Workers and Firms: Where Are We Now?

Where Are We Going?

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- in past decade: explosion of new work using LEED data

- motivated by some key issues/questions:

    rising wage inequality

    increasing sorting across firms

    declining labor share

- and by the longstanding “institutionalist” idea that one’s specific employer matters

Today's talk:

- try to give an overview of main strands of work

- a few key take-aways

- some thoughts on open questions and directions

- apologies in advance for the 'reductionist' / uber-empirical perspective

Strand 1: the AKM model

$$w_{it} = \alpha_i + \psi_{j(i,t)} + X_{it}\beta + r_{it}$$

- generalizes the workhorse earnings generating function

- compare with the "job match" model

$$w_{it} = m_{i,j(i,t)} + X_{it}\beta' + r'_{it}$$

which has a separate effect for each job

- AKM uses up $N + J$ d.f. vs NJ for the match model

- interpretation of FE's requires that:

$$m_{i,j(i,t)} = \alpha_i + \psi_{j(i,t)} + \theta_{i,j(i,t)}$$

where $\theta_{i,j(i,t)}$ is uncorrelated with inter-firm mobility

Everybody hates AKM

1. orginal paper used a bad approximation to invert X'X

Original finding $corr[\alpha_i, \psi_{j(i,.)}] < 0$ unappealing

2. assumption that $\theta_{i,j(i,t)}$ unrelated to mobility $\Rightarrow$ job matching is <u>not</u> driven by idiosyncratic "match quality"

maybe ok if productivity is different from wages

Aside: why do economists love idiosyncratic match models?

- N-dimensional Roy sorting $\Rightarrow$super complicated patterns of selection bias!

Some perspective:

- how important is idiosyncratic match in

  medical residents' match?

  student/school allocations?

  academic job market?

- in many cases, the two sides of the market are ranked and paired off in order of ranks. This process does not have idiosyncratic match values.

Everybody hates AKM, continued

- where does ψ_j come from?

- why do all workers get the same proportional premium?

- note that if

$$\begin{aligned} \log W_{it} \equiv w_{it} &= \alpha_i + \psi_j + junk \\ \Rightarrow W_{it} &= e^{\alpha_i} e^{\psi_j} \end{aligned}$$

so AKM implies complementarity (in wages) between worker's skills and firm's pay policies

What have we learned?

For hourly/daily wages:

1. AKM fits well (adjusted r-sq $\rightarrow$ 90%)

2. match component in most settings is small

3. AKM "looks the same" in different labor markets

e.g.: Germany, Portugal, Brazil

positive correl(worker,firm)

15-20% of variance due to firm effects

Summary of Estimated AKM Models: Portugal, Germany, Brazil

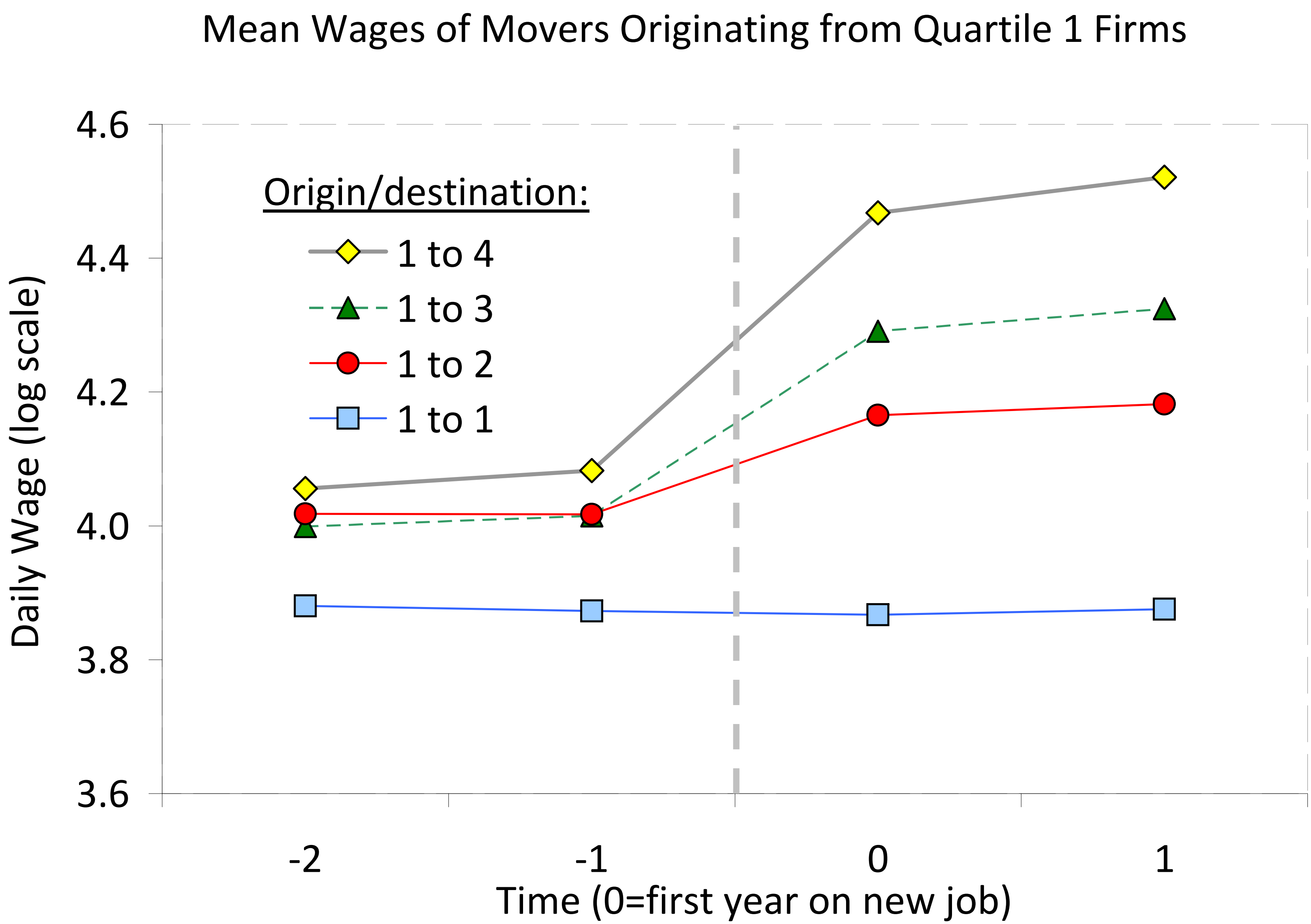
	PT-Men	PT-Fems	German Men	Brazil - WM
Correl. of wkr/firm effects	0.17	0.15	0.25	0.24
Share of variance:				
person effects	57.6	61.0	51.2	44.5
firm effects	19.9	17.2	21.2	20.5
Xb (exp, year*ed, etc)	6.2	7.5	5.2	14.4
cov(person, firm)	11.4	9.9	16.4	13.1
residual	4.9	4.4	5.9	7.5
Adj. R-squared AKM Model	0.93	0.94	0.93	0.90
Adj. R-squared Match Model	0.95	0.95	0.95	0.93
V(Match Eff) / V(Firm Effect)	0.06	0.06	0.11	0.16

