Industry Wage Differentials: A Firm-Based Approach

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Industry wage differentials

- Classical, competitive labor economics models assume the "law of one price":
  A worker is paid his/her marginal product in his/her most productive occupation, and any other job he/she might take would pay the same.

- A classic literature, dating back at least to Krueger and Summers (1988), explores systematic pay differences across industries.
  - Are these violations of the law of one price?
  - Or do they reflect selection into different industries?

- A more recent literature, building from Abowd, Kramarz, and Margolis (1999), documents ***firm*** wage premiums

Cross-sectional estimates and the movers design

- y_{it} = log(earnings) of worker i in period t.
- $f(i,t)$ indexes the firm at which i is employed at t, and $j(f)$ the industry of firm f.

- Cross-sectional estimates of industry effects:

$$y_{it} = \alpha + \psi_{j(f(i,t))} + X_{it}\beta + \varepsilon_{it}.$$

  But unobserved ability may differ.

- Panel data with industry movers to identify effects:

$$y_{i2} - y_{i1} = \psi_{j(f(i,2))} - \psi_{j(f(i,t))} + (\varepsilon_{i2} - \varepsilon_{i1}).$$

  This is equivalent to a worker fixed effects model:

$$y_{it} = \alpha_i + \psi_{j(f(i,t))} + \varepsilon_{it}.$$

Abowd-Kramarz-Margolis (1999) - AKM

- AKM propose a model with *firm* effects on wages, using worker fixed effects to control for worker heterogeneity.

$$y_{it} = \alpha_i + \delta_{f(i,t)} + \varepsilon_{it}.$$

- Identifies firm "wage effect" under assumption of exogenous mobility.
- Evidence of substantial variation in $\delta_{f(i,t)}$

AKM meets industry wage differentials

$$y_{it} = \alpha_i + \delta_{f(i,t)} + \varepsilon_{it}$$

- A natural definition for the industry wage differential is simply the average firm effect across all firms in the industry,

$$\psi_k \equiv \frac{\sum_{j(f)=k} N_f \delta_f}{\sum_{j(f)=k} N_f} \, .$$

- Interpretation: Moving a randomly selected worker from industry *k* to a randomly selected job in industry *k*' yields an average wage change of $\psi_{k'} - \psi_k$.

Summary

- Three ways to estimate industry wage differentials:
  - Cross-sectional: $y_{it} = \alpha + \psi_{j(f(i,t))} + X_{it}\beta + \varepsilon_{it}$
  - Movers design: $y_{it} = \alpha_i + \psi_{j(f(i,t))} + \varepsilon_{it}$
  - AKM based: $y_{it} = \alpha_i + \delta_{f(i,t)} + \varepsilon_{it}$

$$\rightarrow \quad \psi_{j(f(i,t))} \equiv \frac{\sum_{k(f)=j} N_f \delta_f}{\sum_{k(f)=j} N_f}$$

In this paper

- Use administrative data to obtain estimates based on three methods.
- Will show that relative to AKM-based industry premia $\psi_{j(f(i,t))}$:
  - Cross-sectional estimates ($\psi_{j(f(i,t))}$) **overstate** premia due to worker sorting.
  - Movers estimates ($\psi_{j(f(i,t))}$) **understate** premia due to hierarchy term.
- Additional analysis based on $\psi_{j(f(i,t))}$

Data: LEHD

- **Longitudinal Employer Household Dynamics** dataset, developed and maintained by Census Bureau (based on UI programs)
- Data for 50 states (plus DC), 2010-2018.
- We use 4-digit NAICS industries.
- Data have quarterly earnings, not wages. We exclude low-earnings quarters, multiple job-holders, first and last quarters of job spells.
- Estimation sample: 2.5 billion person-quarter observations, 46% move industries
- We estimate our firm AKM model separately by commuting zone, then average across CZs to the national industry level.
- Normalization: Restaurant industry has $\psi_k = 0$ in each CZ.

