz, Dube, Lindner, Zipperer '18

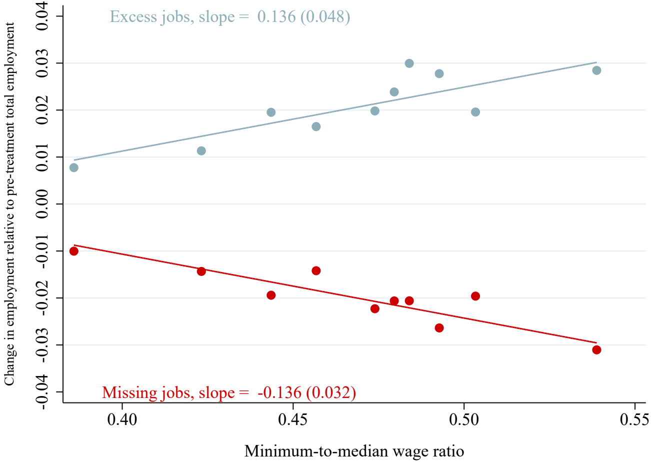
Net employment effects: Pooled event study



(b) Evolution of the employment of the affected workers

Cengiz, Dube, Lindner, Zipperer '18

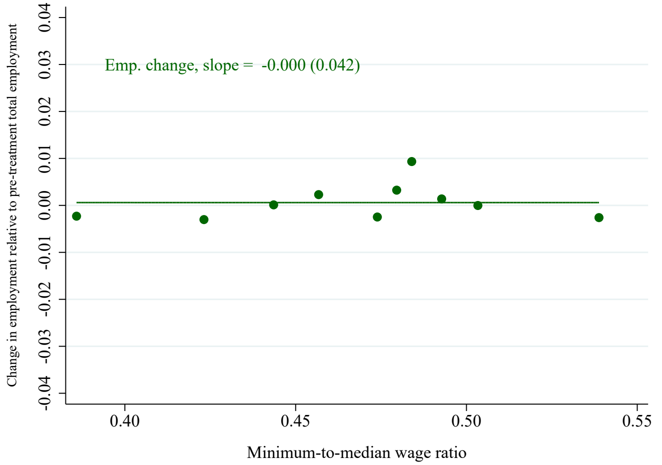
Employment losses – and gains – are monotonically rising in the bite of the minimum wage



(a) Missing and excess jobs

Cengiz, Dube, Lindner, Zipperer '18

Net effect on low wage employment as a function of minimum wage bite

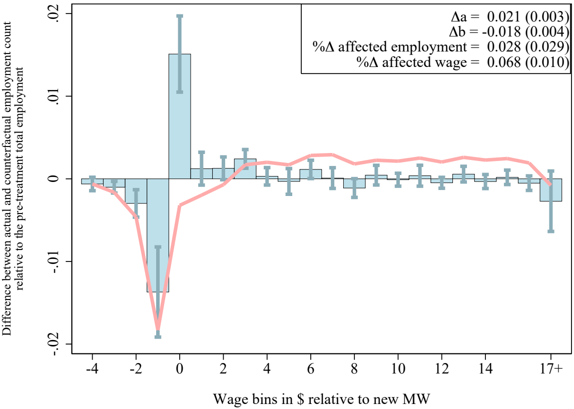


(b) Employment change

Cengiz, Dube, Lindner, Zipperer '18

This plot is killer...

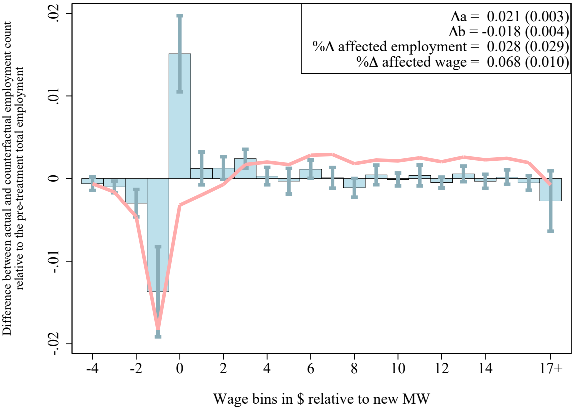
Figure 3: Impact of Minimum Wages on the the Wage Distribution (Pooled Event Study Analysis)



Cengiz, Dube, Lindner, Zipperer '18

Even works well for Washington minimum wage hike in 2000-'04 (not recent hike studied by Jardim et al. '17)

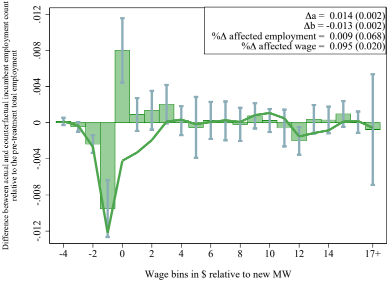
Figure 3: Impact of Minimum Wages on the the Wage Distribution (Pooled Event Study Analysis)



Cengiz, Dube, Lindner, Zipperer '18

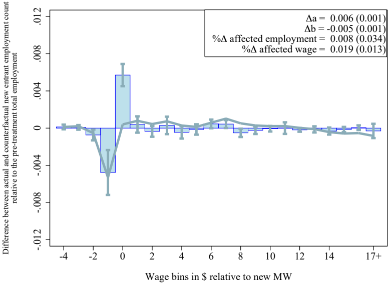
Much larger spike among incumbents than new hires — Consistent with model of employer facing costly search