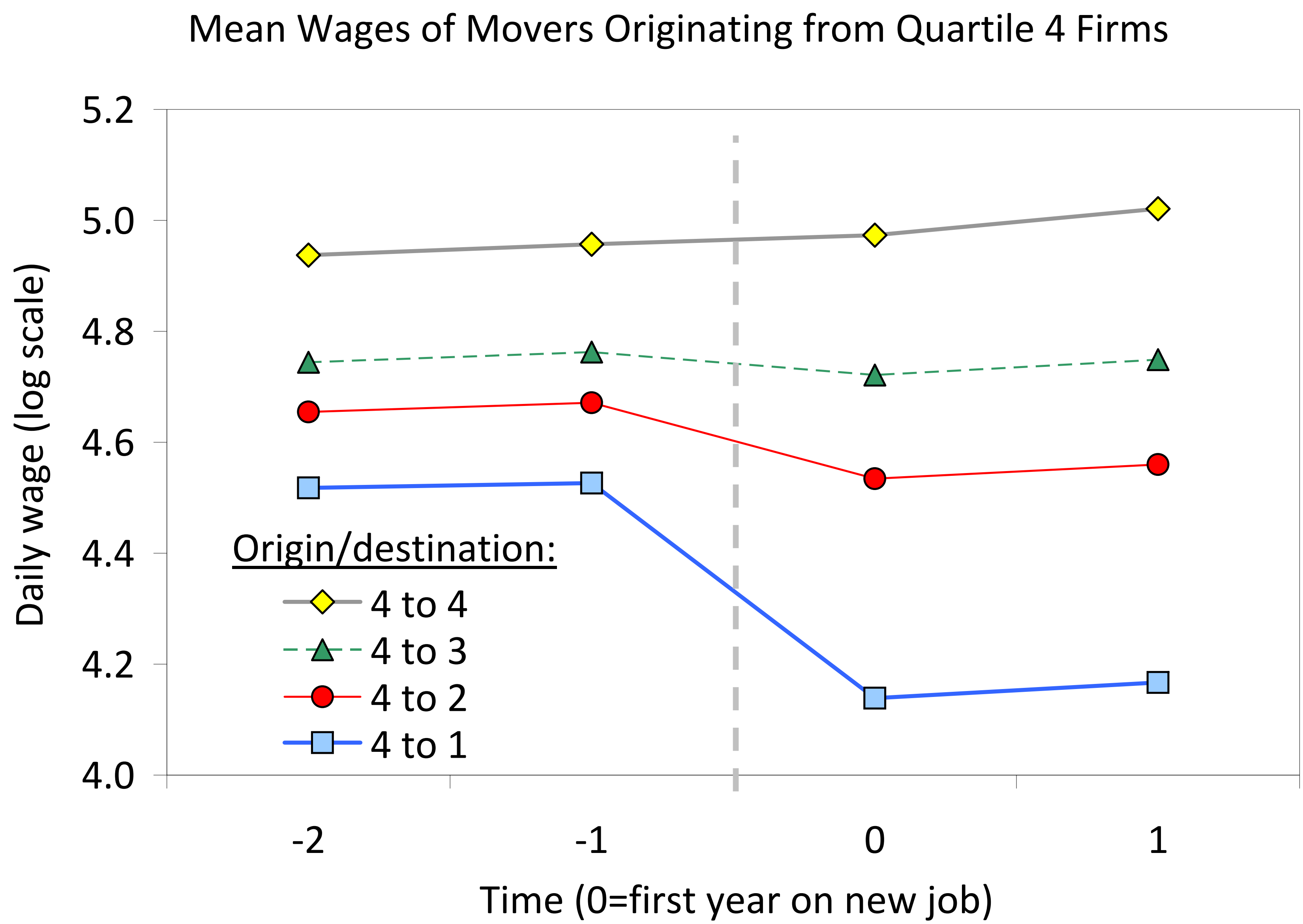
What have we learned (2)