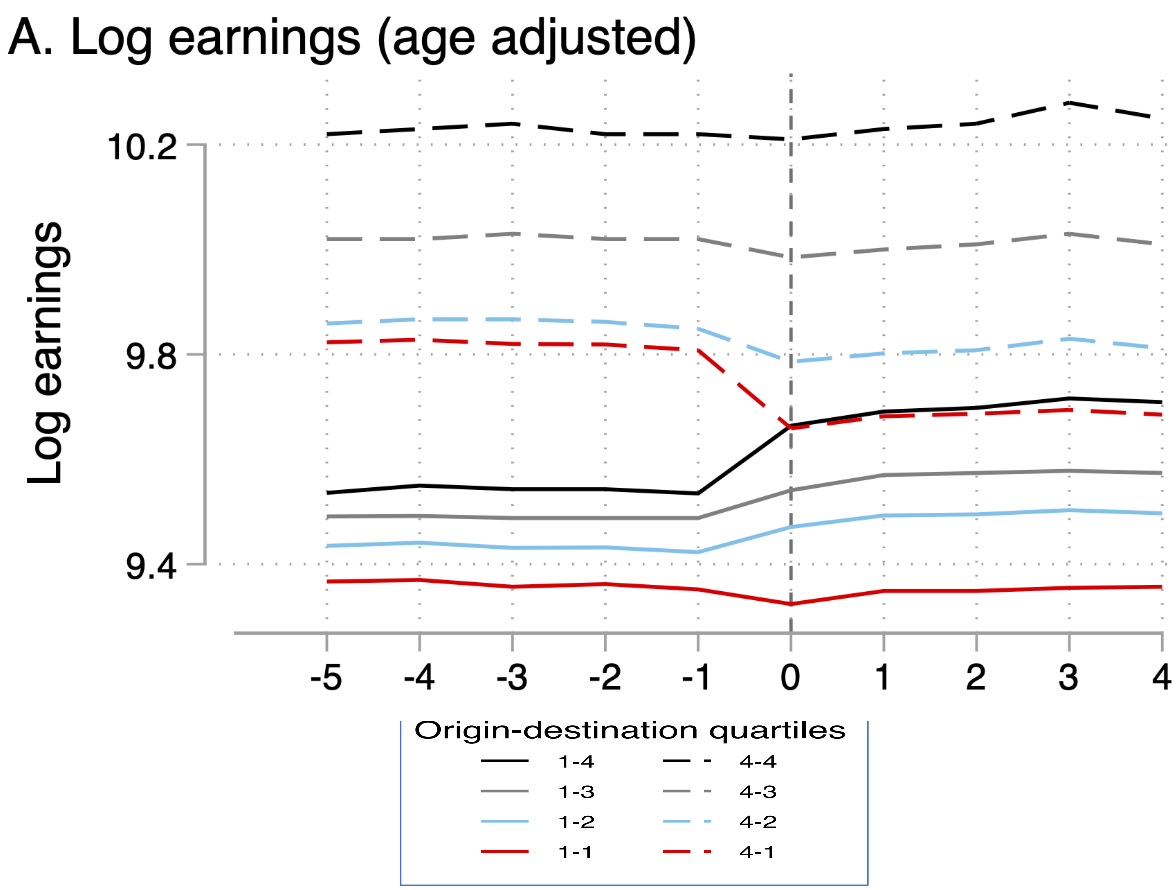
Additive earnings model (AKM)

- Worker i in quarter t, working in firm $f(i,t)$
- Log earnings are y_{it}.
- Decompose into permanent worker effects α_i , firm effects $\delta_{f(i,t)}$, and observables:

$$y_{it} = \alpha_i + \boldsymbol{\delta_{f(i,t)}} + X_{it}\beta + \varepsilon_{it}$$

- Agreggate each component at the industry level:
  - $y_k \equiv \frac{\sum_{j(f(i,t))=k} y_{it}}{N_k}$ $\quad$ $\alpha_k \equiv \frac{\sum_{j(f(i,t))=k} \alpha_i}{N_k}$ $\quad$ $\psi_k \equiv \frac{\sum_{j(f)=k} N_f \delta_f}{\sum_{j(f)=k} N_f}$
- Assumptions:
  - Additive separability of person and firm effects
  - Exogenous mobility – $f(i,t)$ doesn't depend on ε_{it}, ε_{it-1}, etc.
  - Draw on tests developed by Card-Heining-Kline (2013), Card-Cardoso-Kline (2016).

