Graduate Labor Economics

Sorting in the Labor Market

Abowd, Kramarz and Margolis (1999)

Florian Oswald, SciencesPo Paris

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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?

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  - 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?

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  - 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

Introduction

The AKM log-linear fixed effect model

- AKM proper
- Card, Heining and Kline (QJE 2013)
- Limited Mobility Bias: Andrews et al.

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

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  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

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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 $E[\Delta y]$ is equal and opposite for i and s, i.e.

$$E[\Delta y_i] = \psi_j - \psi_k = -(\psi_j - \psi_k) = E[\Delta y_s]$$

  Remark: A more complicated model could assume $\phi(i, j)$ instead of $\alpha_i + \psi_j$.
- We can check this with data $\Rightarrow$ Card et al. (2013).

Introduction

The AKM log-linear fixed effect model

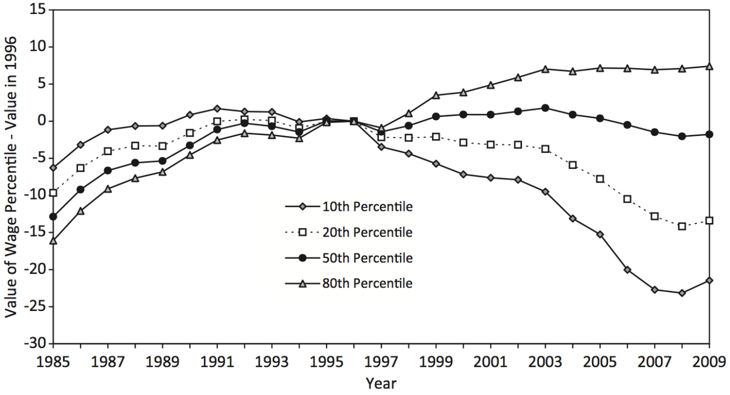
AKM proper

Card, Heining and Kline (QJE 2013)

Limited Mobility Bias: Andrews et al.

Card et al. (2013)

- Focus on increase in (heterogeneous) wage inequality in West Germany.
- This has changed tremendously across the wage distribution.
- 20-80 percentile gap widened 20 log points 1996-2009.



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, $\boxed{\text{justify}}$ linearity assumptions of AKM.

Contributions

- Show that strong separability assumptions form AKM are nearly met in data.
- Find little evidence for endogenous mobility.
- Find that increase in wage inequality stems from both worker and firm FE, but also rise in *assortativeness* of matches.

Historical Background: Germany 1980-2009 I

1. Collapse of Soviet Union and subsequent German reunification
2. Ca 1.7m East Germans moved to the West in early 1990s.
3. Ca 2.8m ethnic Germans from Eastern Bloc.
4. Many of those were unskilled and contributed to a rise in unemployment in Western Germany (Glitz (2012))
5. Political decision to impose West German wage scales on Eastern immigrants led to breakdown in traditional collective bargaining. (83% of workers 1995 vs 63% in 2007 under collective bargaining)

Historical Background: Germany 1980-2009 II

6. By mid 1990s German unemployment hit 10%.
7. 1996 reforms trying to liberalized the labor market.
8. 1999 briefly reverses this trend.
9. Recession of 2001 increases pressure again and leads to Hartz Reforms 2003–2005.
10. Hartz reduces benefits of longterm unemployed, introduces subsidies for low-wage jobs.
11. Also eliminates employee portion of social security taxes for **mini-jobs**.
12. All of this led to an expansion of part-time and **low-wage work**, **reducing unemployment**.

Data

- German Social Security Data. Very high quality: daily wages for universe of population covered by social security (i.e. no mini-jobs), linked to the work establishment.
- Censoring: up to 12% of male wages are top-coded in this data. They use a Tobit model to impute this upper tail.
- Compare this to sample of apprentices (60% of German workforce), but with low censoring rates. Find similar results.

