Graduate Labor Economics

Sorting in the Labor Market

Abowd, Kramarz and Margolis (1999)

Florian Oswald, SciencesPo Paris

February 23, 2017

Table of contents

Intro Wage Dispersion

We already considered the **failure of the law of one price** in the labor market:

- There are big differences in pay across industries,
- ... and across firm sizes.
- A standard human capital wage regression like

$$\ln w_{it} = \beta x_{it} + \epsilon_i t$$

  explains about 30% of wage variation.

- Today we start to talk about (measuring) the remaining 70%.

Intro: Beyond Mortensen (2003)

- We have seen in Mortensen (2003) that a very simple model with homogeneous workers and firms can already generate wage dispersion.
- Obviously workers and firms are not all identical.
- Does it matter that I am firm j and you are worker i?

Intro: Beyond Mortensen (2003)

- We have seen in Mortensen (2003) that a very simple model with homogeneous workers and firms can already generate wage dispersion.
- Obviously workers and firms are not all identical.
- Does it matter that I am firm j and you are worker i?
  - What's the role of a worker-firm-specific **match effect**?
  - Are all 24 year old graduates from ScPo identically valuable to a potential employer?

Intro: Beyond Mortensen (2003)

- We have seen in Mortensen (2003) that a very simple model with homogeneous workers and firms can already generate wage dispersion.
- Obviously workers and firms are not all identical.
- Does it matter that I am firm j and you are worker i?
  - What's the role of a worker-firm-specific **match effect**?
  - Are all 24 year old graduates from ScPo identically valuable to a potential employer?
- Unobserved worker and firm heterogeneity seem to be very important.
  - How important, and which matters more?
  - How could we to measure those things

Abowd et al. (1999) (AKM)

- Why do high-paying firms pay high wages?
- Use matched employer-employee data.
- Measure person and firm fixed effects.
- Find that
  1. Person effect is more important
  2. Person and firm effect are **not** highly correlated.

AKM Fixed Effects Model

In a series of papers, AKM introduce

$$y_{it} = \alpha_i + \psi_{j(i,t)} + x_{it}\beta + \epsilon_{it} \tag{1}$$

Observed:

- y_{it}: Outcome of person i (log wages for example)
- $x_{it}\beta$: Observable characteristics rewarded equally at all firms
  year, age, education, industry, ...
- ϵ_{it}: Residuals

AKM Fixed Effects Model

In a series of papers, AKM introduce

$$y_{it} = \alpha_i + \psi_{j(i,t)} + x_{it}\beta + \epsilon_{it} \tag{1}$$

Observed:

- y_{it}: Outcome of person i (log wages for example)
- $x_{it}\beta$: Observable characteristics rewarded equally at all firms
  year, age, education, industry, ...
- ϵ_{it}: Residuals

Unobserved:

- α_i: premium for person i (at all firms). **person FE**
- ψ_j: premium for anyone working at firm j. **firm FE**
  $j(i,t)$: i is employed by j in t.

AKM Identification Problem

How is (1) identified?

$$y_{it} = \alpha_i + \psi_{j(i,t)} + x_{it}\beta + \epsilon_{it}$$

i	t	j	y_{it}
1	1	1	12
1	2	1	14
1	3	1	21
1	4	1	23
1	5	1	30

AKM Identification Problem

How is (1) identified?

$$y_{it} = \alpha_i + \psi_{j(i,t)} + x_{it}\beta + \epsilon_{it}$$

i	t	j	y_{it}
1	1	1	12
1	2	1	14
1	3	1	21
1	4	2	23
1	5	2	30

AKM Identification Problem

How is (1) identified?

$$y_{it} = \alpha_i + \psi_{j(i,t)} + x_{it}\beta + \epsilon_{it}$$

i	t	j	y_{it}
1	1	1	12
1	2	1	14
1	3	1	21
1	4	2	23
1	5	2	30

Clearly, we need **movers**.