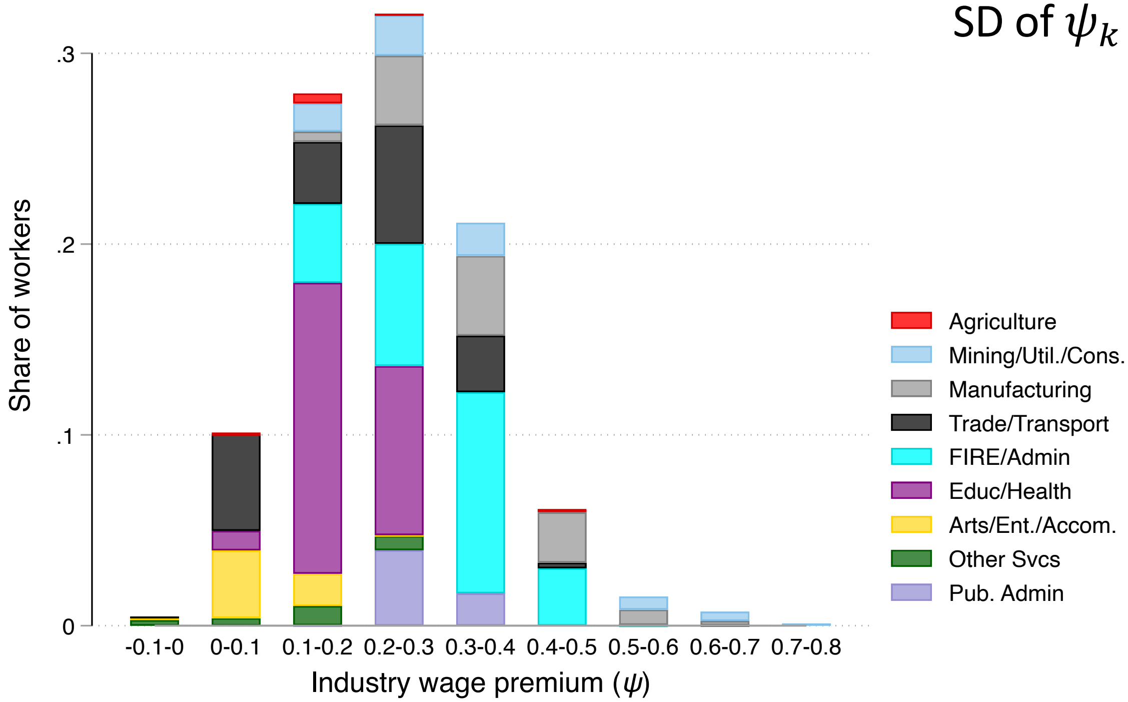
Event study of between-industry movers



AKM-based industry premiums

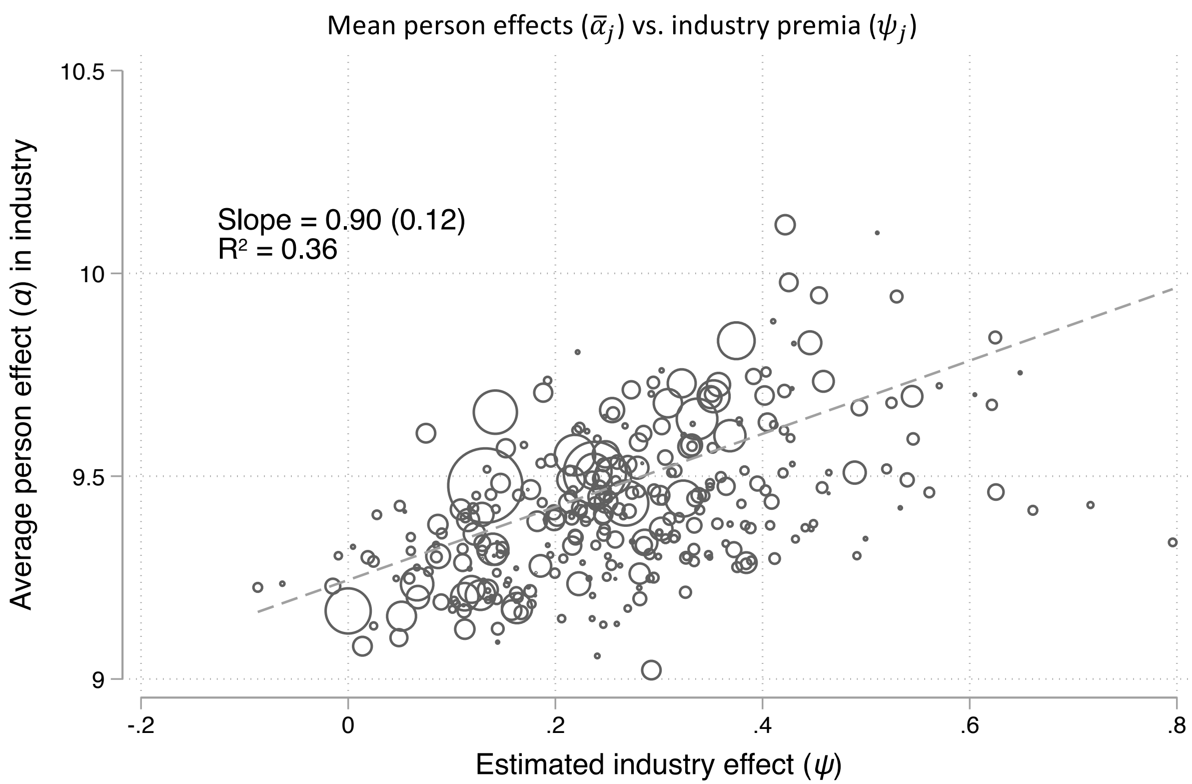
Distribution of AKM-based industry premiums (4-digit)