Summary Stats

TABLE I

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

Inequality Trends I

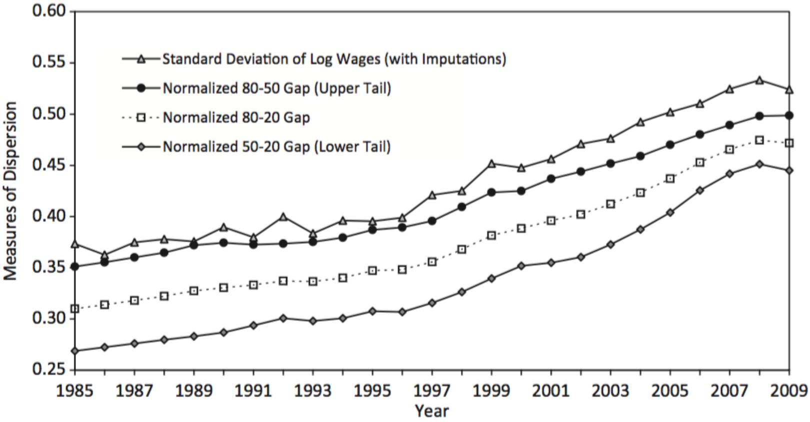


FIGURE II

Trends in Wage Inequality for Full-Time Male Workers

This figure shows measures of dispersion in real daily wage for full-time male workers. Normalized percentile gaps are differences in percentiles divided by corresponding differences in percentiles of standard normal variate.

Inequality Trends II

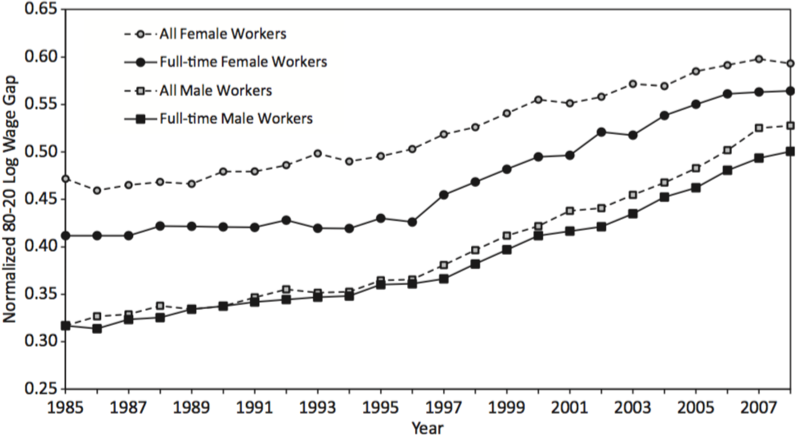


FIGURE III

Wage Inequality Trends for Alternative Samples of Workers

Based on tabulations of SIAB. Measured wage is average daily wage in job with highest total earnings in the year. Wage gap is the difference between the 80th percentile of log real wages and the 20th percentile, divided by 80–20 gap for a standard normal variate.

Inequality Trends III

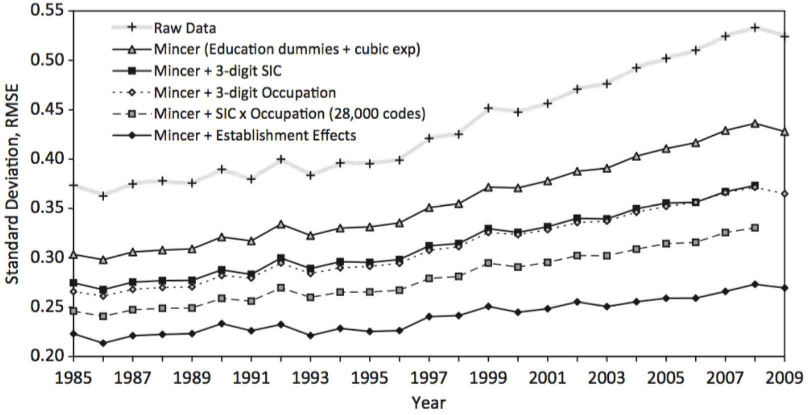


FIGURE IV

Raw and Residual Standard Deviations from Alternative Wage Models

See note to Figure II. Figure shows measures of dispersion in actual and residual real daily wage for full-time male workers. Residual wage is residual from linear regression model. "Mincer" refers to model with dummies for education categories and cubic in experience, fit separately in each year. Other models add controls as indicated.