Identifying Assumptions

1. Exogenenous Mobility:

$$\mathbb{E}\left[\epsilon_{it} | i, t, j(i,t), x_{it}\right] = 0$$

   - Once we condition on types i, j, there is no additional info in ϵ to predict y
   - Rules out offer sampling, or other selection of workers on match-specific component

2. No serial correlation in ϵ:

$$Cov\left(\epsilon_{it}, \epsilon_{ns}, | i, t, n, s, j(i,t), j(n,s), x_{it}, x_{ns}\right) = 0 \text{ if } i \neq n \text{ or } n \neq s$$

   - past ϵ_{it-k} can't influence current ϵ_{it}.
   - Mr n's ϵ_{nt} can't influence your ϵ_{it}.

3. Firms have to be in the same connected set:

   - Indentification relies on **moving** workers.
   - If 2 firms are not connected by a mover, they can't be compared.

Estimation

- Linear model.
  - capture identity effects with a dummy
- Usual approach:
  1. Recover firm fixed effect from movers by FD:
     - $y_{it'} - y_{it} = \psi_{j(i,t')} - \psi_{j(i,t)} + \epsilon_{it'} - \epsilon_{it}$
     - Do for **movers only**: $j(i,t') \neq j(i,t)$.
  2. Recover **worker** fixed effect
     - $\hat{\alpha}_i = \frac{1}{n_i} \sum_t (y_{it} - \hat{\psi}_{j(i,t)})$
     - Do for full connected sample
- Can use non-movers only to get hedonic $\hat{\beta}$

$$y_{it} = x_{it}\beta + \nu_{it}$$

AKM: Data

- French data from Declaration Annuelles des Salaires (DAS) 1976-1987
- Can track work history at worker/establishment level
- 5.3 million observations

AKM: Results

- Surprisingly, $corr(\alpha, \psi) \leq 0$
- Across specifications, there is either zero or negative association between worker and firm FE.
- Suggests that there is no or negative sorting in the labor market.
- Better firms hire worse workers.

Other Results. From Lopez de Melo's JMP

Country	US 1[a]	US 2	FR	GE	IT	DE[b]	BR
$Var(x\beta)$	0.03	0.14	0.02	—	0.01	—	0.02
$Var(\theta)$	0.29	0.23	0.21	0.05	0.05	0.08	0.40
$Var(\psi)$	0.08	0.053	0.08	0.013	0.01	0.00	0.18
$\frac{Var(\psi)}{Var(\theta+\psi)}$	0.22	0.19	0.32	0.22	0.23	0.03	0.31
$Corr(\theta,\psi)$	−0.01	−0.03	−0.28	−0.19	0.04	0.00	0.04[f]
$Corr\left(\theta,\widetilde{\theta}\right)$	—	—	—	—	0.17[c]	0.40[d]	0.52
R^2	0.89	0.9	0.84	—	—	0.85	0.93
Sample Statistics							
Years	90-99	84-93	76-87	93-97	81-97	94-03	95-05
Nobs	$37.7M$	$4.3M$	$5.3M$	$4.8M$	—	$6.9M$	$16.0M$
Nworkers	$5.2M$	$293K$	$1.2M$	$1.8M$	$1.7M$	$563K$	$2.0M$
Nfirms	$476K$	$80K$	$500K$	1821	$421K$	$53.6K$	$137K$
% 1st Group[e]	—	99.1%	88.3%	94.9%	99.5%	—	98.6%