SD of ψ_k =.12

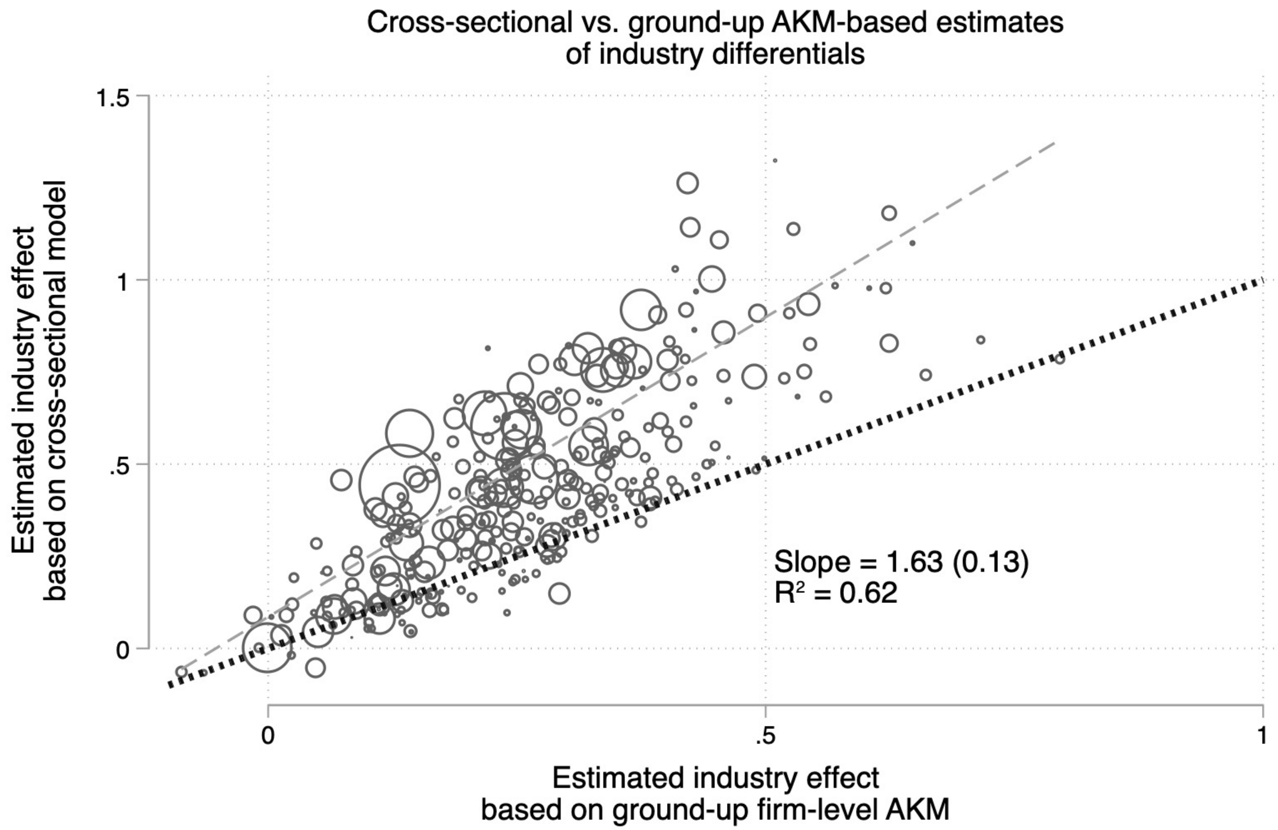


Worker sorting and industry premia

$$\bar{y}_j = \hat{\alpha}_j + \hat{\psi}_j$$



Cross-sectional estimates overstate ground-up, AKM-based industry premia



AKM industry wage differentials vs. movers design

- If AKM specification is right, then industry wage differentials movers design is:

$$y_{it} = \alpha_i + \psi_{j(f(i,t))} + \left[\left(\delta_{f(i,t)} - \psi_{j(f(i,t))}\right) + \varepsilon_{it}\right].$$

- Our AKM industry effect definition ($\psi_k \equiv \frac{\sum_{j(f)=k} N_f \delta_f}{\sum_{j(f)=k} N_f}$) ensures that the error term has mean zero under AKM model assumptions.
- We can think of the first component of the error term, $h(f) \equiv \delta_f - \psi_{j(f)}$, as representing the firm's position within the industry wage hierarchy – we call it the *hierarchy* term.