Incumbents



(a) Incumbents

New Hires



(a) New entrants

Cengiz, Dube, Lindner, Zipperer '18

Main estimates

Table 1: Impact of Minimum Wages on Employment and Wages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Missing jobs below new MW (Δb)	-0.018***	-0.018***	-0.018***	-0.016***	-0.016***	-0.015***	-0.018***	-0.018***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
Excess jobs above new MW (Δa)	0.021***	0.018***	0.020***	0.016***	0.014***	0.015***	0.021***	0.018***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
%Δ affected wages	0.068***	0.057***	0.068***	0.049***	0.043***	0.050***	0.069***	0.058***
	(0.010)	(0.010)	(0.012)	(0.010)	(0.010)	(0.011)	(0.009)	(0.010)
%Δ affected employment	0.028	0.000	0.022	-0.002	-0.019	-0.000	0.036	0.000
	(0.029)	(0.023)	(0.021)	(0.021)	(0.021)	(0.023)	(0.048)	(0.026)
Employment elasticity w.r.t. MW	0.024	0.000	0.019	-0.001	-0.016	-0.000	0.031	0.000
	(0.025)	(0.020)	(0.018)	(0.018)	(0.018)	(0.019)	(0.041)	(0.022)
Emp. elasticity w.r.t. affected wage	0.411	0.006	0.326	-0.032	-0.449	-0.003	0.523	0.008
	(0.430)	(0.402)	(0.313)	(0.439)	(0.574)	(0.455)	(0.676)	(0.446)
Jobs below new MW ($\bar{b}_{-1}$)	0.086	0.086	0.086	0.086	0.086	0.086	0.086	0.086
%Δ MW	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101
Number of events	138	138	138	138	138	138	138	138
Number of observations	847,314	847,314	847,314	847,314	847,314	847,314	847,314	847,314
Number of workers in the sample	4,694,104	4,694,104	4,694,104	4,694,104	4,694,104	4,694,104	4,694,104	4,694,104
Controls								
Bin-state FE	Y	Y	Y	Y	Y	Y	Y	Y
Bin-period FE	Y	Y	Y	Y	Y	Y	Y	Y
Bin-state linear trends		Y	Y		Y	Y		
Bin-state quadratic trends			Y			Y		
Bin-division-period FE				Y	Y	Y		
State-period FE							Y	
Bin-state upper tail wage controls								Y

Robustness

Table 2: Robustness of the Impact of Minimum Wages to Alternative Workforce, Treatment and Sample Definitions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Missing jobs below new MW (Δb)	-0.027***	-0.020***	-0.013***	-0.033***	-0.016***	-0.018***	-0.017***
	(0.003)	(0.003)	(0.003)	(0.008)	(0.004)	(0.004)	(0.003)
Excess jobs above new MW (Δa)	0.026***	0.019***	0.016***	0.036***	0.017***	0.022***	0.019***
	(0.002)	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.002)
%Δ affected wages	0.065***	0.067***	0.073***	0.094***	0.082***	0.077***	0.070***
	(0.007)	(0.012)	(0.012)	(0.020)	(0.014)	(0.011)	(0.010)
%Δ affected employment	-0.009	-0.010	0.044	0.029	0.028	0.046	0.028
	(0.034)	(0.021)	(0.033)	(0.035)	(0.039)	(0.042)	(0.030)
Employment elasticity w.r.t. MW	-0.010	-0.009	0.029	0.029	0.017	0.039	0.022
	(0.036)	(0.019)	(0.022)	(0.035)	(0.024)	(0.036)	(0.024)
Emp. elasticity w.r.t. affected wage	-0.139	-0.157	0.601	0.306	0.337	0.590	0.401
	(0.530)	(0.326)	(0.442)	(0.392)	(0.496)	(0.536)	(0.418)
Jobs below new MW ($\bar{b}_{-1}$)	0.099	0.083	0.067	0.104	0.061	0.087	0.079
%Δ MW	0.093	0.096	0.101	0.101	0.101	0.101	0.100
Number of events	44	369	138	138	138	138	138
Number of observations	847,314	847,314	847,314	847,314	847,314	847,314	847,314
Number of workers in the sample	4,694,104	4,694,104	4,561,684	2,824,287	4,402,488	4,694,104	4,694,104
Set of events	No tip credit states	State & Federal	Primary	Primary	Primary	Primary	Primary
Sample	All workers	All workers	FTE	Hourly workers	Non-tipped occupations	CPS-Raw	Unweighted

Estimates by sector

Table 4: Impact of Minimum Minimum Wages on Employment and Wages by Sectors (1992-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Missing jobs below new MW (Δb)	-0.019***	-0.016*	-0.066***	-0.003	-0.011***	-0.101***	-0.033***	-0.017**
	(0.004)	(0.008)	(0.007)	(0.002)	(0.003)	(0.015)	(0.003)	(0.008)
Excess jobs above new MW (Δa)	0.020***	0.011	0.072***	0.005	0.011***	0.101***	0.041***	0.011
	(0.003)	(0.008)	(0.011)	(0.006)	(0.002)	(0.015)	(0.010)	(0.009)
%Δ affected wages	0.058***	0.058	0.056***	0.097	0.056***	0.049***	0.060***	0.073
	(0.011)	(0.073)	(0.014)	(0.086)	(0.013)	(0.012)	(0.021)	(0.078)
%Δ affected employment	0.008	-0.111	0.022	0.051	0.009	-0.001	0.062	-0.101
	(0.031)	(0.136)	(0.037)	(0.163)	(0.044)	(0.026)	(0.080)	(0.145)
Employment elasticity w.r.t. MW	0.007	-0.056	0.060	0.019	0.005	-0.002	0.086	-0.052
	(0.027)	(0.069)	(0.103)	(0.059)	(0.026)	(0.117)	(0.111)	(0.074)
Emp. elasticity w.r.t. affected wage	0.140	-1.910	0.387	0.530	0.166	-0.011	1.040	-1.385
	(0.523)	(3.922)	(0.597)	(1.311)	(0.763)	(0.542)	(1.058)	(2.956)
Jobs below new MW ($\bar{b}_{-1}$)	0.087	0.050	0.270	0.036	0.057	0.434	0.136	0.050
%Δ MW	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098
Number of events	118	118	118	118	118	118	118	118
Number of observations	554,931	554,931	554,931	554,931	554,931	554,931	554,931	554,931
Number of workers in the sample	2,652,792	358,086	384,498	274,812	1,504,643	156,634	315,397	349,749
Sector:	Overall	Tradable	Nontradable	Construction	Other	Restaurants	Retail	Manufacturing