Sorting?

- Figure IV in particular shows that dummies for each establishment greatly reduce the variance of the residual in the wage equation.
- Implies a rise of only 0.05 in std error vs 0.13 in standard model.
- Suggests: different employers used increasingly different wage policies.
- **Caution:** There may be non-random sorting of workers to firms. Here this is problematic becase no way to control for worker unobserved heterogeneity.
- could estimate an **establishment effect** purely from composition of **workforce**, even in the absence of an employer effect (remember definition of this effect!)

Identifying Sorting

- If variation in wages comes only from sorting, a mover will not experience large wage changes. They will **sort** into a similar firm.
- Contrarily, suppose different firms pay different av. wage premiums.
- Then **all movers** (no matter their characteristics) who move to high-paying firm will experience wage increase on average.
- This is symmetric for moves to low-paying firms.
- Authors look at movers' wage data, classified by whether origin and destination firms where high/low paying firms.

Remember AKM: Linear Specification

- We where looking for suggestive evidence that linear FE model is correct.
- Linearity implies **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 $E[\Delta y]$ is equal and opposite for i and s, i.e.

$$E[\Delta y_i] = \psi_j - \psi_k = -(\psi_j - \psi_k) = E[\Delta y_s]$$

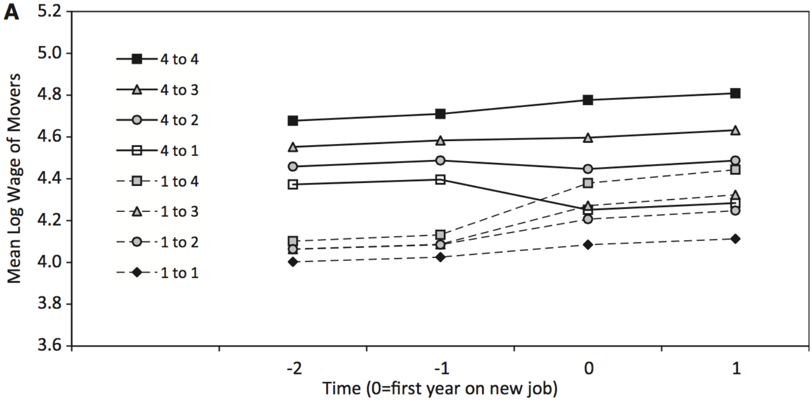
Event Study: Effect of Job Changes on Wage

Remember from AKM: *Linear setup implies that $E[\Delta y]$ is equal and opposite for i and s.*

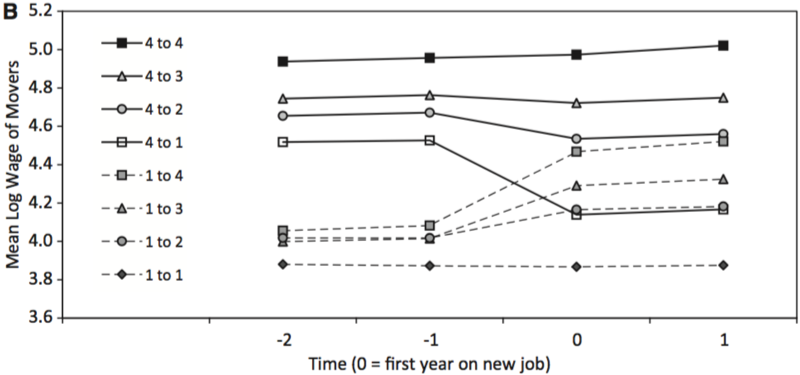
- They look at the mean of wages for movers before/after moves
- Additionally, classify the firms by mean of **co-worker's** wages into 4 bins.
- This is a proxy for $\Delta\psi$, the firm FE in AKM.
- We want to see whether $\Delta\psi$ is different for differently directed moves.
- Picture shows only moves from/to top/bottom quartile.