(a) "US1" from Woodcock [41], which covers two non-identified states, and includes all workers who were employed in 1997. "US2" and "Fr" from Abowd et al [2]. The US data covers 1/10 of workers in the state of Washington, whereas the French data covers 1/25 of all workers. "GE" from Andrews et al [4] and uses data from around 2000 establishments in West Germany. "IT" from Iranzo et al [22], which covers 1200 plants with at least 50 workers. "DE" from Bagger and Lentz [5], which covers covers all Danish population. "BR" refers to our own calculations.
(b) This study uses a random effects estimator under the assumption that the two components of heterogeneity are orthogonal.
(c) Iranzo et al [22] compute the index of segregation proposed by Kremer and Maskin [24], using worker fixed effects from the AKM regression as their measure of skill. When firms are large (as in their sample) that measure is very similar to our worker co-worker measure. However, they use Pearson correlations instead of rank correlations.
(d) This number was provided by the authors, and may not come from the same sample described on the table. Also, that was computed using the fixed effects method, not random effects.
(e) This denotes the fraction of the sample in the largest connected group.
(f) We use rank correlations.

Assortative Matching

- **Positive** Assortative Matching (PAM)
- **Negative** Assortative Matching (NAM)
- We will talk more about this later.
- for now: what could motivate NAM?
- Why does the AKM setup find this result?

Criticism

1. Maybe the model is misspecified. Nonlinear model needed?
2. Bias because of either small T or N?

   Maybe we observe to few movers?
3. Maybe mobility is not exogenous as assumed?

Linear Specification

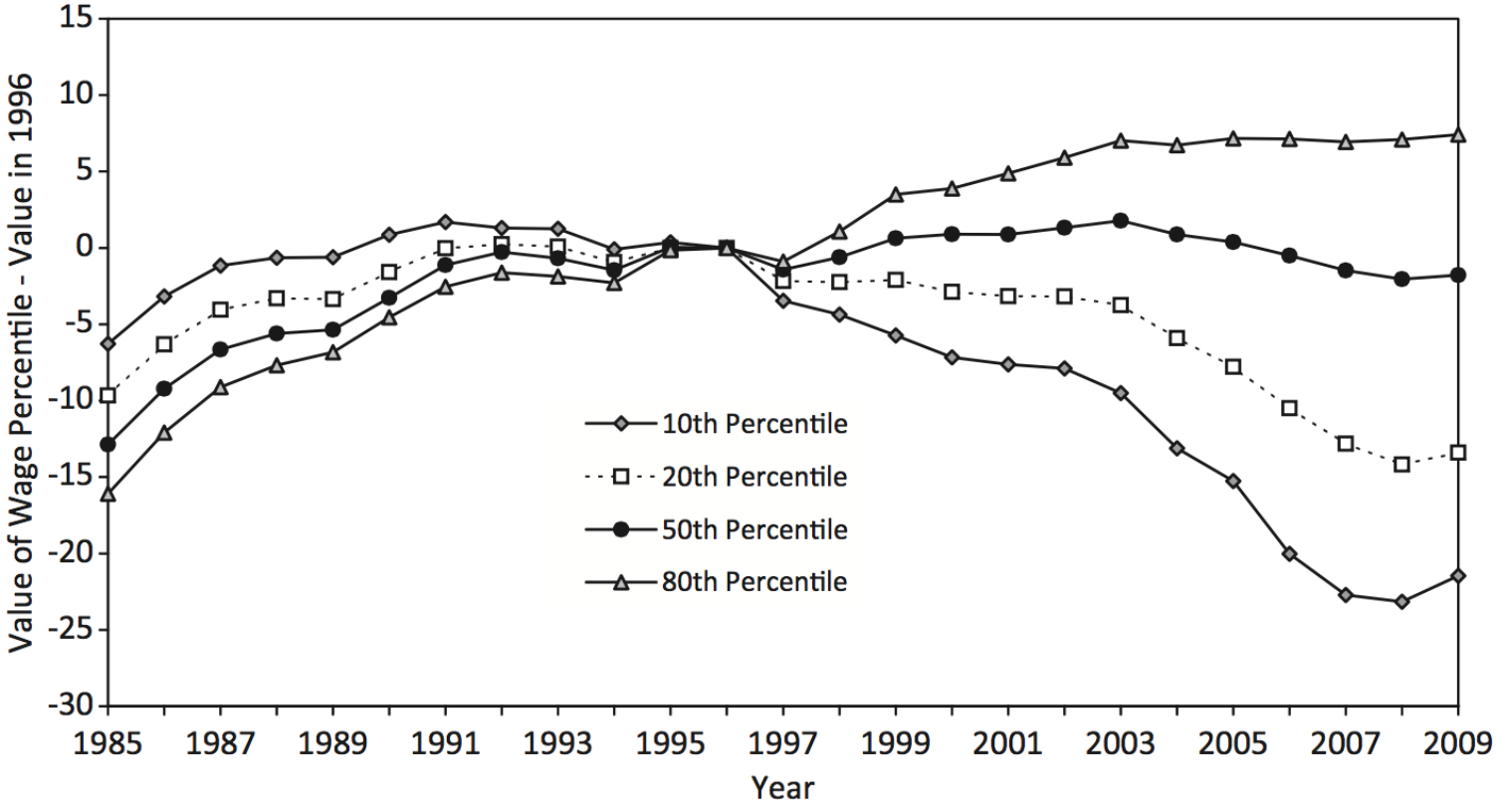
- We want suggestive evidence that linear FE model is correct.
- **Symmetric** wage changes for moves in opposite directions?
- Consider people (i, s) moving between firms (j, k):