4. patterns of wage changes for movers appear to (broadly) support "exogenous mobility"

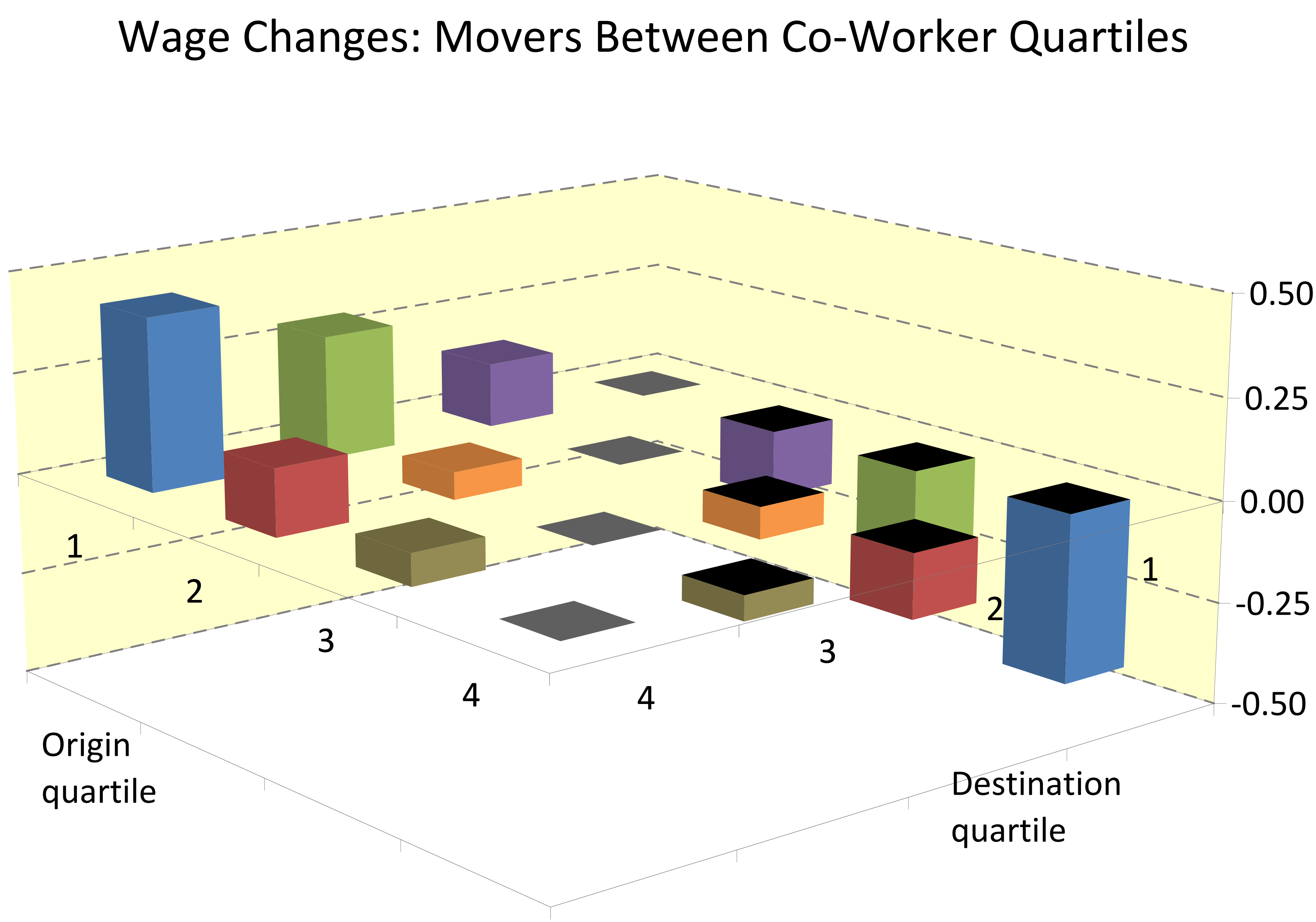
i) no pretrends for movers up/down ladder

ii) approximately symmetric changes for up vs. down the ladder


Mean Wages of Movers Originating from Quartile 1 Firms
Origin/destination:
1 to 4
1 to 3
1 to 2
1 to 1
Daily Wage (log scale)
4.6
4.4
4.2
4.0
3.8
3.6
-2
-1
0
1
Time (0=first year on new job)