Event Study: Effect of Job Changes on Wage, 1985-1991

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



Event Study: 2002-2009



- Different movers-to-be have different mean wages.
- Gains/losses appear to be symmetric.
- Gains/losses are more pronounced in the later period.

Econometric Model

$$y_{it} = \alpha_i + \psi_{j(i,t)} + x_{it}\beta + r_{it} \tag{2}$$

- They use a standard AKM model.
- Specify a richer error r and discuss potential threats to identification.
- Interpretation of ψ: rent-sharing, efficiency wage premium or strategic wage posting (Burdett-Mortensen)

Error Structure r

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

All components have mean zero:

- η_{ij}: idiosyncratic premium for i working at j. A random match effect.
- ζ_{it}: unobs human capital accumulation, health shocks, outside offers. Random walk with drift.
- ε_{it}: other mean-reverting factors.

Identifying assumption: Connected Set

- Establishment and person effects are identified only within a **connected set** of firms. They are linked by moving workers.
- Estimation performed only on that connected set. 95% of workers and 90% of firms.

Assumption on Job Assignment

- The composite error r needs to be orthogonal to person and firm effects, as well as covariates x.
- Key issue is whether $E[f^j r] = 0$?
- Sufficient condition on employment probability function G:

$$P(j(i,t) = j|r) = P(j(i,t) = j) = G_{jt}(\alpha_i, \psi_1, \ldots, \psi_J), \forall i, t$$

- Does not preclude systematic patterns of employent moves
- estimator conditions on job sequence.

Endogenous Mobility?

- Is there sorting based on η, ie the match effect?
  - If such sorting, interpretation of psi changes. because workers will have different premia at different employers, depending on their match value in each case.
  - test: if workers select on this match component, should see differential changes in wage for up and down movers. we dont.
  - Also: run fully saturated model with a dummy for each job and see if it performs better in terms of stat fit.
- drift: some abilities may be slow to reveal. so workers who turn out worse than expected are paid less than expected and vice versa. Also Postel-Vinay and Robin 2002 wage poaching. however, cannot explain moves to low wage establishments.
- Also rule out cyclic moves between high and low wage employers.

Results: Estimation Sample

TABLE II

Summary Statistics for Overall Sample and Individuals in Largest Connected Set

	All full-time men, age 20–60				Individuals in largest connected set			
			Log real daily wage				Log real daily wage	
Interval	(1) Number person/yr. obs.	(2) Number individuals	(3) Mean	(4) Std. dev.	(5) Number person/yr. obs.	(6) Number individuals	(7) Mean	(8) Std. dev.
1985–1991	86,230,097	17,021,779	4.344	0.379	84,185,730	16,295,106	4.351	0.370
Ratio: largest connected/all					97.6	$\boxed{95.7}$	100.2	97.7
1990–1996	90,742,309	17,885,361	4.391	0.392	88,662,398	17,223,290	4.398	0.384
Ratio: largest connected/all					97.7	$\boxed{96.3}$	100.2	97.9
1996–2002	85,853,626	17,094,254	4.397	0.439	83,699,582	16,384,815	4.405	0.432
Ratio: largest connected/all					97.5	$\boxed{95.8}$	100.2	98.3
2002–2009	93,037,963	16,553,835	4.387	0.505	90,615,841	15,834,602	4.397	0.499
Ratio: largest connected/all					97.4	$\boxed{95.7}$	100.2	98.8
Change from first to last interval			0.043	0.126			0.045	0.128

Notes. Sample consists of full-time male workers ages 20–60 employed in nonmarginal jobs and not currently in training. Daily wage is imputed for censored observations using a Tobit model. "Connected set" refers to group of firms connected by worker mobility over the sample interval (for details, see Abowd, Creecy, and Kramarz 2002).