Wage effects: Direct effects and spillover

Table 5: The Size of the Wage Spillovers

	%Δ affected wage		Spillover share of wage increase
	$\%\Delta w$	$\%\Delta w_{\text{No spillover}}$	$\frac{\%\Delta w - \%\Delta w_{\text{No spillover}}}{\%\Delta w}$
Overall	0.068***	0.041***	0.397***
	(0.010)	(0.009)	(0.119)
Less than high school	0.077***	0.048***	0.370***
	(0.013)	(0.009)	(0.078)
Teen	0.081***	0.053***	0.347***
	(0.015)	(0.007)	(0.059)
High school or less	0.073***	0.043***	0.402***
	(0.013)	(0.011)	(0.100)
Women	0.070***	0.045***	0.359***
	(0.011)	(0.010)	(0.120)
Black or Hispanic	0.045***	0.037***	0.179
	(0.012)	(0.010)	(0.265)
Tradable	0.058	0.065**	-0.114
	(0.073)	(0.028)	(1.157)
Non-tradable	0.056***	0.043***	0.237
	(0.014)	(0.006)	(0.191)
Incumbent	0.095***	0.055***	0.422**
	(0.020)	(0.011)	(0.181)
New entrant	0.019	0.023***	-0.178
	(0.013)	(0.006)	(0.748)

Observations

1. **Methodology is compelling**
    - Results are frankly amazing—seizes the momentum of this literature
    - Probably the most persuasive min wage study since C&K '94
2. **Not clear that the model is a good fit**
    - Spike theory is interesting—addresses a puzzle
    - Cannot rationalize wage spillovers
    - Cannot explain why larger effects on incumbents than new entrants
    - Perhaps a search model is a better conceptual fit...

Agenda

1. Labor market consequences of binding minimum wages
2. **Firm rents, compensating differentials, and worker mobility**
3. Outsourcing and inequality

Context: What determines a worker's pay?

- **Classical view in labor economics**
  - Market prices for human capital education
  - Experience
  - Other worker skills (possibly unobserved)
  - Compensating differentials (Rosen '86)
- **Much new evidence from matched employer-employee data**
  - Firm FEs play a large role wage dispersion
- **What are these FE's:**
  1. Compensation for firm-level job disamenities?
  2. Rents/profit-sharing?
  3. Unobserved worker skills?

Sorkin QJE forthcoming: "Ranking Firms Using Revealed Preference"

Frequent worker transitions to jobs with lower annual salary

- 37% of employment-to-employment transitions involve wage cuts
- 52% of EE transitions to firms with lower firm FE have earnings cuts
- 43% of EE transitions are firms with lower firm FE

Probability of a quarterly wage decline following employer change: LEHD data 2000–2008

Table II: Earnings declines, value changes, and firm-level pay

Panel A. Pr($y \downarrow$)	All	EE	ENE
Unconditional	0.429	0.374	0.469
Unconditional (nominal)	0.402	0.343	0.445
When moving to a			
...higher-paying firm	0.297	0.268	0.321
...lower-paying firm	0.578	0.515	0.618
Panel B. Pr($\Psi \uparrow$)	All	EE	ENE
Unconditional	0.530	0.570	0.501

Sorkin, QJE forthcoming

Sorkin QJE forthcoming: "Ranking Firms Using Revealed Preference"

Why do workers switch to lower-wage jobs?

Sorkin QJE forthcoming: "Ranking Firms Using Revealed Preference"

- **Why do workers switch to lower-wage jobs?**
  1. Amenities
  2. Investments
  3. Involuntary terminations
- **Sorkin: Job switching as a metric of revealed preference**

Using revealed preference to rank firms

Additive fixed effects model for log wages

$$y_{it} = \alpha_i + \Psi_{J(i,t)} + x_{it}'\beta + r_{it}$$

Variance decomposition

$$\text{Var}(y_{it}) = \text{Cov}(\alpha_i, y_{it}) + \text{Cov}\left(\psi_{J(i,t)}, y_{it}\right) + \text{Cov}\left(x_{it}'\beta, y_{it}\right)$$

- Share of the variance of earnings accounted for by firms

$$\frac{\text{Cov}\left(\psi_{J(i,t)}, y_{it}\right)}{\text{Var}(y_{it})}$$

- In this decomposition in Sorkin's LEHD data, firms account for 21% of variance

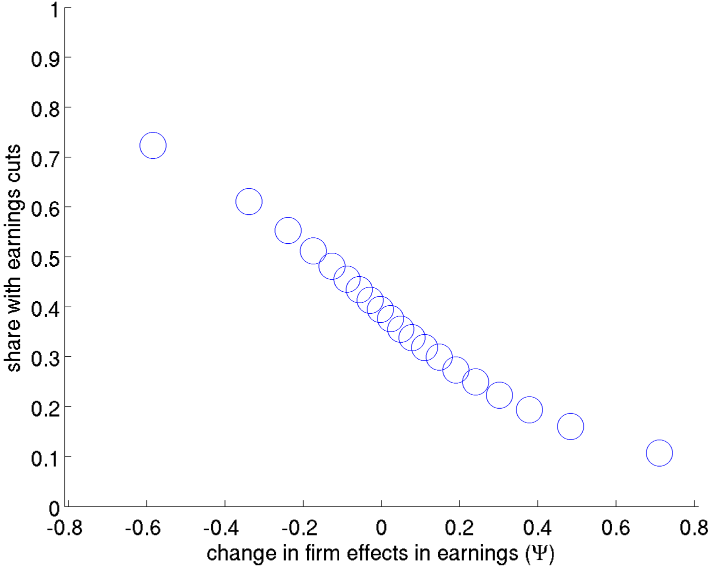
Variance decomposition: LEHD data 2000–2008

Table I: Summary statistics and the variance of earnings

	All	$\geq$ 15 people-years (per year)	Strongly Connected by EE	Strongly Connected by EE (restrictions)
	(1)	(2)	(3)	(4)
Sample size				
People-years	504, 945, 000	411, 088, 000	409, 550, 000	408, 961, 000
People	105, 921, 000	91, 142, 000	90, 895, 000	90, 803, 000
Employers	6, 155, 000	484, 000	476, 000	472, 000
Summary statistics				
Mean log earnings	10.43	10.48	10.48	10.48
Variance of log earnings	0.70	0.67	0.67	0.67
Ensemble decomposition				
Employers			0.21	
People			0.57	
Xb			0.11	

Sorkin, QJE forthcoming

Probability of a quarterly earnings loss for an EE transition as a function of $\Psi_{J,New} - \Psi_{J,Old}$



Here's the idea

Suppose we observe N workers choosing between firms k and j

- Out of these N workers, M^o_{kj} workers choose k and $M^o_{jk} = N - M^o_{kj}$ choose j
- This is a simplistic setting because all choices observed (that's what o denotes)
- Leaves ambiguous how to think about workers choosing M^o_{jj}
- The observed choices will reflect firm desirability and worker prefs
- Sorkin is interested in the *desirability* component