Exploring the hierarchy term

- We have

$$y_{it} = \alpha_i + \psi_{j(f(i,t))} + [h_{f(i,t)} + \varepsilon_{it}],$$

  where $h_f \equiv \delta_f - \psi_{j(f)}$ is the hierarchy effect.

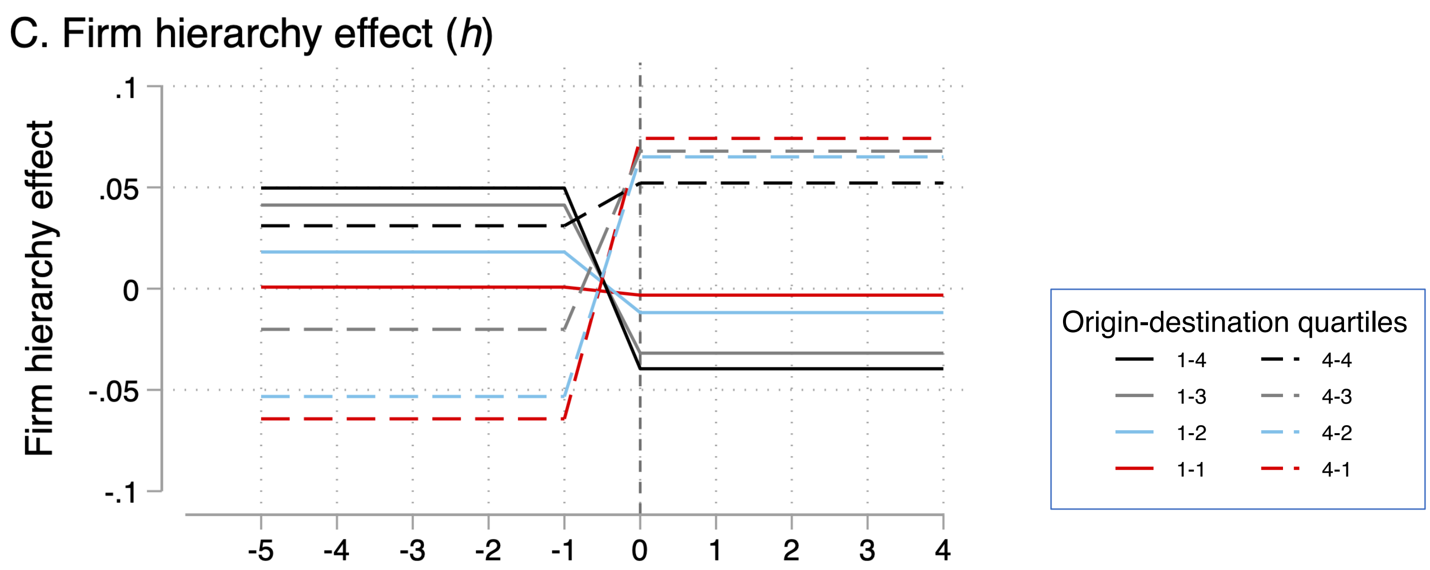
- In mover design models, identification of the industry effects is based on wage changes for people who move between industries.
- Problem: industry movers may be non-randomly selected with respect to the industry hierarchy components of their origin or destination firms.
  - Consider a job ladders model, where job switchers tend to move to new firms with similar δ_f as their origin firms – both within and across industries.
  - $\delta_f^{ORIG} \equiv \psi_{j(f)}^{ORIG} + h_f^{ORIG}$
  - $\delta_f^{DEST} \equiv \psi_{j(f)}^{DEST} + h_f^{DEST}$
  - In this case, Δh will be negatively correlated with $\Delta\psi$
  - Implication is that movers estimates are *attenuated*.

Between-industry moves are selective in terms of the origin and destination firms.

- Recall that the industry movers design has a composite error term:

$$y_{it} = \alpha_i + \psi_{j(i,t)} + \left[(\boldsymbol{\delta_f} - \boldsymbol{\psi_{j(f)}}) + \varepsilon_{it} \right].$$