Parameter Estiamtes

- both person and firm effects variance increase
- correlation between both also rises
- high explanatory power (compare RMSE and R2)
- small fit improvement from fully saturated match effect model interpreted as match effects being uncorrelated random effects.

Results: Parameter Estimates

TABLE III

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

Notes. Results from OLS estimation of equation (1). See notes to Table II for sample composition. Xb includes year dummies interacted with education dummies, and quadratic and cubic terms in age interacted with education dummies (total of 39 parameters in intervals 1–3, 44 in interval 4). Match model includes Xb and separate dummy for each job (person-establishment pair).

*Standard deviation of match effect estimated as square root of difference in mean squared errors between AKM model and match effect model.

How do particular cominbations of workers/firms look?

- We want to further investigate particalur combinations of matches.
- say high skilled workers at low wage firms should have a very large mean residual wage.
- That should show up as a large residual variance in AKM (and invalidate the model)

Results: Residuals

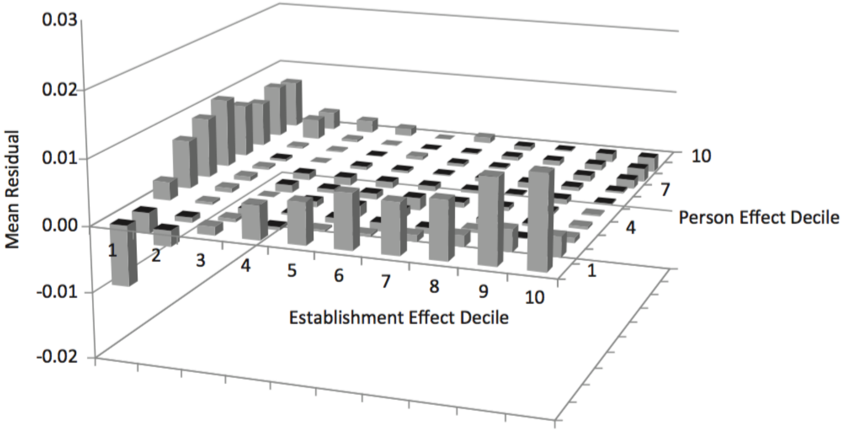


FIGURE VI

Mean Residuals by Person/Establishment Deciles, 2002–2009

Figure shows mean residuals from estimated AKM with cells defined by decile of estimated establishment effect, interacted with decile of estimated person effect. See column (4) of Table III for summary of model parameters.