Mean Wages of Movers Originating from Quartile 4 Firms
Daily wage (log scale)
5.2
5.0
4.8
4.6
4.4
4.2
4.0
-2
-1
0
1
Time (0=first year on new job)
Origin/destination:
4 to 4
4 to 3
4 to 2
4 to 1



Wage Changes: Movers Between Co-Worker Quartiles
0.50
0.25
0.00
-0.25
-0.50
1
2
3
4
Origin quartile
4
3
2
1
Destination quartile

What have we learned (3)

5. Sorting of different groups to high/low ψ firms matters

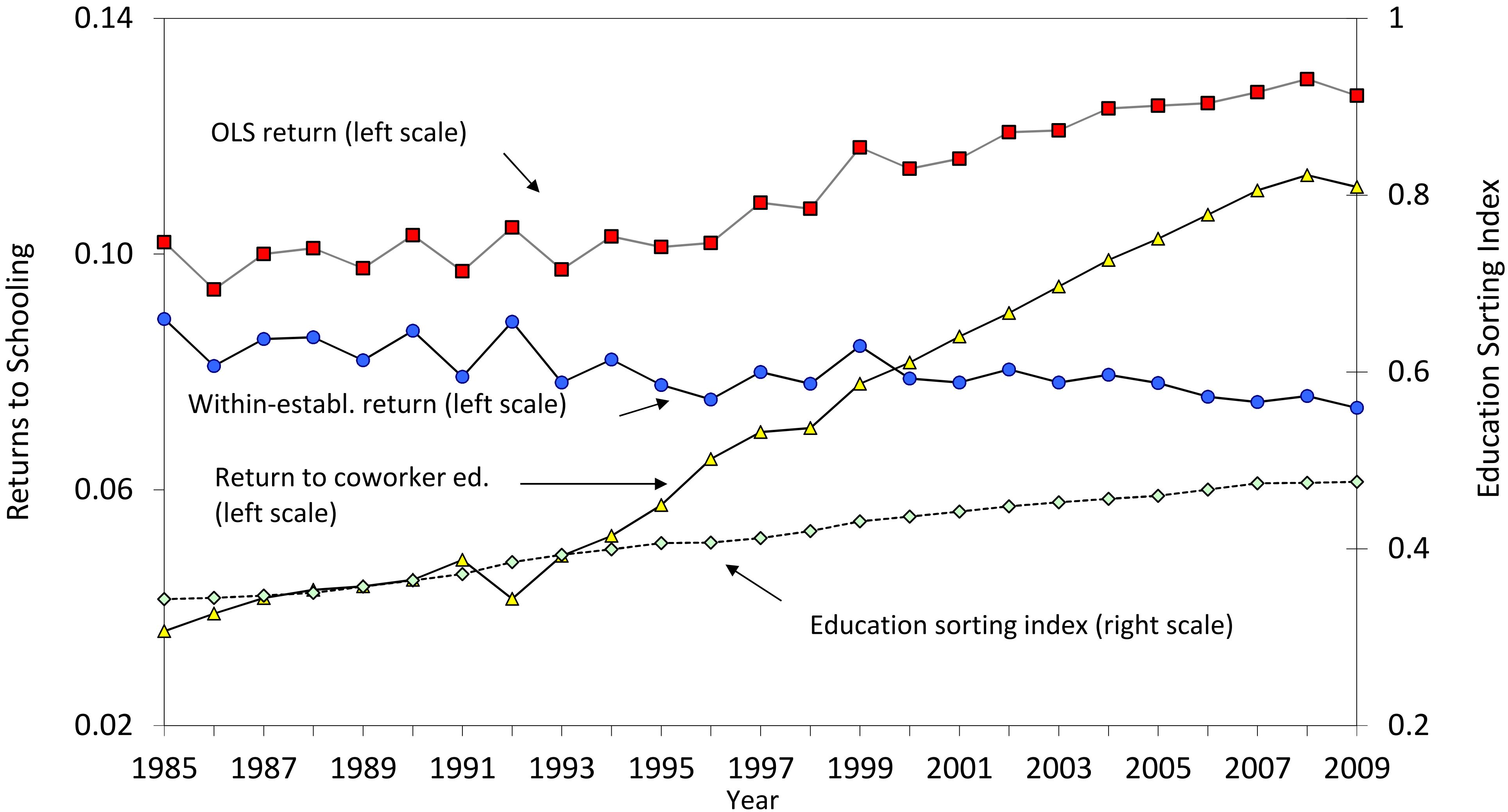
i) assortativeness is rising over time (CHK, Germany) helping to explain rising wage inquality (esp. residual inequality)

ii) rising tendency of high-ed workers to work at high-ψ firms explains rise in returns to educ. (CHK, Germany)

iii) differential sorting of men vs. women to high- ψ firms explains 20% of gender gap (CCK, Portugal)