Setting up the inference

- Suppose that the common amenity value for firm k is $\tilde{V}_k^{EE}$
- Workers take into account the common value k as well as an idiosyncratic draw ι
- ι is distributed type I extreme value with scale parameter 1
- Probability of a worker of choosing j over k is

$$\frac{\exp\left(\tilde{V}_k^{EE}\right)}{\exp\left(\tilde{V}_k^{EE}\right)+\exp\left(\tilde{V}_j^{EE}\right)}$$

- This would produce the following simple estimate of amenity value of firm k over j

$$\frac{M_{kj}^o}{N}\times\frac{N}{M_{jk}^o}=\frac{M_{kj}^o}{M_{jk}^o}=\frac{\exp\left(\tilde{V}_k^{EE}\right)}{\exp\left(\tilde{V}_j^{EE}\right)}$$

Setting up the inference

Issues with this estimate of amenity value

$$\frac{M^o_{kj}}{N} \times \frac{N}{M^o_{jk}} = \frac{M^o_{kj}}{M^o_{jk}} = \frac{\exp\left(\tilde{V}^{EE}_k\right)}{\exp\left(\tilde{V}^{EE}_j\right)}$$

- May not be unique, e.g., $j \succcurlyeq k \succcurlyeq l \succcurlyeq j$
- Not all j, k pairs observed

The big idea

- Relax pairwise restrictions, impose only one restriction per firm
- If $j \succcurlyeq k$ and $k \succcurlyeq l$, then assume that $j \succcurlyeq l$
- Provides an exactly identified system
- The conditions for a unique solution much weaker

Setting up the inference

Let Θ equal the set of all employers

$$\frac{M^o_{kj}}{N} \times \frac{N}{M^o_{jk}} = \frac{M^o_{kj}}{M^o_{jk}} = \frac{\exp\left(\tilde{V}^{EE}_k\right)}{\exp\left(\tilde{V}^{EE}_k\right)} \Rightarrow M^o_{kj} \exp\left(\tilde{V}^{EE}_j\right) = M^o_{jk} \exp\left(\tilde{V}^{EE}_k\right), \ \forall j \in \Theta$$

$$\Rightarrow \underbrace{\sum_{j \in \Theta} M^o_{kj}}_{\#\text{ entering } k} \exp\left(\tilde{V}^{EE}_k\right) = \underbrace{\sum_{j \in \Theta} M^o_{jk}}_{\#\text{ exiting } k} \exp\left(\tilde{V}^{EE}_k\right)$$

Rearranging

$$\frac{\overbrace{\sum_{j \in \Theta} M^o_{kj} \exp\left(\tilde{V}^{EE}_k\right)}^{\text{value weighted entry}}}{\underbrace{\sum_{j \in \Theta} M^o_{jk}}_{\text{exits}}} = \underbrace{\exp\left(\tilde{V}^{EE}_k\right)}_{\text{amenity value of firm } k}$$

Setting up the inference

Implies one linear restriction per firm, i.e., on $\tilde{V}_k^{EE}$

$$\frac{\overbrace{\sum_{j\in\Theta} M_{kj}^o \exp\left(\tilde{V}_j^{EE}\right)}^{\text{value weighted entry}}}{\underbrace{\sum_{j\in\Theta} M_{jk}^o}_{\text{exits}}} = \underbrace{\exp\left(\tilde{V}_k^{EE}\right)}_{\text{amenity value of firm } k}$$

- Of course $\tilde{V}_k^{EE}$ is defined in terms of all $\tilde{V}_{j\in\Theta}^{EE}$: recursive definition
- Must be solved recursively, analogous to page rank algorithm
- **"Good firms hire from other good firms and few workers leave"**

Aside: Note on recursion

Recursive factorial procedure

$$\text{define}\ \ \text{factorial}(x)\{$$

$$\text{factorial}(x) == \begin{cases} \text{if } x > 1, & x \cdot \text{factorial}(x-1) \\ \text{if } x = 1, & 1 \end{cases}$$

$$\}$$

$$\begin{aligned} \text{factorial}(4) &= 4 \times \text{factorial}(3) \\ &= 4 \times 3 \times \text{factorial}(2) \\ &= 4 \times 3 \times 2 \times \text{factorial}(1) \\ &= 4 \times 3 \times 2 \times 1 \\ &= 24 \end{aligned}$$

Matrix version of this equation

$$\sum_{j\in\Theta} M^o_{kj} \exp\left(\tilde{V}^{EE}_j\right) / \sum_{j\in\Theta} M^o_{jk} = \underbrace{\exp\left(\tilde{V}^{EE}_k\right)}_{\text{amenity value of firm } k}$$

- Define a diagonal matrix S_o with k^{th} diagonal entry $S^o_{kk} = \sum_{j\in\Theta} M^o_{kj}$
- Define M^o to be the matrix with the (j,k) entry being M^o_{jk}
- $\exp\left(\tilde{V}^{EE}\right)$ is $|\Theta| \times 1$ vector of firm-level $\exp\left(\tilde{V}^{EE}_k\right)$'s

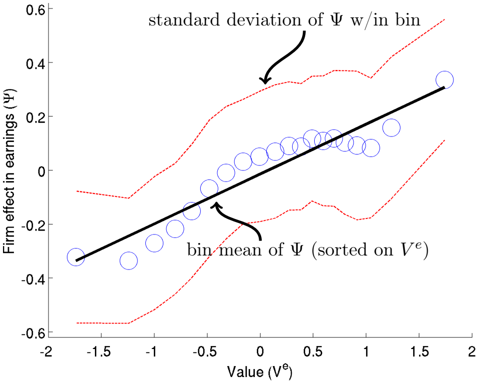
$$\underbrace{S^{0,-1}M^0}_{\text{normalized flows}} \exp\left(\tilde{V}^{EE}_k\right) = \exp\left(\tilde{V}^{EE}_k\right)$$

- Thus, vector $\exp\left(\tilde{V}^{EE}\right)$ is a fixed point of this system for the strongly connected set SC
- **SC defined recursively**: employer is in SC if she hires a worker from SC <u>and</u> one of her workers is hired by employer in SC