Redo Event Study with Estimated Model

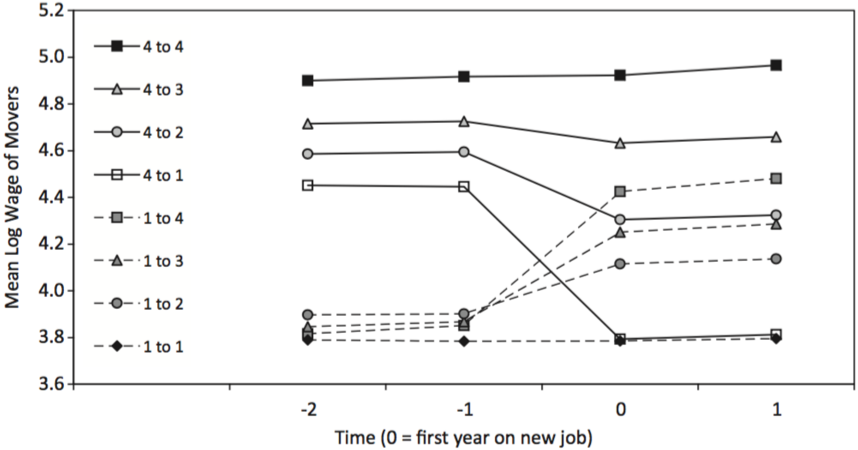


FIGURE VII

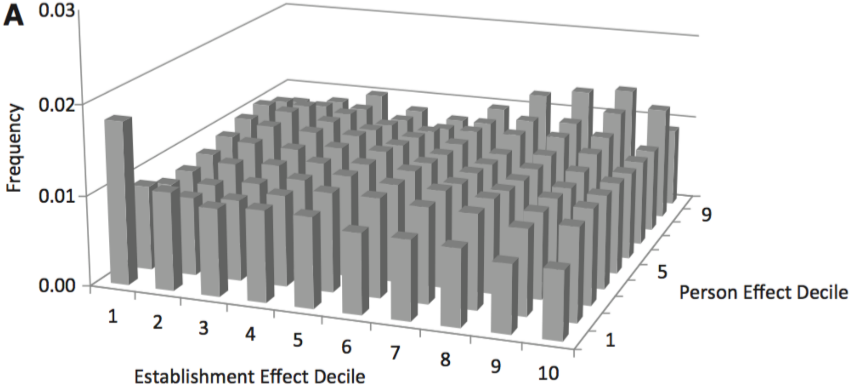
Mean Wages of Movers Classified by Quartile of Establishment Effects for Origin and Destination Firms, 2002–2009

Figure shows mean wages of male workers observed in 2002–2009 who change jobs in the interval and held the preceding job for two or more years,

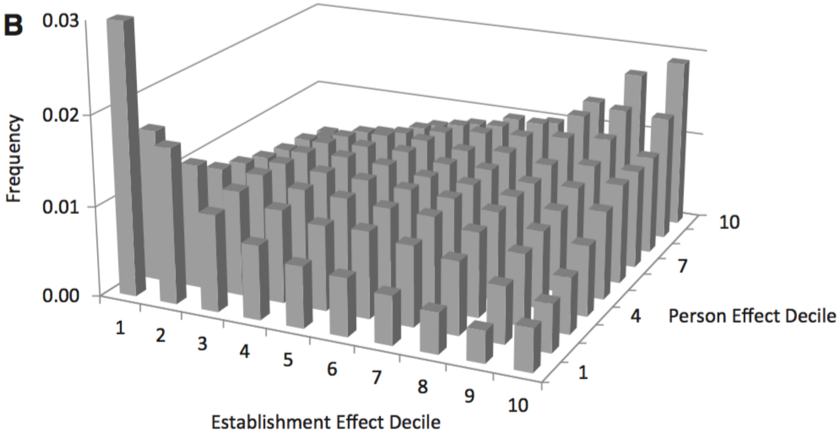
What Changed in the German Labor Market?

- we have seen ineq increase.
- corr of person and firm effects increased
- individual ineq increased (alpha)
- but how are those distributed among high/low rank firms and indivduals?
- in other words, how did sorting change?

Sorting in 1985-1991



Sorting in 2002–2009



Decomposing Effects

- Which component was most relevant in increase of $Var(y)$ between interval 1 and 4?
- person effect: 40%
- firm effect: 40%
- covariance term is 34% of total rise in wage variance.

Firms changed - Collective bargaining status?

- we see big differences between interval 1 and 4 in firm premium.
- how did those differences occur?
- Did existing firms change their wage policies, or did new firms start with new policies, or was it a combination?
- How does this relate to collective bargaining coverage of german workers?
- Calculate std.dev of firm effects in each interval by birth year of the firm.