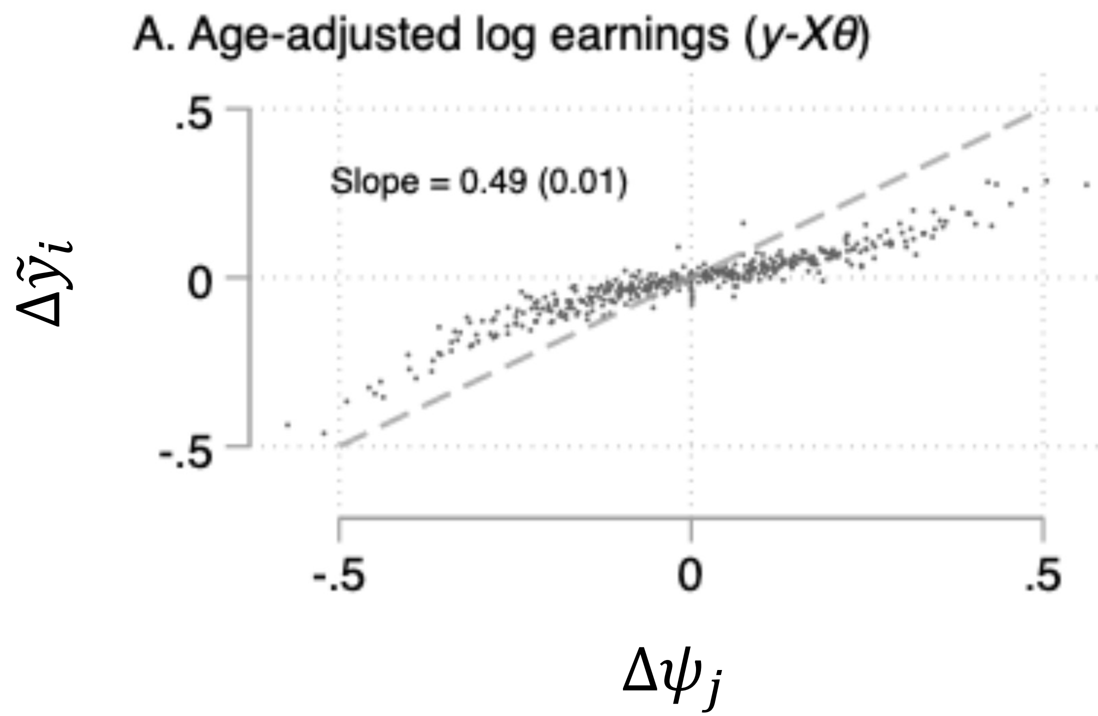
- The hierarchy term is negatively correlated with the change in industry effects.



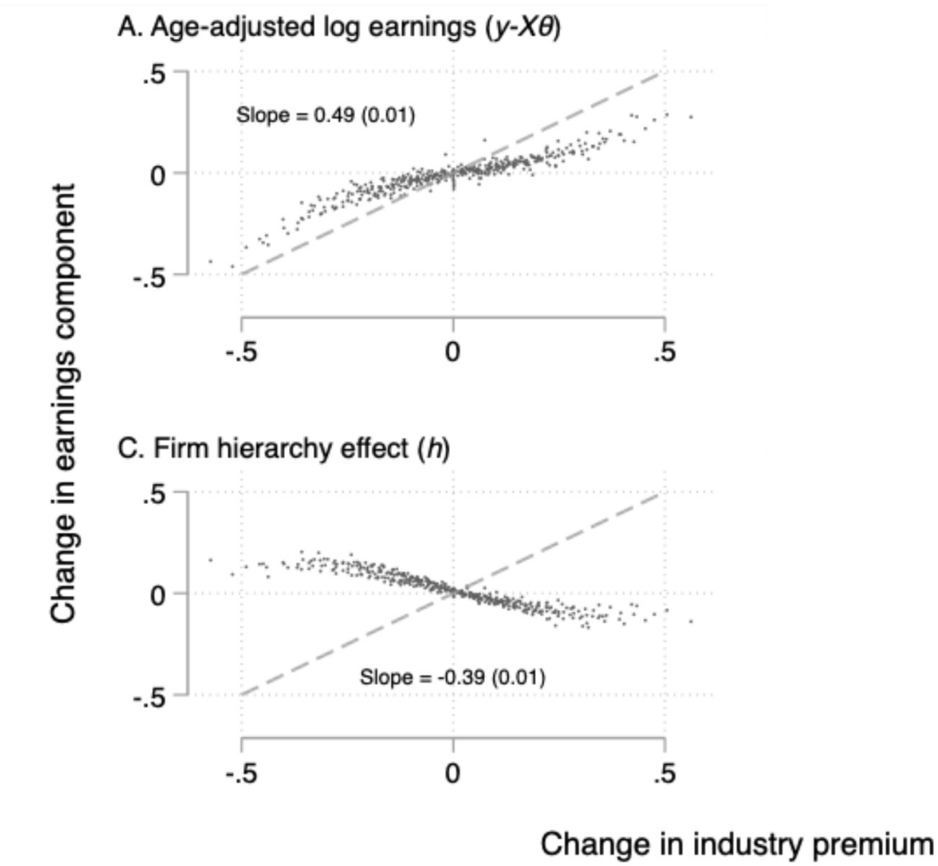
Do industry movers see expected changes in earnings?