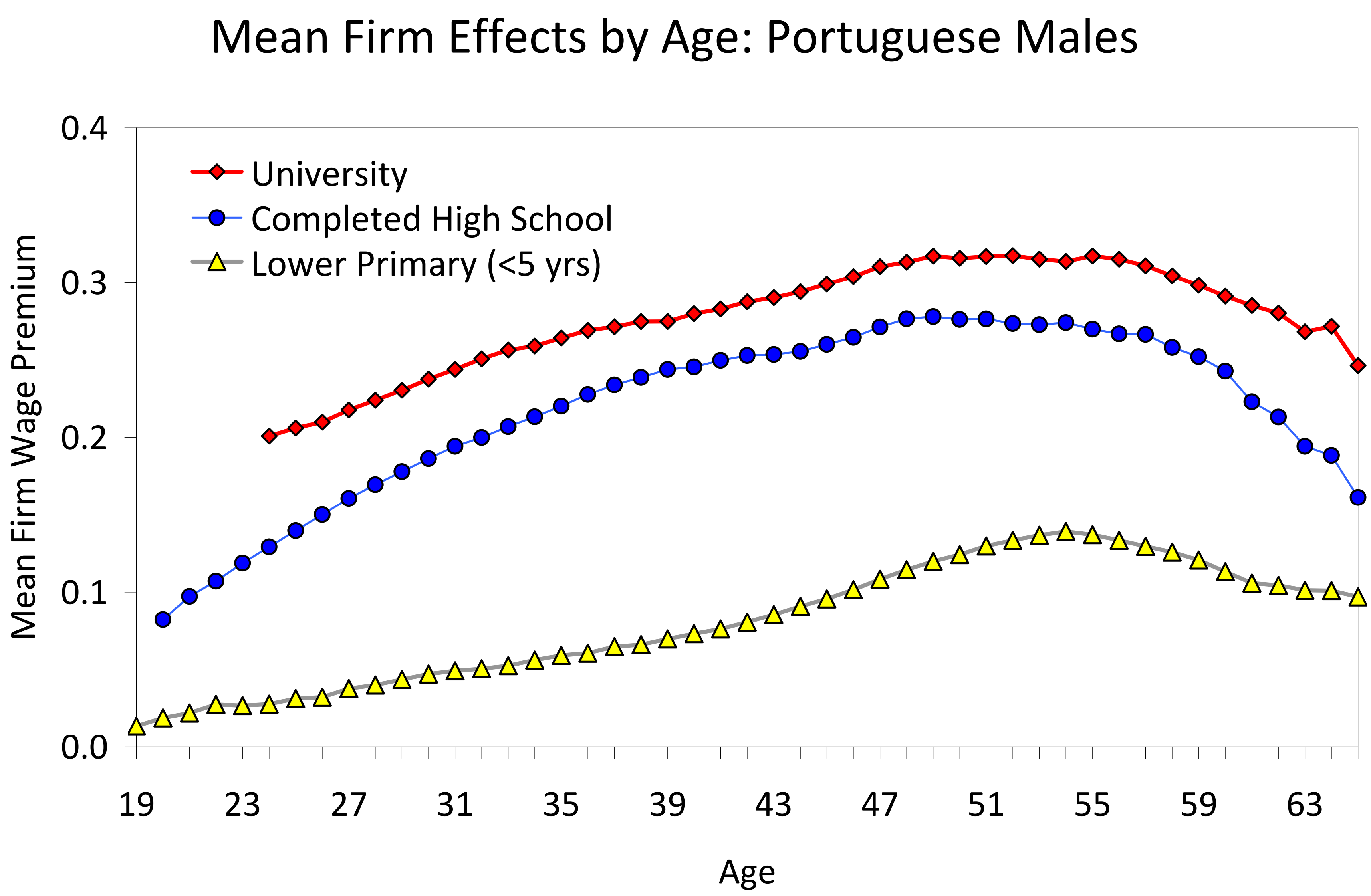
iv) differential sorting of W vs. NW to high- ψ firms explains 20% of racial wage gap (GLSC, Brazil) (*2/3 of this sorting is explained by general pattern of assortative matching)*