Estimated relationship between Ψ and V^e

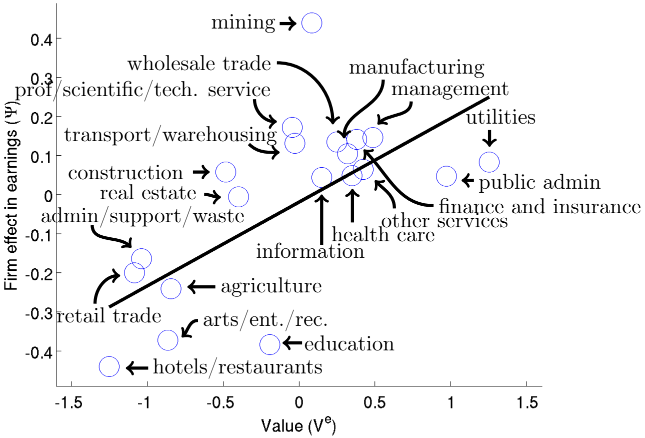
Figure V: Relationship between values and earnings

(a) Overall



Sorkin, *QJE* forthcoming

Sector relationships between Ψ and V^e

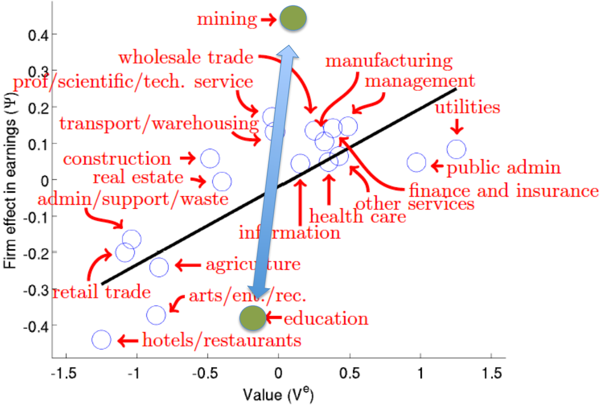


Sorkin, *QJE* forthcoming

Vertical slices of figure: Rosen compensating differentials

Compare the average firms for the mining vs. education sectors:

- **ca. 120% (80 log points) higher earnings in mining**
- **but workers value mining just slightly higher**

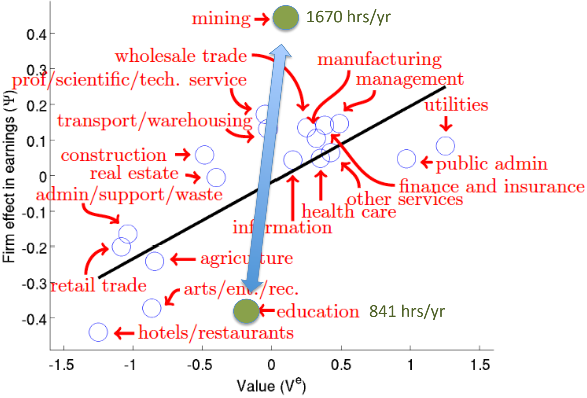


Dorn '17: comment on Sorkin, *QJE* forthcoming

High compensating differential sectors seem to have long hours

Compare the average firms for the mining vs. education sectors:

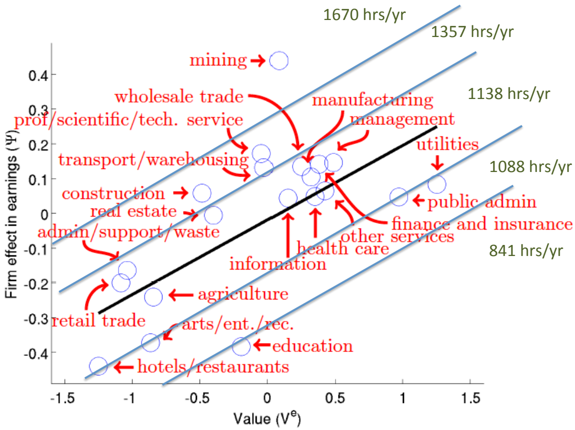
- **ca. 120% (80 log points) higher earnings in mining**
- **ca. 100% higher annual hours in mining (Census 2000)**



Dorn '17: comment on Sorkin, *QJE* forthcoming

High compensating differential sectors seem to have long hours

Sectors with unattractive amenities (top left) have longer work hours



Dorn '17: comment on Sorkin, *QJE* forthcoming

How do compensating differentials affect inequality?

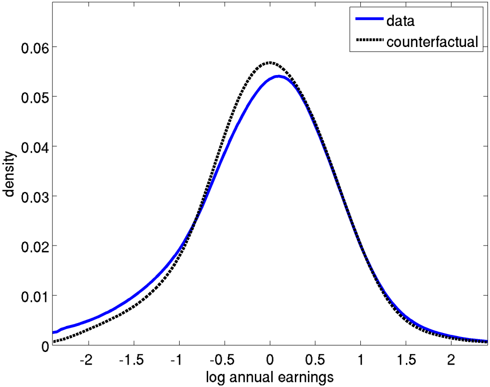
Depends on the correlation between nonpay characteristics and overall inequality

1. High wage workers often have good working conditions
   - Monetizing nonpay job characteristics would *raise* measured inequality
2. MIT administrative assistants: moderate pay but 9-to-5 jobs with limited after-work stress
   - Monetizing their nonpay job characteristics would *reduce* measured inequality

Monetizing compensating differentials moderates inequality by pulling in lower tail...