Cohort Effects: Firm age

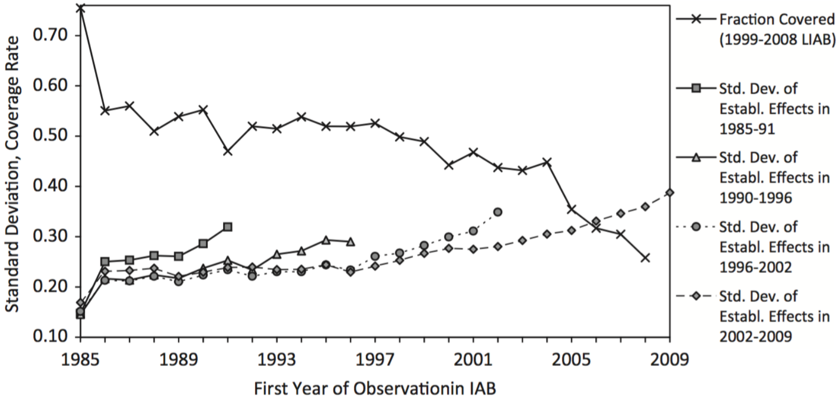


FIGURE IX

Standard Deviation of Establishment Effects and Fraction Covered by Collective Agreements, by Birth Year of Establishment

Figure shows standard deviation of estimated establishment effects in a given observation interval (1985–1991, 1990–1996, 1996–2002, or 2002–2009) for establishments that are present in that interval and first appeared in the IEB data in the "birth year" indicated on the horizontal axis. Figure also shows fraction of establishments in a given birth year surveyed in the 1999 2008

Conclusions

- Germany experienced substantial increase in wage inequality in the last 25 years.
- Was this due to changes in demand and supply of factors (trade and technology), or labor market institutions?
- Here, show that inequality widened in both firm and worker dimensions.
- Moreover, high wage **workers** are more concentrated at high paying **firms**.
- AKM linearity assumption seems to hold in this data.
- Large connected set seems to be important.
- How important? $\Rightarrow$ Andrews et al. (2012)

Introduction

The AKM log-linear fixed effect model

- AKM proper
- Card, Heining and Kline (QJE 2013)
- Limited Mobility Bias: Andrews et al.

Limited Mobility Bias: Andrews et al. (2012)

- Limited mobility of workers may explain why many studies find zero or negative correlation in worker and firm FEs.
- Positive correlation would imply **positive assortative matching** (PAM) in the labor market. This would be intuitive and in line with Roy, Becker and Sattinger.
- However, AKM and followups find negative correlation.

Attempts at explaining the AKM result

1. structural models attempting to replicate this finding fail. in fact, kircher and eeckhout show that itfftts impossible to identify from wage data alone.
2. Maybe the 2-way FE model is misspecified? What about match effects? (Remember Card et al. (2013) though)
3. **Limited mobility bias**. Fewer movers imply downward bias of estimated correlation if there is in fact PAM.

Methodology

The literature uses linked employer-employee data to estiamte

$$y_{it} = \alpha_i + \psi_{j(i,t)} + x_{it}\beta + \epsilon_{it} \tag{3}$$

for $i = 1, \ldots, N$ workers and $j = 1 \ldots, J$ firm over $t = 1, \ldots, T$ years.

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$$y_{it} = \alpha_i + \psi_{j(i,t)} + x_{it}\beta + \epsilon_{it} \tag{3}$$

for $i = 1, \ldots, N$ workers and $j = 1 \ldots, J$ firm over $t = 1, \ldots, T$ years.

- Workers move between firms. We observe M moves.
- Main assumption is **strict exogeneity**:

$$E[\epsilon_{it} | x_{it}, \alpha_i, \psi_j] = 0$$

  meaning moves are independent of ϵ but can be functions of α and ψ.
- Evidence for PAM comes from observing/estimating

$$\text{Corr}(\alpha_i, \psi_j) > 0$$

Bias

Andrews et al. (2008) show that estimation of $\text{Corr}(\hat{\alpha}_i, \hat{\psi}_j)$ is biased:

$$\hat{\alpha}_i - \alpha_i = -x_i(\hat{\beta} - \beta) - (\overline{\hat{\psi}}_i - \overline{\psi}_i) + \overline{\epsilon}_i$$

- If ψ is overestimated, α is underestimated on average.
- and vice versa.
- If true correlation would be positive, estimated one is downward biased.
- They show that as M increases, the bias decreases.