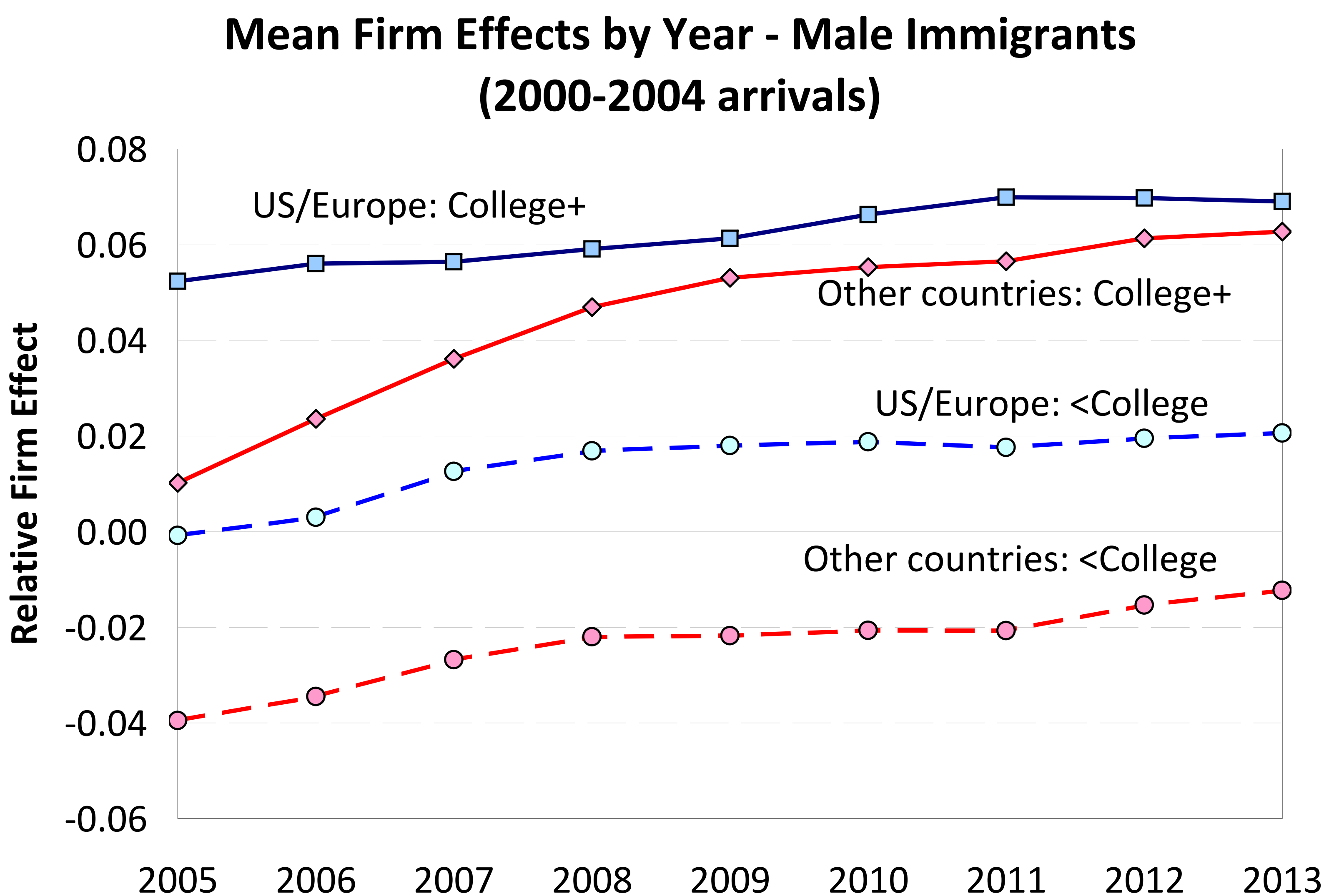
Mundlak Decomposition of Return to Education (CHK unpub.)



Mundlak decomposition:

OLS = Within + (sorting index) × Return to coworker schooling


Mean Firm Effects by Age: Portuguese Males
University
Completed High School
Lower Primary (<5 yrs)
Mean Firm Wage Premium
0.4
0.3
0.2
0.1
0.0
19
23
27
31
35
39
43
47
51
55
59
63
Age


Mean Firm Effects by Year - Male Immigrants
(2000-2004 arrivals)
Relative Firm Effect
0.08
0.06
0.04
0.02
0.00
-0.02
-0.04
-0.06
US/Europe: College+
Other countries: College+
US/Europe: <College
Other countries: <College
2005
2006
2007
2008
2009
2010
2011
2012
2013

What have we learned (4)

- $\psi's$ are strongly correlated with firm profitability (CCK; Lamadon et al)

- worker separation rates and firm death rates are strongly negatively correlated with $\psi's$ (CCK)

- E-E separations are strongly negatively correlated with rank of ψ_j

- the connection between wage premiums and separation rates suggests that part of the wage premium is a compensating diff (Sorkin)