Figure VII: Counterfactual inequality

(a) Counterfactual



Sorkin, *QJE* forthcoming

NEWS IN BRIEF

Boss Wants Friendly, Relaxed Company Culture In Place By Friday

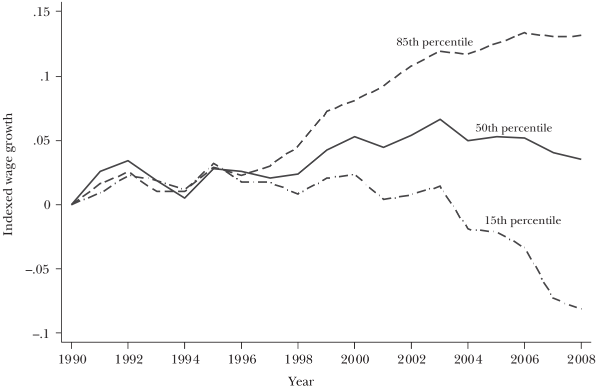
1/25/16 8:34am • SEE MORE: LOCAL

Agenda

1. Labor market consequences of binding minimum wages
2. Firm rents, compensating differentials, and worker mobility
3. **Outsourcing and inequality**

Evolution of Wage Inequality in West Germany, 1990 – 2008

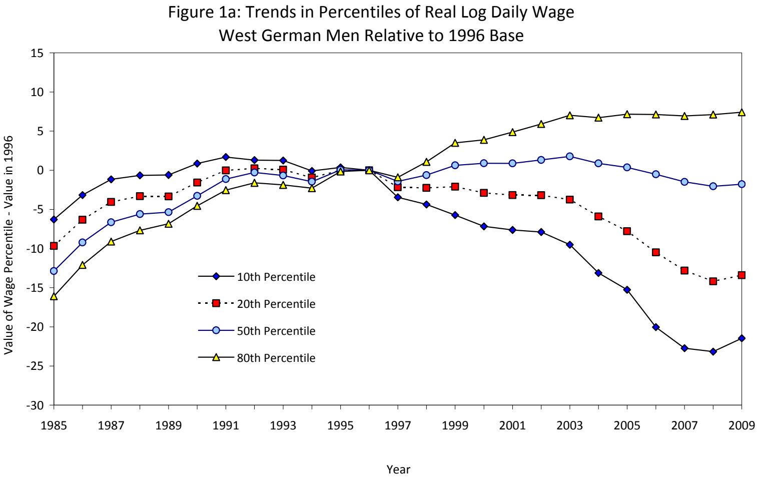
Indexed Wage Growth of the 15th, 50th, 85th Percentiles, West Germany, 1990–2008



Notes: Calculations based on SIAB Sample for West German Full-Time Workers between 20 and 60 years of age. The figure shows the indexed (log) real wage growth of the 15th, 50th, and 85th percentiles of the wage distribution, with 1990 as the base year. Nominal wages are deflated using the consumer price index (1995 = 100) provided by the German Federal Statistical Office.

Dustmann, Fitzenberger, Schönberg and Spitz-Oener, 2014

Trends in percentiles of real log daily wage west German men relative to 1996 base

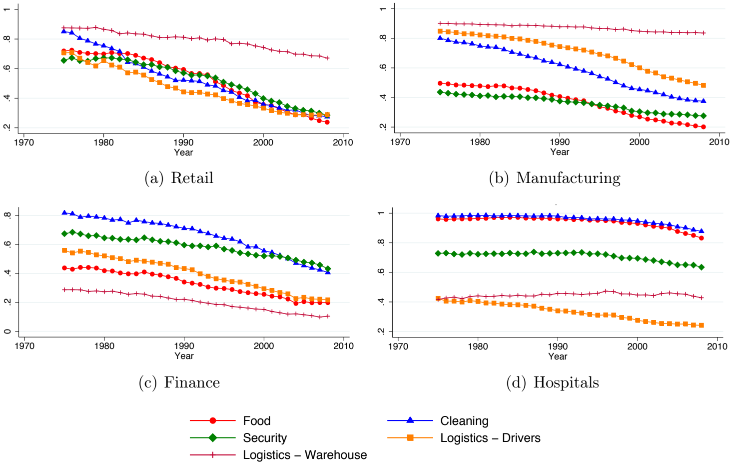


Note: figure shows percentiles of log real daily wage for full time male workers on their main job, deviated from value of same percentile in 1996 and multiplied by 100.

Card, Heining, Kline 2013

Where did all of the food, cleaning, security and logistics workers (FCSL) go?

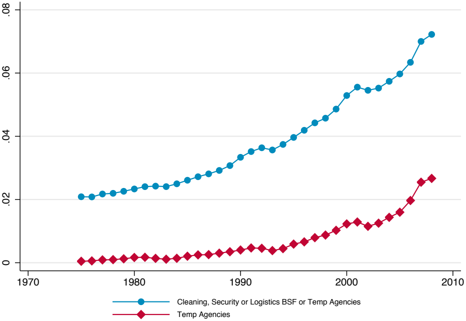
Figure I: Share of Firms with any Food/Cleaning/Security/Logistics workers, by Industry



Goldschmidt and Schmieder 2015

Growing employment in temp agencies, cleaning, security, logistics, and business service firms

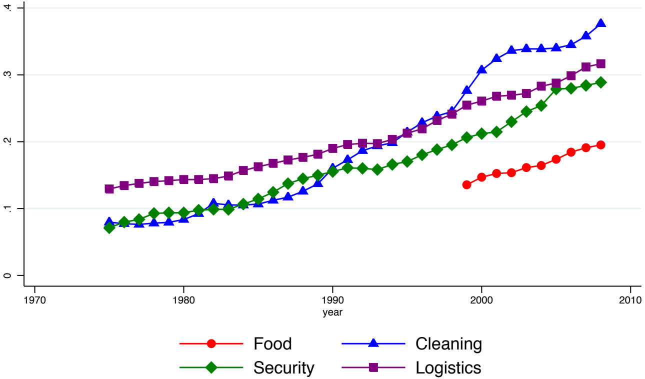
Figure II: Share of Workers employed by Business Service Firms and Temp Agencies over time



(a) Worker in all Occupations

Goldschmidt and Schmieder 2015

Large share of FCSL workers now employed in temp agencies and business services

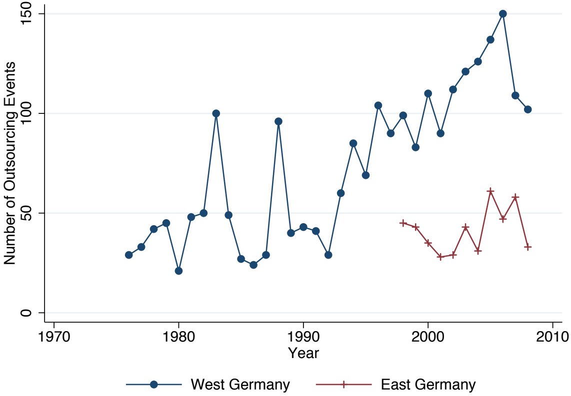


(b) Workers in Food / Cleaning / Security / Logistics Occupations

Goldschmidt and Schmieder 2015

Establishments with on-site outsourcing events

On-site outsourcing events are defined as groups of workers leaving large establishments and moving to business service firms