Data

- German Federal Office of Labour (Beschafkftigtenstatistik)
- These are all social insurance-registered workers.
- Know workplace.
- Limit analysis to 3 states Bavaria, North Rhine Westphalia and Saxony.

An Experiment

- Want a clean experiment that increases M *only*.
- choose a 10% random sample of workers ($p = 0.1$) and remember firm id's of those workers.
- increase p until 1 in steps
- but keep the set of firms fixed from step 1.

Experiment Setup

Table 1
Increasing the proportion of workers sampled in a fixed sample of establishments increases the number of worker movements per establishment.

p	Bavaria $J = 65{,}032$		North-Rhine Westphalia $J = 84{,}564$		Saxony $J = 19{,}877$	
	N^*	M/J	N^*	M/J	N^*	M/J
0.1	1,779,562	4.2	2,309,319	4.4	436,766	3.6
0.2	3,393,479	7.0	4,409,560	7.4	820,059	5.7
0.3	5,003,038	9.8	6,519,154	10.5	1,205,597	7.9
0.5	8,214,938	15.4	10,735,633	16.6	1,977,795	12.2
1.0	16,278,473	29.6	21,270,334	31.9	3,904,445	23.1

Main Result

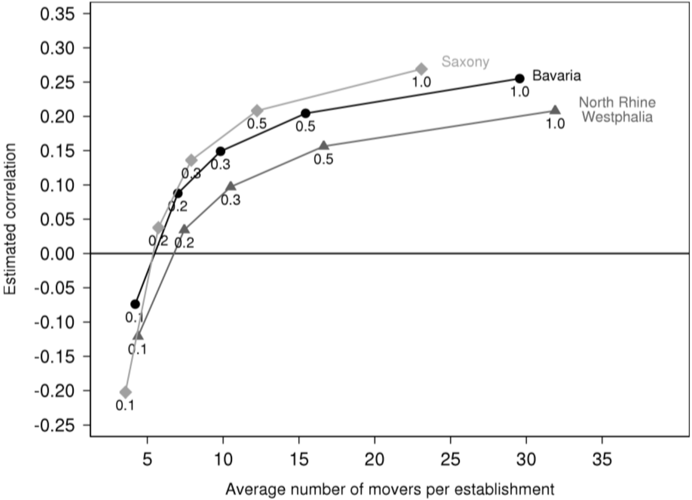

Fig. 1. Increasing the number of movers per establishment in a fixed sample of establishments increases Corr$(\hat{\theta}_i, \hat{\psi}_j)$.

Discussion

- There is clearly a **positive** corrlation in German data.
- Many studies donffttıt find this because they sample from anywher in the M/J axis
- Notice that increase the sample size alone does not help! We really need to have **sufficiently many** movers per firm.

Result

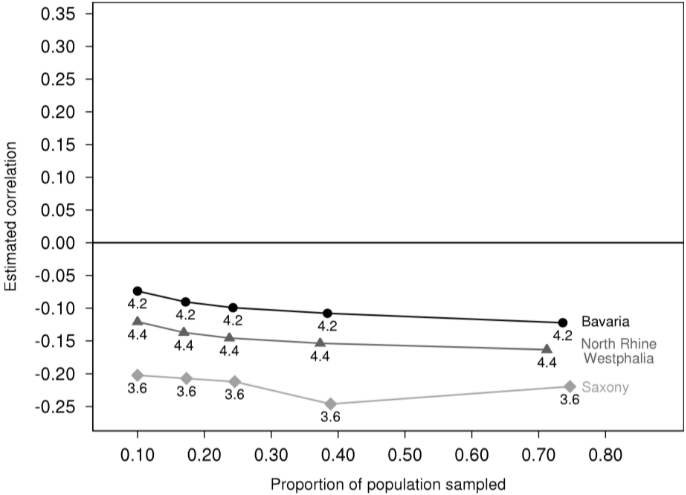

Fig. 2. Increasing the number of observations per establishment, but keeping the number of movers constant does not increase Corr($\hat{\theta}_i$, $\hat{\psi}_j$).

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