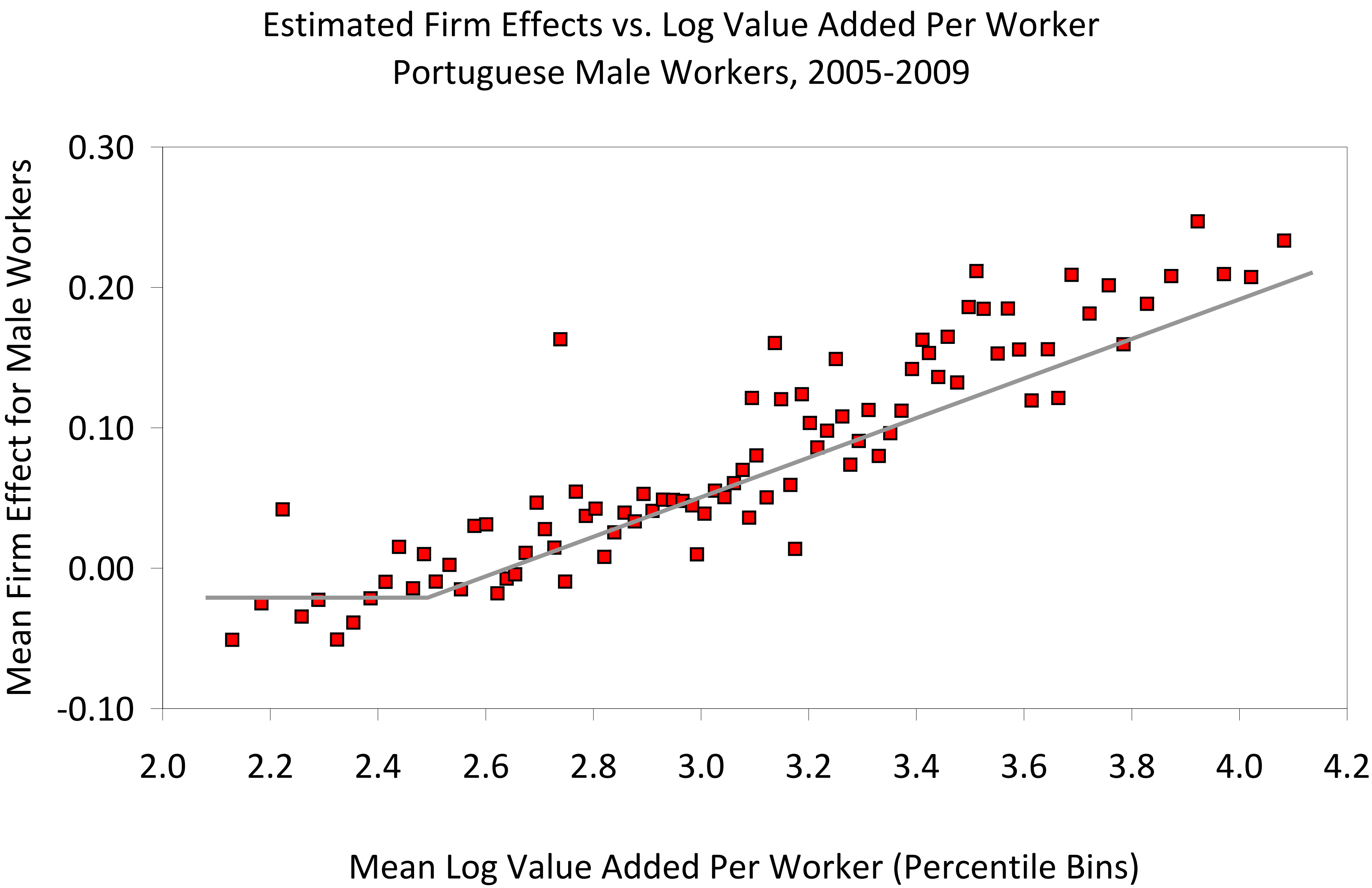
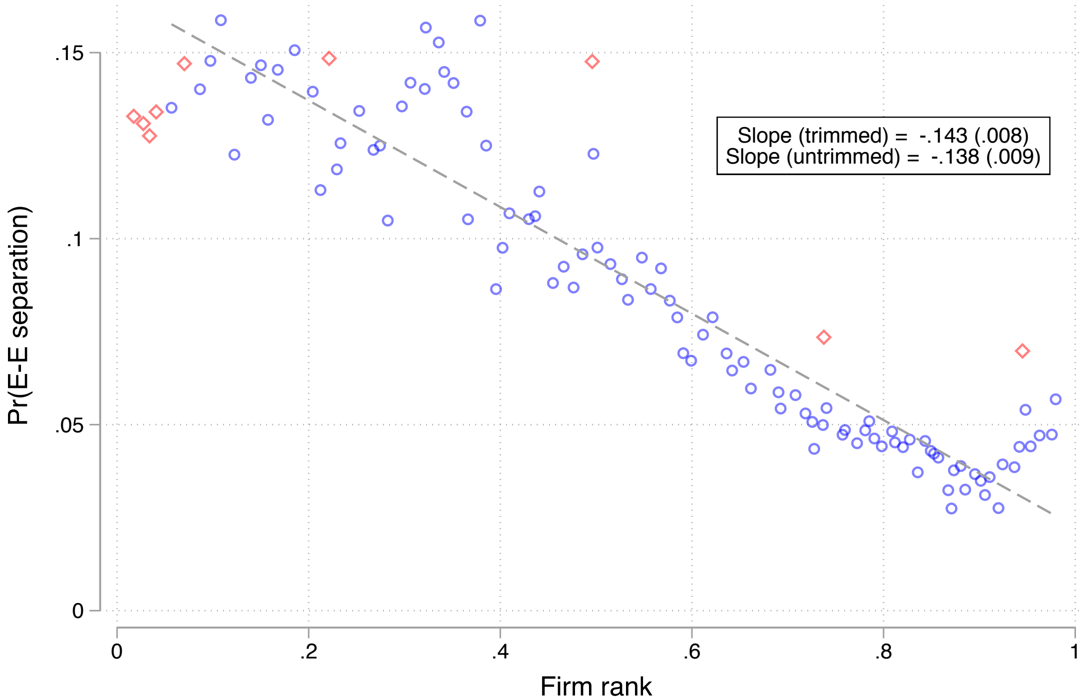