$$y_{i1} - y_{i0} = \psi_j - \psi_k + \epsilon_{i1} - \epsilon_{i0}$$
$$y_{s1} - y_{s0} = \psi_k - \psi_j + \epsilon_{s1} - \epsilon_{s0}$$

- Linear setup implies that Δy is equal and opposite for i and s.
  Remark: A more complicated model could assume $\phi(i, j)$ instead of $\alpha_i + \psi_j$.
- We can check this with data.

Card et al. (2013)

- Focus on increase in (heterogeneous) wage inequality in West Germany.
- This has changed tremendously across the wage distribution.



Card et al. (2013) are using AKM

Want to separately identify rising inequality of pay ...

- ... across **different** workers, and
- across **jobs** for the same worker.
- They divide 1885-2009 into 4 intervals and do AKM on each.
- and compare estimates across those intervals.

Along the way, justify linearity assumptions of AKM.

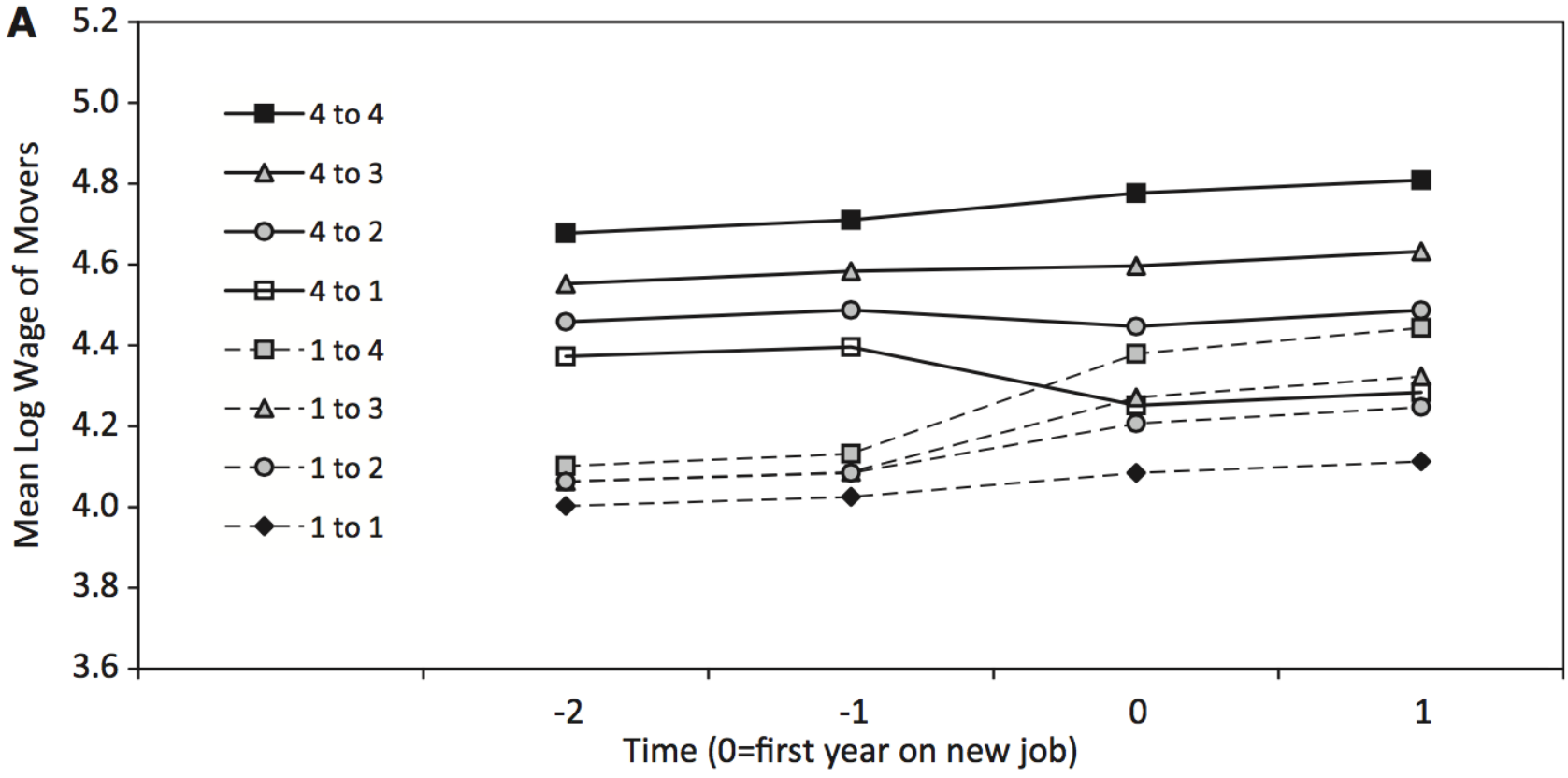
Event Study: Effect of Job Changes on Wage

Remember: *Linear setup implies that Δy is equal and opposite for i and s.*

- They look at the mean of wages for movers before/after moves
- Additionally, classify the firms by mean of **co-worker's** wages into 4 bins
- Proxy for ψ
- Look at wage change for movers across different bins

