Graduate Labor Economics

Lecture 11: Inter-Firm Wage Differentials

Brendan M. Price*
Federal Reserve Board

 Email: brendan.m.price@frb.gov. These notes are adapted from UC Davis course ECN 250A, which I taught in Winter 2018 and Spring 2019. Any views or opinions expressed here are my own and do not necessarily represent the views or policies of the Board of Governors of the Federal Reserve System or its staff. This version: March 21, 2020.

Today's lecture

- Previously: wage dispersion due to differences in skill
- Today: wage dispersion among "equally skilled" workers
    - Inter-industry wage differentials
    - Inter-firm wage differentials

Why might wages differ across jobs?

- Neoclassical benchmark: law of one price
- Why might this break down?
    - Compensating differentials
    - Institutional wage-setting (unions, gov't)
    - Monopsony power
- "Efficiency wages": Π increasing in w (over some range)
    - $w \uparrow \implies$ less turnover (Salop 1979)
    - $w \uparrow \implies$ less shirking (Shapiro and Stiglitz, 1984)
    - $w \uparrow \implies$ better morale (Akerlof 1982)
    - $w \uparrow \implies$ better applicants (Weiss 1980)
- Firms differ in their reliance on efficiency wages
    - Heterogeneous costs of screening, training, monitoring

Inter-industry wage premia

- Slichter (1950): industries pay similar workers different wages
- Analyzed by (among others) Krueger and Summers (1988)
  - Let $K(i)$ denote worker i's industry
  - Regress log wages on industry FEs

$$y_i = \gamma + \theta_{K(i)} + x_i'\beta + \varepsilon_i$$

    where x_i contains human capital/demographic controls
  - Estimate separately in 1974, 1979, and 1984 CPS
- Interested in dispersion, persistence of the industry FEs

Large, persistent inter-industry wage differentials

ESTIMATED WAGE DIFFERENTIALS FOR ONE-DIGIT INDUSTRIES—MAY CPS[a]
(Standard Errors in Parentheses)

Industry	(1) 1974	(2) 1979	(3) 1984	(4) 1984 Total Compensation
Construction	.195	.126	.108	.091
	(.021)	(.031)	(.034)	(.035)
Manufacturing	.055	.044	.091	.131
	(.020)	(.029)	(.032)	(.032)
Transportation & Public Utilities	.111	.081	.145	.203
	(.021)	(.031)	(.034)	(.034)
Wholesale & Retail Trade	−.128	−.082	−.111	−.136
	(.020)	(.030)	(.033)	(.033)
Finance, Insurance and	.047	−.010	.055	.069
Real Estate	(.022)	(.035)	(.034)	(.034)
Services	−.070	−.055	−.078	−.111
	(.021)	(.030)	(.032)	(.032)
Mining	.179	.229	.222	.231
	(.035)	(.058)	(.075)	(.075)
Weighted Adjusted Standard Deviation of Differentials[b]	.097**	.069**	.094**	.126**
Sample Size	29,945	8,978	11,512	11,512

[a] Other explanatory variables are education and its square, 6 age dummies, 8 occupation dummies, 3 region dummies, sex dummy, race dummy, central city dummy, union member dummy, ever married dummy, veteran status, marriage × sex interaction, education × sex interaction, education squared × sex interaction, 6 age × sex interactions, and a constant. Each column was estimated from a separate cross-sectional regression.
[b] Weights are employment shares for each year.
** *F* test that industry wage differentials jointly equal 0 rejects at the .000001 level.

(Krueger and Summers, 1988, Table 1)

Premium wages or some other explanation?

- Might be "true" pay premia, but might reflect ...
  - Sorting on unmeasured ability
  - Compensating differentials
- Stack across years, add worker fixed effects:

$$y_{it} = \alpha_i + \gamma_t + \theta_{K(i,t)} + x'_{it}\beta + \varepsilon_{it}$$

- Estimate in first differences:

$$\Delta y_{it} = \Delta\gamma_t + \Delta\theta_{K(i,t)} + \Delta x'_{it}\beta + \Delta\varepsilon_{it}$$

- "Switchers model" (identified by industry-changers)
  - Many spurious switches: KS adjust for measurement error

Industry premia survive inclusion of worker FEs

THE EFFECTS OF UNMEASURED LABOR QUALITY[a]