Compare changes in y for industry movers to predicted change in *industry* premia ($\Delta\psi_j$)

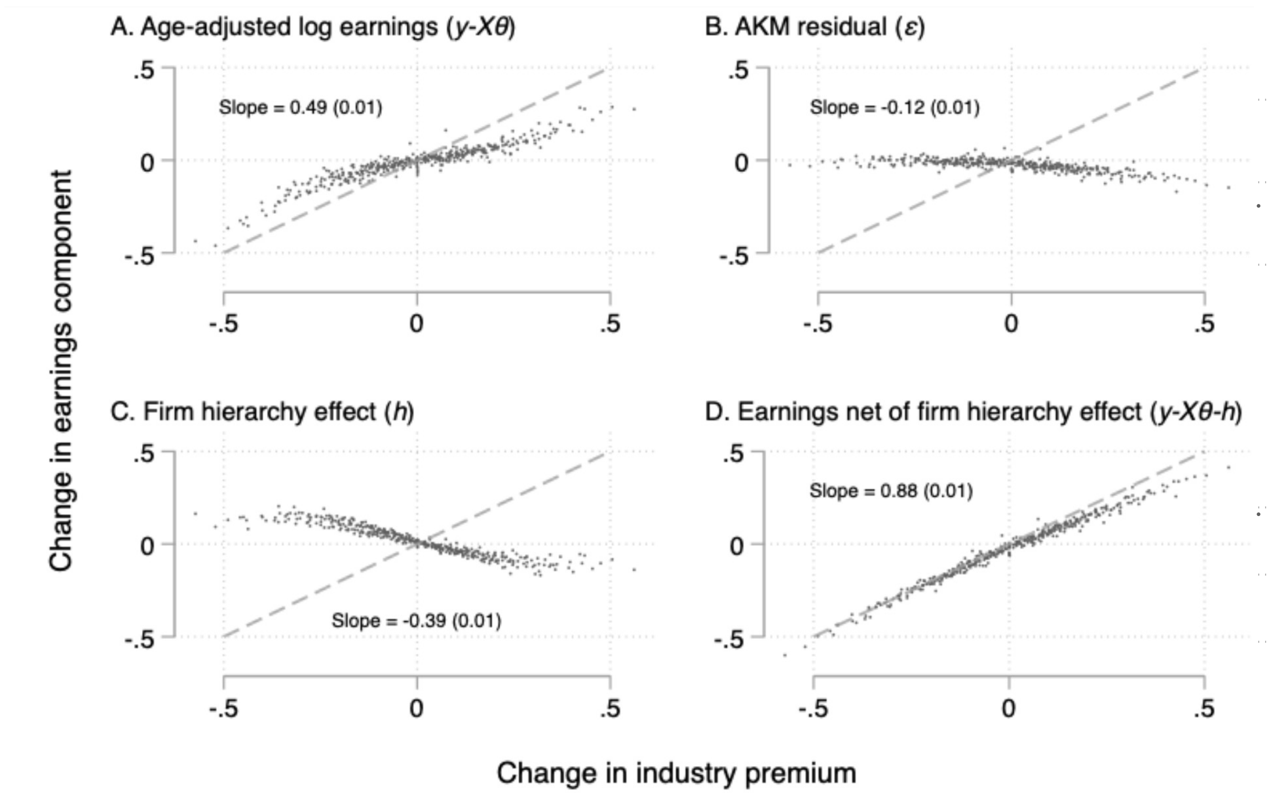
Earnings don't change as expected due to hierarchy term