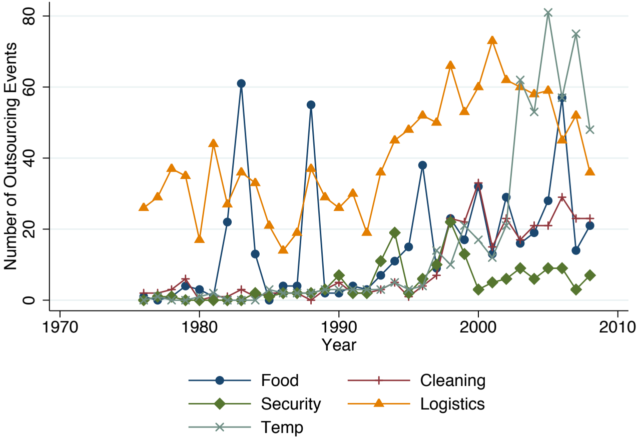


(a) Number of Outsourcing Establishments in East and West Germany

Goldschmidt and Schmieder 2015

On-site outsourcing events by occupation

On-site outsourcing events are defined as groups of workers leaving large establishments and moving to business service firms

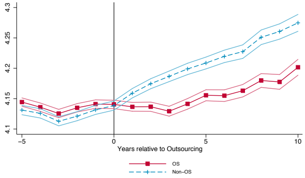


(b) Number of Outsourcing Establishments by Type of Outsourcing

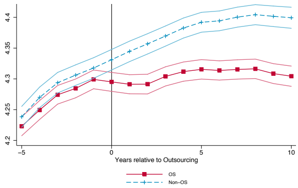
Goldschmidt and Schmieder 2015

Event studies of outsourced workers versus matched comparison groups

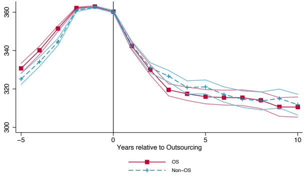
Figure IV: Employment Outcomes of Outsourced and Non-Outsourced Workers Before and After On-site Outsourcing



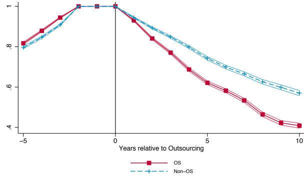
(a) Log Daily Wage



(b) Log Daily Wage - Balanced Panel



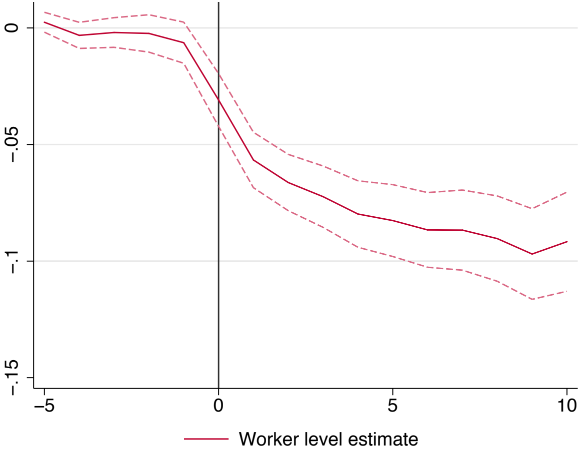
(c) Days Worked Per Year



(d) Probability of working at outsourced job

Goldschmidt and Schmieder 2015

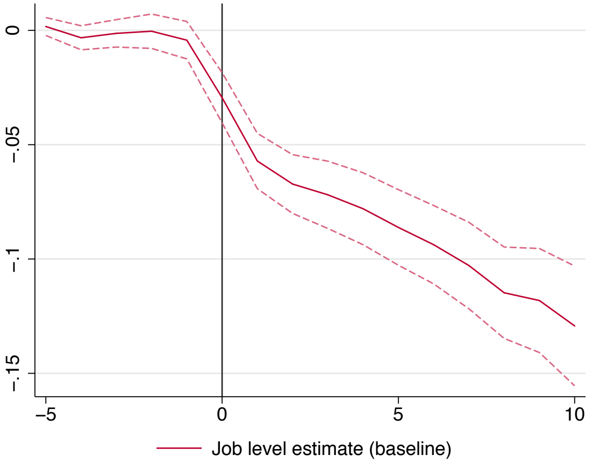
Log wage comparisons: Outsourced workers versus matched comparison groups



(a) All worker observations before and after outsourcing

Goldschmidt and Schmieder 2015

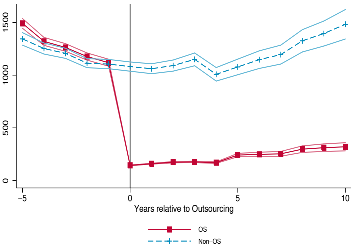
Wage comparisons: Outsourced workers remaining at same job versus matched comparison groups



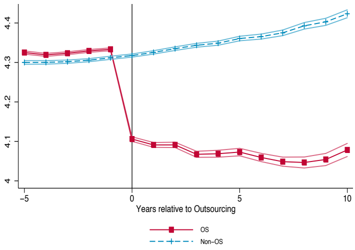
(b) Sample restricted to observations remaining at the same job

Goldschmidt and Schmieder 2015

Establishment characteristics of outsourced and non-outsourced jobs before and after outsourcing



(a) Size of Employer (Establishment)