Industry	(1) Fixed Effects Unadjusted for Measurement Error	(2) Fixed Effects Adjusted for Measurement Error I[b]	(3) Fixed Effects Adjusted for Measurement Error II[c]	(4) Levels
Construction	.063	.098	.174	.174
	(.033)	(.060)	(.060)	(.024)
Manufacturing	.028	.055	.107	.064
	(.031)	(.058)	(.058)	(.022)
Transportation and	.019	.060	.049	.114
Public Utilities	(.035)	(.059)	(.059)	(.024)
Wholesale and	−.042	−.068	−.125	−.133
Retail Trade	(.031)	(.056)	(.056)	(.023)
Finance, Insurance	.027	.017	.018	.035
and Real Estate	(.036)	(.061)	(.061)	(.025)
Services	−.040	−.088	−.128	−.079
	(.032)	(.056)	(.057)	(.023)
Mining	.067	.122	.142	.156
	(.004)	(.057)	(.058)	(.040)

[a] Data set is three matched May CPS's pooled together: 1974–1975, 1977–1978, and 1979–1980. Sample size is 18,122. Levels are 1974, 1977, and 1979 data pooled. Results of the 1975, 1978, and 1980 sample are qualitatively the same. Controls for fixed effects regressions are change in education and its square, change in occupation, 3 region dummies, change in union membership, experience squared, change in marital status, year dummies, and a constant. Controls for level regressions are the same as Table I plus year dummies.

[b] Adjustment I assumes 3.4 per cent error rate and that misclassifications are proportional to industry size. See Appendix for description.

[c] Adjustment II assumes average error rate is 3.4 per cent and misclassifications are allocated according to employer-employee mismatches. See Appendix for description.

(Krueger and Summers, 1988, Table 4)

Symmetric effects in either direction

(We'll see this again shortly when we turn to firm-level wage premia)

There are potentially important selection problems involved in studying workers who voluntarily change industries . . . The selection effects operating on workers going from industry i to j are likely to be different from those operating on workers going from industry j to industry i. We were unable, however, to reject the hypothesis that wage changes were the same for joiners and leavers. This suggests that selectivity forces are not very important in the longitudinal analysis and provides some support for the first difference specification.

The case for industry-level rents

- Krueger and Summers interpretation: pure premia (rents)
    - Not explained by worker unobservables
    - Not explained by (observed) differences in working conditions
- Auxiliary evidence of rents:
    - Industry premia are shared across occupations
    - Displaced workers lose their industry premia
    - High-paying industries have lower turnover
    - Industry premia correlated w/profitability

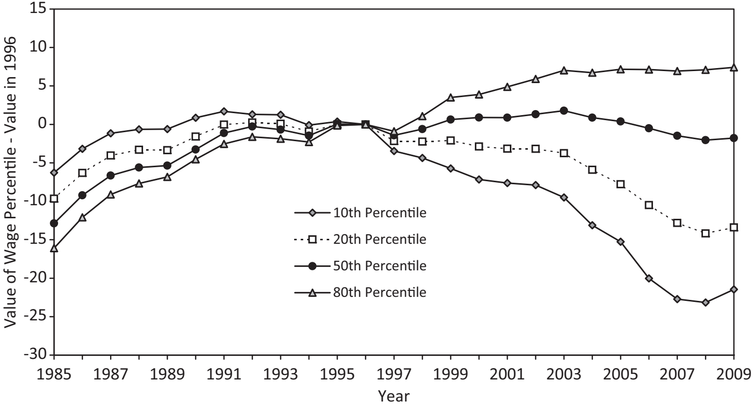
From industries to firms

- Modern approach: estimate *firm* (or establishment) FEs
  - Industry FEs are weighted averages of firm FEs
  - Preferable to look at firm effects directly (if we can)
- Pioneered by Abowd, Kramarz, and Margolis (1999)
  - Original paper is quite technical
  - Tricky computational issues
- Instead: learn AKM via Card, Heining, and Kline (2013)
  - Substantive analysis of the German wage structure
- Analogous studies of the US wage structure:
  - Barth, Bryson, Davis, and Freeman (2016)
  - Song, $\underbrace{\text{Price}}_{\text{not me}}$, Guvenen, Bloom, von Wachter (2018)