Event Study: Effect of Job Changes on Wage

Remember: *Linear setup implies that Δy is equal and opposite for i and s.*



Limited Mobility Bias: Andrews et al. (2012)

Limited Mobility Bias: Andrews et al. (2012)

Limited Mobility Bias: Andrews et al. (2012)

Introduction

The AKM log-linear fixed effect model

- AKM proper
- Card et al
- Limited Mobility Bias
- Bonhomme, Lamadon, Manresa

BLM

References

Dale T Mortensen. *Wage Dispersion: Why Are Similar Workers Paid Differently?* The MIT Press, 2003.

John M Abowd, Francis Kramarz, and David N Margolis. High wage workers and high wage firms. *Econometrica*, 67(2):251–333, 1999.

David Card, Jörg Heining, and Patrick Kline. Workplace heterogeneity and the rise of west german wage inequality. *The Quarterly Journal of Economics*, 128(3):967–1015, 2013.

M.J. Andrews, L. Gill, T. Schank, and R. Upward. High wage workers match with high wage firms: Clear evidence of the effects of limited mobility bias. *Economics Letters*, 117(3):824 – 827, 2012. ISSN 0165-1765. doi: http://dx.doi.org/10.1016/j.econlet.2012.07.033. URL http://www.sciencedirect.com/science/article/pii/S0165176512004272.