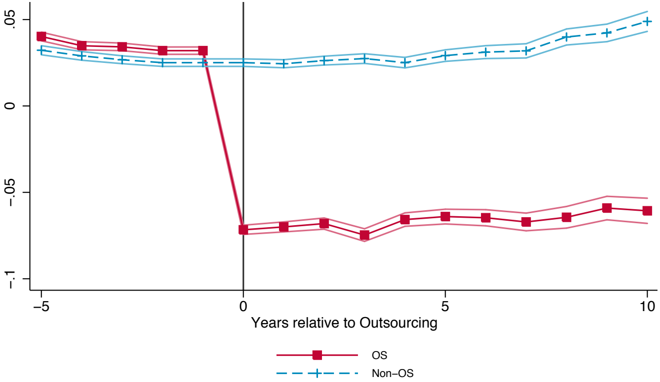


(b) Average Log Wage of Coworkers

Goldschmidt and Schmieder 2015

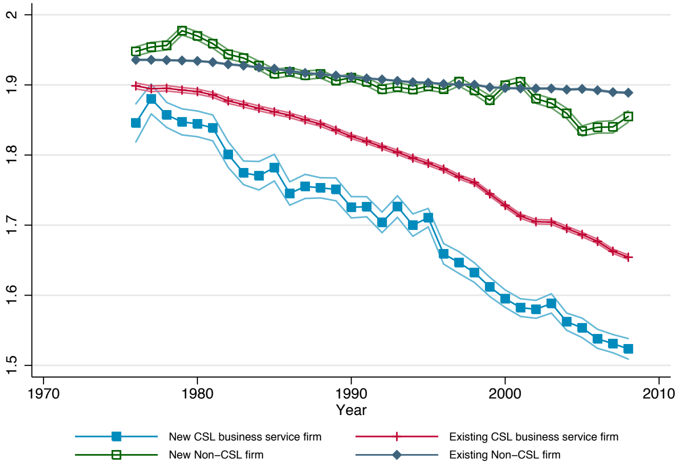
Evolution of AKM effects among outsourced workers

Figure VI: On-site Outsourcing and Establishment (AKM) Effects



Goldschmidt and Schmieder 2015

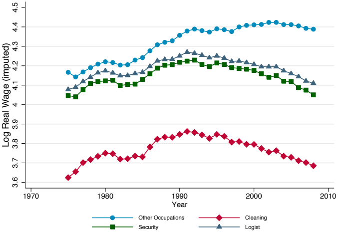
Evolution of AKM effects of cleaning, service, and logistics establishments versus others: Incumbents and entrants



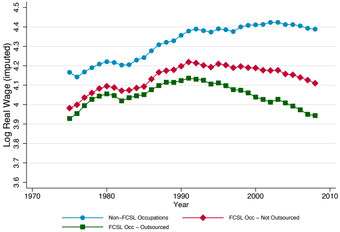
(a) AKM Effects of New and Existing Establishments by Year

Goldschmidt and Schmieder 2015

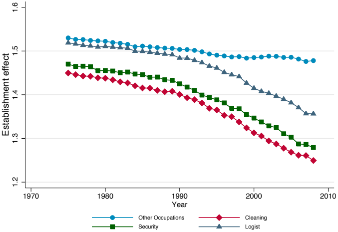
Decoupling of wages in logistics, cleaning and security occupations from overall German wage growth



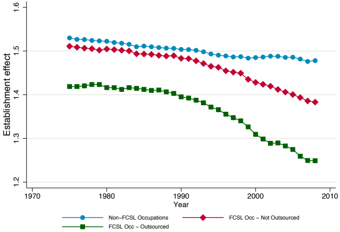
(a) Evolution of Wages by Occupations



(b) Evolution of Wages by Outsourced Status



(c) Evolution of AKM effects by Occupations



(d) Evolution of AKM Effects by Outsourced Status

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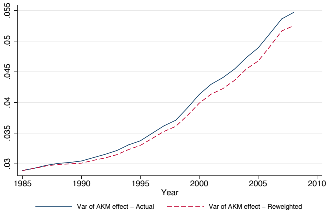
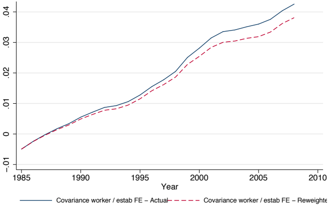
DFL AKM counterfactual: Holding FCLS at 1985 level

Figure X: The Evolution of the West German Wage Structure for Men, Actual and DFL Reweighted

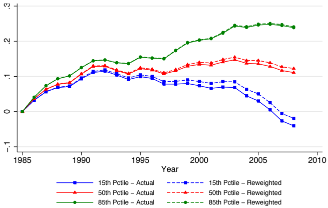
(a) Var(log wage)



(b) Var(establishment effect)



(c) Cov(estab effect, person effect)



(d) Percentiles (15-50-85) of log wage dist.

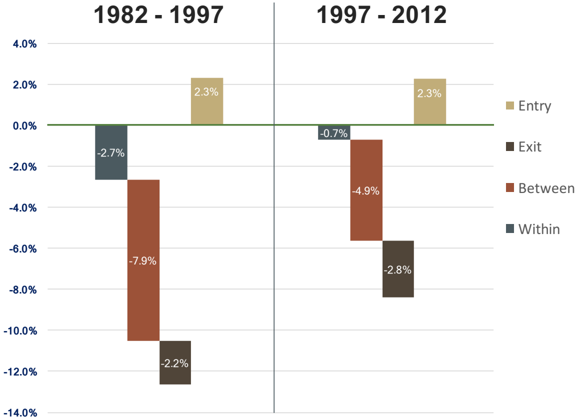
Goldschmidt and Schmieder 2015

the ONION®

5. Für die Stichprobenverteilungsfunktion von $Z_1^*, \ldots, Z_n^*$ verwenden wir die folgende Notation

$$\widehat{F}^*(z) = n^{-1} \sum_{i=1}^{n} \mathbf{1}\{Z_i^* \leq z\}.$$

Complementary evidence on 'Superstar firms'



Notes: MP decomposition over 5 year periods, aggregated to two 15 year periods

Autor, Dorn, Katz, Patterson, Van Reenen '17

SCIENCE

Study Finds Jack Shit

BALTIMORE—A team of scientists at Johns Hopkins University announced Monday that a five-year study examining the link between polyphenols and lower cholesterol rates has found jack shit.

"I can't explain what happened," head researcher Dr. Jeremy Ingels said. "We meticulously followed correct scientific procedure. Our methods were sufficiently rigorous that they should have produced some sort of result. Instead, we found out nothing."

Added Ingels: "Nothing!"

As Ingels stepped aside to compose himself, fellow researcher Dr. Thomas Chen took the podium to discuss the $7 million jack-shit-yielding study.

"We can't say zip about whether it lowers cholesterol," Ingels said. "We don't know if it raises cholesterol. Hell, we don't know if it joins with cholesterol to form an unholy alliance to take over your gall bladder. At this point, I couldn't prove that a male donkey has nuts if they were swinging in my face."