Digression: how to learn methods

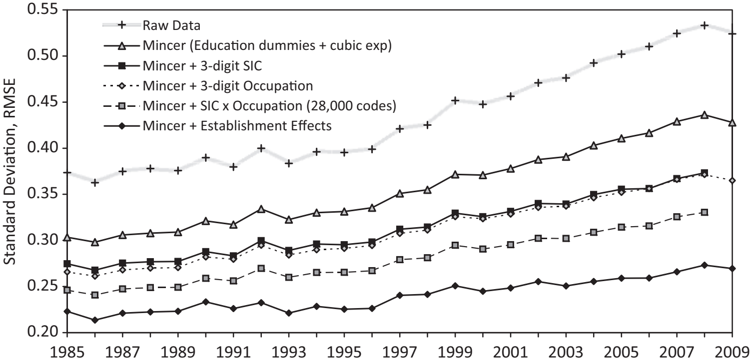
- Which methods should I learn, and in how much detail?
  - Is it being used in applied work?
  - Does it come up a lot in seminars?
  - Would I be embarrassed not to know it?
- One heuristic: partition into three kinds
  - Tools I know how to use (e.g., IV, event-study, clustered SEs)
  - Tools I know when to use (e.g., IK bandwidth for RD designs)
  - Tools I can probably survive without (e.g., stochastic calculus)
- Look for "practitioners' guides"
  - Don't start with the *Econometrica* paper
  - Explanatory discussions in applied papers
  - How-to guides (e.g., Cameron and Miller JHR 2015)

The rise of (male) West German wage inequality



(Card et al., 2013, Figure 1)

Adding estab. FEs reduces rise of residual inequality



(Card et al., 2013, Figure 4)

Card et al. (2013)

- How has employer heterogeneity contributed to inequality?
  - Seems important to explaining residual inequality
  - May also help explain between-group inequality
- Build on Abowd et al. (1999)
  - AKM is now a workhorse statistical model
  - CHK shed light on identifying assumptions
- Focus on West Germany over 1985–2009
  - German reunification circa 1990
  - Weakening of collective bargaining
  - Hartz reforms in mid-2000s

Linked longitudinal worker-firm data

- AKM requires large, linked worker-firm datasets
  - Collected for payroll taxes, unemployment insurance, etc.
  - Growing presence in labor economics
  - German IAB, US LEHD, France, Denmark, Brazil ...
- Many advantages
  - Large samples, both sides of the market
  - Follow workers over many years
  - Accurate (administrative) records
- But many barriers to entry
  - Applying for access
  - Computational intensity
  - Disclosure review

Sample construction and data issues

- Restrict to male full-time workers ages 20–60
  - Women have lower LFP, more part-time jobs
  - But results pretty similar for women
- Retain the job with highest earnings over each year
  - Don't observe hours $\implies$ "wage" $\equiv \frac{\text{earnings}}{\text{days worked}}$
- Observe "establishments" not "firms"
  - May comprise multiple work sites in the same area
  - Spurious entries/exits due to ownership changes, etc.
- Impute top-coded wages
  - Earnings censored at the social security limit
  - Use Tobit model to impute censored wages

Summary statistics

SUMMARY STATISTICS FOR SAMPLES OF FULL-TIME MEN AND WOMEN

		Log real wage, unallocated			Log real wage, allocated	
	(1) Number observations	(2) Mean	(3) Std. dev.	(4) Percent censored	(5) Mean	(6) Std. dev.
Panel A. Full-time men						
1985	11,980,159	4.221	0.387	10.63	4.247	0.429
1990	13,289,988	4.312	0.398	11.92	4.342	0.445
1995	13,101,809	4.340	0.415	9.78	4.361	0.447
2000	12,930,046	4.327	0.464	10.31	4.352	0.502
2005	11,857,526	4.310	0.519	9.36	4.336	0.562
2009	12,104,223	4.277	0.535	10.00	4.308	0.586
Panel B. Full-time women						
1985	6,068,863	3.836	0.462	1.52	3.840	0.470
1990	7,051,617	3.942	0.476	2.01	3.947	0.486
1995	7,030,596	4.026	0.483	1.95	4.030	0.491
2000	7,009,075	4.019	0.532	2.47	4.026	0.545
2005	6,343,006	3.999	0.573	2.36	4.006	0.588
2009	6,566,429	3.979	0.587	2.80	3.988	0.606

(Card et al., 2013, Table 1)

The AKM model

- Standard AKM regression model

$$y_{it} = \alpha_i + \phi_{J(i,t)} + x'_{it}\beta + r_{it}$$

  - Worker i employed by establishment $J(i,t)$ in year t
  - x_{it} includes year dummies, age, and education
  - Estimate over 1985–91, 1990–96, 1996–02, 2002–09
- Identified by job-to-job switchers
  - Only identified for the "largest connected set"
  - Limited mobility bias (Andrews et al. 2008)
- Computationally intensive
  - AKM could only get approximate solutions
  - CHK use an exact algorithm from Abowd et al. (2002)

What is a “good worker”? What is a “good firm”?