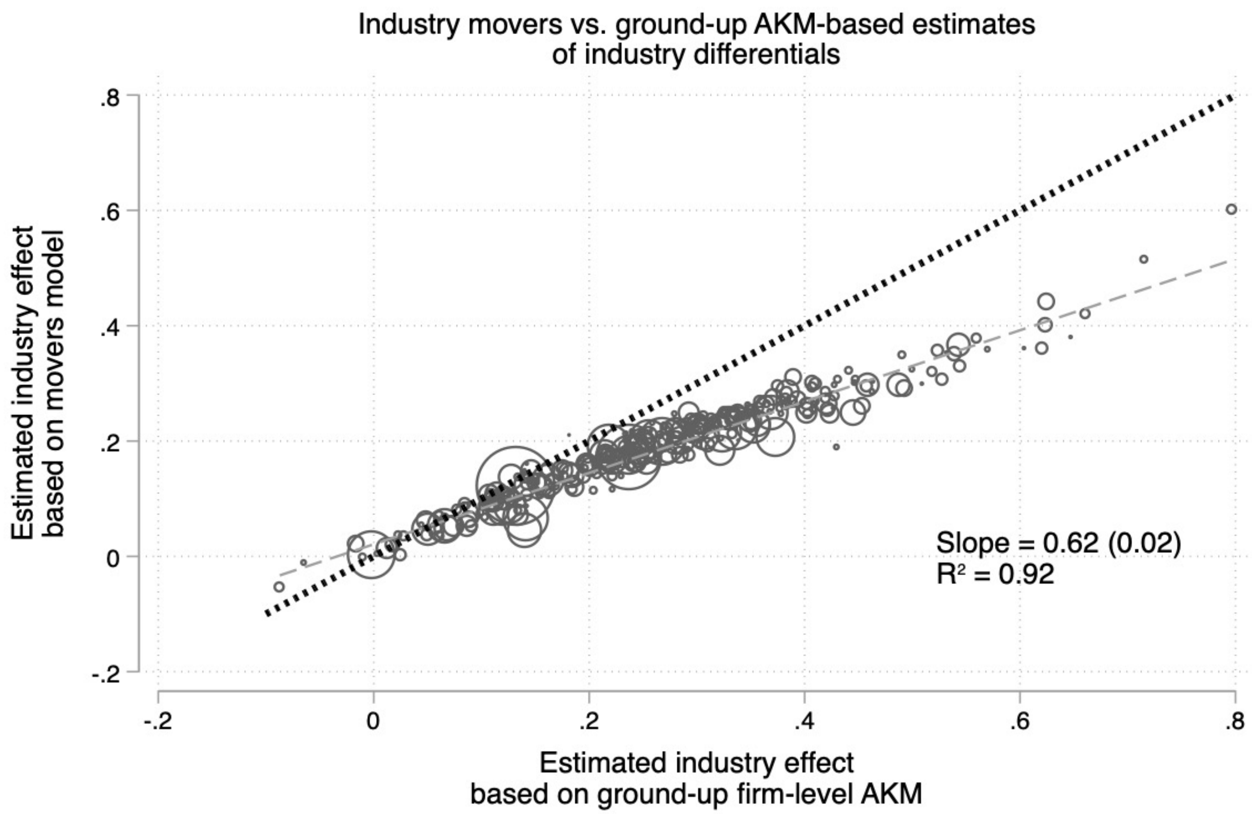
Earnings don't change as expected due to hierarchy term



Once hierarchy term is removed, short-run changes are close to predictions



Movers estimates *understate* ground-up, AKM-based industry premia



Movers estimates *understate* ground-up industry premia

Table 4. Comparisons of industry effects from alternative models

	Preferred model	Cross-sectional models			Movers models		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Alternative model controls for:							
Time-varying controls		X	X	X	X	X	X
Time invariant controls			X	X			
CZ FEs				X		X	
Industry-by-CZ FEs							X
Individual FEs					X	X	X
Standard deviation of industry effects	0.122	0.271	0.254	0.240	0.079	0.079	0.082
Regression of alternative model estimates	1.00	1.86	1.63	1.61	0.62	0.62	0.66
on preferred model estimates (N=311)		(0.12)	(0.13)	(0.12)	(0.02)	(0.02)	(0.01)
R^2 (adj)		0.707	0.614	0.672	0.929	0.924	0.954

Other results

- Hierarchy effects over time
- Role of geography
- Industry effects by education groups

Workers climb the hierarchy a bit with experience

Table 3. Worker experience and the industry hierarchy effect

	Young workers		Older workers	
	(1)	**(2)**	**(3)**	**(4)**
Number of quarters in industry/10	0.012	0.010	0.007	0.006
	(0.002)	(0.001)	(0.001)	(0.001)
$(\text{Number of quarters in industry}/10)^2$	-0.0033	-0.0029	-0.0016	-0.0016
	(0.0006)	(0.0003)	(0.0003)	(0.0002)
Controls for worker, CZ, industry, time FEs	N	Y	N	Y
N (millions of person-quarter observations)	89.8	89.8	421.8	421.8
R2 (adj.)	0.0004	0.7340	0.0002	0.8370
Experience (in quarters) at which slope=0	18.1	17.2	21.8	18.3
Cumulative effect of 5 years of experience	0.011	0.008	0.008	0.005

Conclusion

- Modern firm-based methods indicate substantial variation (SD=0.12) in wage effects across industries, not explained by worker sorting.
- Comparison to earlier methods:
  - Cross-sectional estimates overstate premia due to worker sorting.
  - Movers estimates understate premia due to hierarchy term.
- Other results:
  - Hierarchy ladder: hierarchy term increases with experience
  - The role of geography: industry premia vary across locations, industry composition plays significant role
  - Education: College and non-college workers sort similarly within industry.
- Movers estimates attenuation bias has implications for other studies that use a relatively coarse aggregation of units (e.g. place effects)