- AKM’s original description:
  - “A high-wage worker is a person with total compensation higher than expected on the basis of observable characteristics like labor force experience, education, region, or sex.”
  - “A high-wage firm is an employer with compensation higher than expected given these same observable characteristics.”
- Focus here is on wages, not necessarily productivity
  - Worker FE: productive skills, negotiation, discrimination
  - Firm FE: productive assets, union wages, efficiency wages

Identifying assumptions

- The AKM model again:

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

- Key assumptions:
    - Additive separability (in logs)
    - Exogenous mobility

Endogenous mobility

- Suppose r_{it} has match, unit-root, and transitory components

$$r_{it} = \eta_{iJ(i,t)} + \zeta_{it} + \varepsilon_{it}$$

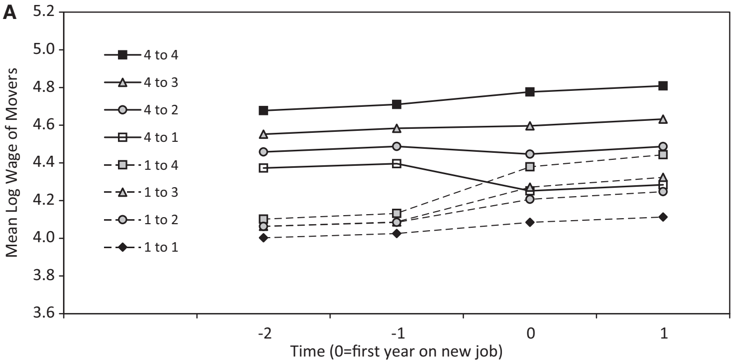
- Some kinds of job mobility are perfectly fine
  - High-α workers tend to move to high-ϕ firms
  - More workers move to better firms than to worse firms
- Three forms of problematic job mobility
  - Selection on match quality ($J(i,t)$ correlated with η)
  - Selection on "drift" ($J(i,t)$ correlated with ζ_{it})
  - Selection on transitory shocks ($J(i,t)$ correlated with ε_{it})

Testable implications of the identifying assumptions

- Selection on match quality?
  - No: wage gains and losses are symmetric
  - No: adding match FEs yields only slightly better fit
- Selection on drift?
  - No: switchers don't exhibit pre-trends (or post-trends)
- Selection on transitory shocks?
  - No: we don't see any "Ashenfelter's dip" before a move

Movers event study (1985–1991)

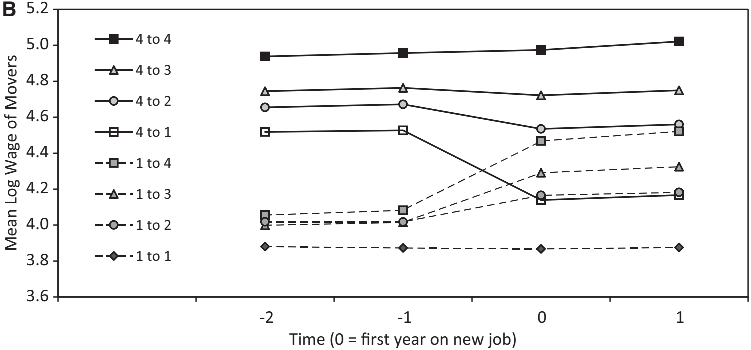
Symmetric gains/losses from upward/downward moves



(Card et al., 2013, Figure 5A)

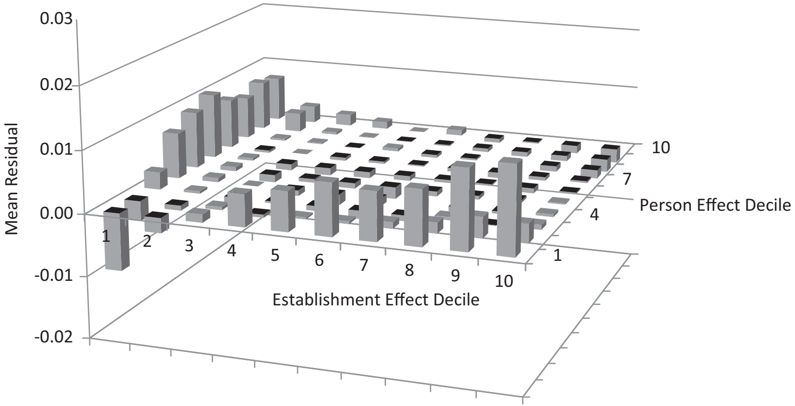
Movers event study (2002–2009)

Gains and losses have grown over time



(Card et al., 2013, Figure 5B)

Systematic departures from additive separability—but small



(Card et al., 2013, Figure 6)

AKM estimates

ESTIMATION RESULTS FOR AKM MODEL, FIT BY INTERVAL

	(1) Interval 1 1985–1991	(2) Interval 2 1990–1996	(3) Interval 3 1996–2002	(4) Interval 4 2002–2009
Person and establishment parameters				
Number person effects	16,295,106	17,223,290	16,384,815	15,834,602
Number establishment effects	1,221,098	1,357,824	1,476,705	1,504,095
Summary of parameter estimates				
Std. dev. of person effects (across person-year obs.)	0.289	0.304	0.327	0.357
Std. dev. of establ. Effects (across person-year obs.)	0.159	0.172	0.194	0.230
Std. dev. of Xb (across person-year obs.)	0.121	0.088	0.093	0.084
Correlation of person/establ. Effects (across person-year obs.)	0.034	0.097	0.169	0.249
Correlation of person effects/Xb (across person-year obs.)	−0.051	−0.102	−0.063	0.029
Correlation of establ. effects/Xb (across person-year obs.)	0.057	0.039	0.050	0.112
RMSE of AKM residual	0.119	0.121	0.130	0.135
Adjusted R-squared	0.896	0.901	0.909	0.927
Comparison match model				
RMSE of match model	0.103	0.105	0.108	0.112
Adjusted R^2	0.922	0.925	0.937	0.949
Std. dev. of match effect*	0.060	0.060	0.072	0.075
Addendum				
Std. dev. log wages	0.370	0.384	0.432	0.499
Sample size	84,185,730	88,662,398	83,699,582	90,615,841

(Card et al., 2013, Table 3)

Decomposing the rise of wage inequality

- Start with the AKM model:

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

- Apply law of total variance:

$$\begin{aligned} Var(y_{it}) = & \operatorname{Var}(\alpha_i) + \operatorname{Var}(\phi_{J(i,t)}) + \operatorname{Var}(x_{it}'\beta) \\ & + 2\operatorname{Cov}(\alpha_i, \phi_{J(,it)}) + 2\operatorname{Cov}(\phi_{J(,it)}, x_{it}'\beta) \\ & + 2\operatorname{Cov}(\alpha_i, x_{it}'\beta) + \operatorname{Var}(r_{it}) \end{aligned}$$

- Covariance terms reflect *sorting*
    - Potential for positive assortative matching
    - Emerges from assignment models under supermodularity (Sattinger 1993, Tervio 2008)

Results from the AKM decomposition

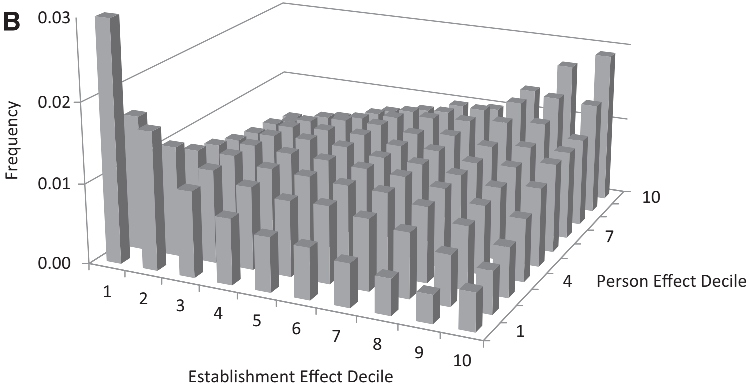
Main drivers: var of person FEs, var of estab. FEs, and assortative matching

Decomposition of the Rise in Wage Inequality

	Interval 1 (1985–1991)		Interval 4 (2002–2009)		Change from interval 1 to 4	
	(1) Var. component	(2) Share of total	(3) Var. component	(4) Share of total	(5) Var. component	(6) Share of total
Total variance of log wages	0.137	100.0	0.249	100.0	0.112	100
Components of variance:						
Variance of person effect	0.084	61.3	0.127	51.2	0.043	39
Variance of establ. effect	0.025	18.5	0.053	21.2	0.027	25
Variance of Xb	0.015	10.7	0.007	2.8	–0.008	–7
Variance of residual	0.011	8.2	0.015	5.9	0.003	3
2cov(person, establ.)	0.003	2.3	0.041	16.4	0.038	34
2cov(Xb, person + establ.)	–0.001	–1.0	0.006	2.4	0.007	7
Counterfactuals for variance of log wages*						
1. No rise in correl. of person/estab. effects	0.137		0.213		0.077	69
2. No rise in var. of estab. effect	0.137		0.209		0.072	64
3. Both 1 and 2	0.137		0.184		0.047	42

(Card et al., 2013, Table 4)

Assortative matching, 2002–2009



(Card et al., 2013, Table 8B)

Between-group inequality

- Group-specific wages depend on worker and employer FEs

$$\mathbb{E}_g[y_{it}] = \mathbb{E}_g[\alpha_i] + \mathbb{E}_g[\phi_{J(i,t)}] + \mathbb{E}_g[x'_{it}\beta]$$

- Use estimated FEs to reevaluate between-group inequality
- Establishments account for much of the rise in ...
  - Rising inter-education wage gaps
  - Rising inter-occupation wage gaps
  - Rising inter-industry wage gaps

Highly educated workers match with high-wage firms

Decomposition of Changes in Relative Wages by Education Level, 1985–1991 versus 2002–2009

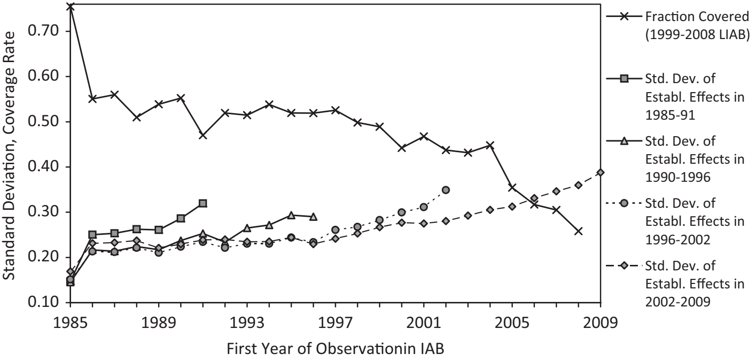
	(1) Change in mean log wage relative to apprentices	(2) Change in mean person effect	(3) Change in mean establishment effect	(4) Remainder
Highest education qualification				
1. Missing/none	–14.6	1.8	–12.2	–4.2
2. Lower secondary school or less (no vocational training)	–10.5	–0.1	–6.3	–4.1
4. Abitur with or without vocational training*	10.1	0.0	2.6	7.5
5. University or more	5.7	1.5	3.9	0.3

(Card et al., 2013, Table 5)

Why is employer dispersion rising?

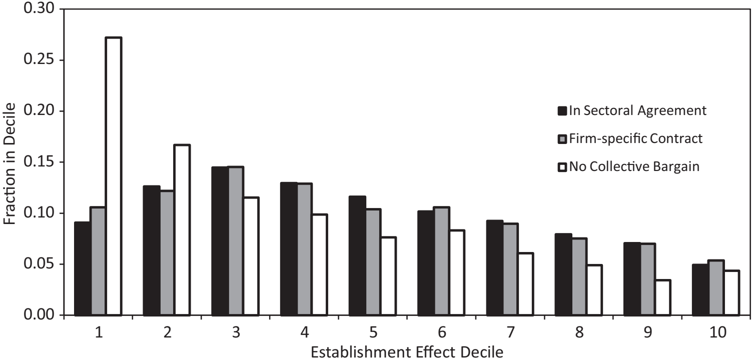
- Last section offers suggestive evidence on mechanisms
  - Breakdown of collective bargaining system
  - Low-wage firms are newer, less likely to bargain

Newer establishments exhibit greater wage dispersion



(Card et al., 2013, Figure 9)

Lowest-paying firms opting out of collective bargaining



(Card et al., 2013, Figure 10)

What if you don't work on workers?

- AKM has opened new doors in understanding wage structure
  - Rising inequality (CHK; Song et al. 2018)
  - Costs of job loss (Lachowska, Mas, and Woodbury 2018)
  - Gender gap (Card, Cardoso, and Kline (2015)
- But (i, j) don't have to be workers and firms!
  - Finkelstein, Gentzkow, and Williams (2016): healthcare utilization (patient and area FEs)
  - Sacarny (2018): physician behavior (doctor and hospital FEs)
  - Closely related to value-added modeling in education
- Key requirements: two-sided matching, mobility, large N