Estimated Firm Effects vs. Log Value Added Per Worker
Portuguese Male Workers, 2005-2009
Mean Firm Effect for Male Workers
0.30
0.20
0.10
0.00
-0.10
2.0
2.2
2.4
2.6
2.8
3.0
3.2
3.4
3.6
3.8
4.0
4.2
Mean Log Value Added Per Worker (Percentile Bins)

Figure 3: **Job to job separations and rank of firm wage effect**



Note: The figure illustrates the split sample approach using a control function. Residuals are calculated from a regression of own-sample firm rank on the complement-sample firm rank, and used as a control in a regression of E-E separations on own-sample firm rank. The plotted points show the residualized points of this latter regression (i.e. depicting the partial correlation), re-centred around the original mean values. The blue points represent quantiles of the trimmed sample, which excludes the top and bottom 2.5 percent of the firm effects distribution. The red points represent quantiles of the excluded sample only, which we consider outliers. The linear trendline is fitted to the trimmed sample.

the rank of a firm's wage offer and its separation rate, and Figure 3 shows that the linear fit is indeed quite good, implying substantial search frictions, with $\lambda = .14$. This is in the range of the same parameter, between 0.07 and .15, calibrated by Hornstein, Krusell, and Violante (2011) from monthly job-to-job flows. Note, however, that unlike in the Burdett-Mortensen model, the job-to-job separation rates do not equal zero at the top of the distribution, and some job-to-job transitions are to lower paid jobs.

These results are fairly robust to alternative specifications, as shown in Table 2. Controlling for tenure reproduces a similar pattern: the labor supply elasticity jumps from 1.3 under

What have we learned (5)

- the firm (and person) effects in an AKM model are estimated with error, and $correl(\widehat{\alpha}_i - \alpha_i, \widehat{\psi}_{j(i,.)} - \psi_{j(i,.)}) < 0$

- this leads to negative bias in estimated degree of assortative matching and positive bias in variance contribution of firm effects

- in short panels/thinner networks the bias can be large

- in longer panels (10+ years) the bias appears to be small

(Lachowska et al, LMSW)

- AKM in quarterly earnings vs hourly wages is similar BUT firm and sorting components are larger in earnings (LMSW)

Table 4: Variance Decomposition - Pooled Data 2002-2014

	Log Wages				***Log Earnings***			
	AKM		*TV-AKM*		*AKM*		*TV-AKM*	
	Variance Component	Share of Total (%)	Variance Component	Share of Total (%)	Variance Component	Share of Total (%)	Variance Component	Share of Total (%)
Variance of Log Wages	0.4074	100.00%	0.4074	100.00%	0.5821	100.00%	0.5821	100.00%
Variance Decomposition: Plug-In								
Variance of Person Effects	0.2567	63.01%	0.2596	63.72%	0.3136	53.86%	0.3190	54.80%
Variance of Firm Effects	0.0480	11.77%	0.0570	13.99%	0.1111	19.09%	0.1190	20.44%
2*Cov of Person, Firm Effects	0.0679	16.67%	0.0591	14.51%	0.1014	17.42%	0.0920	15.81%
Variance Decomposition: KSS								
Variance of Person Effects	0.2502	61.40%	0.2534	62.20%	0.3071	52.75%	0.3131	53.79%
Variance of Firm Effects	0.0473	11.60%	0.0549	13.47%	0.1147	19.70%	0.1209	20.76%
2*Cov of Person, Firm Effects	0.0687	16.87%	0.0604	14.81%	0.0944	16.21%	0.0845	14.52%

Note: All variance decomposition parameters are calculated in the corresponding leave one out connected set described in Table 1, Panel (b) and are person-year weighted. TV-AKM corresponds to an AKM model where firm effects are allowed to vary over-time. The AKM model includes a set of year fixed effects. Plug-in reports the variance components without adjusting for sampling error in the estimated person and firm effects. KSS adjusts each variance component using the leave out approach detailed by Kline, Saggio and Sølvsten (2019) by leaving a person year observation out. Source: WA administrative records.

Table 6: Measures of Assortative Matching

	W Male	NW Male	W Fem.	NW Fem.
Correlation of person/establishment effects	0.273	0.153	0.255	0.086
Regression coefficient of person effect on establishment effect:				
OLS estimate	0.549	0.249	0.620	0.181
OLS estimate w/ micro-region effects	0.521	0.214	0.598	0.154
IV estimate	0.672	0.523	0.746	0.638
IV estimate w/ micro-region effects	0.660	0.520	0.756	0.678
1st stage coefficients, using est. effect for opposite race as instrument				
First stage coefficient	0.763	0.812	0.706	0.737
First stage coefficient w/ micro region effects	0.731	0.796	0.656	0.711

What have we learned (6)

- one effect of a higher minimum wage is to re-allocate workers to higher-'quality' employers (Dustmann et al)

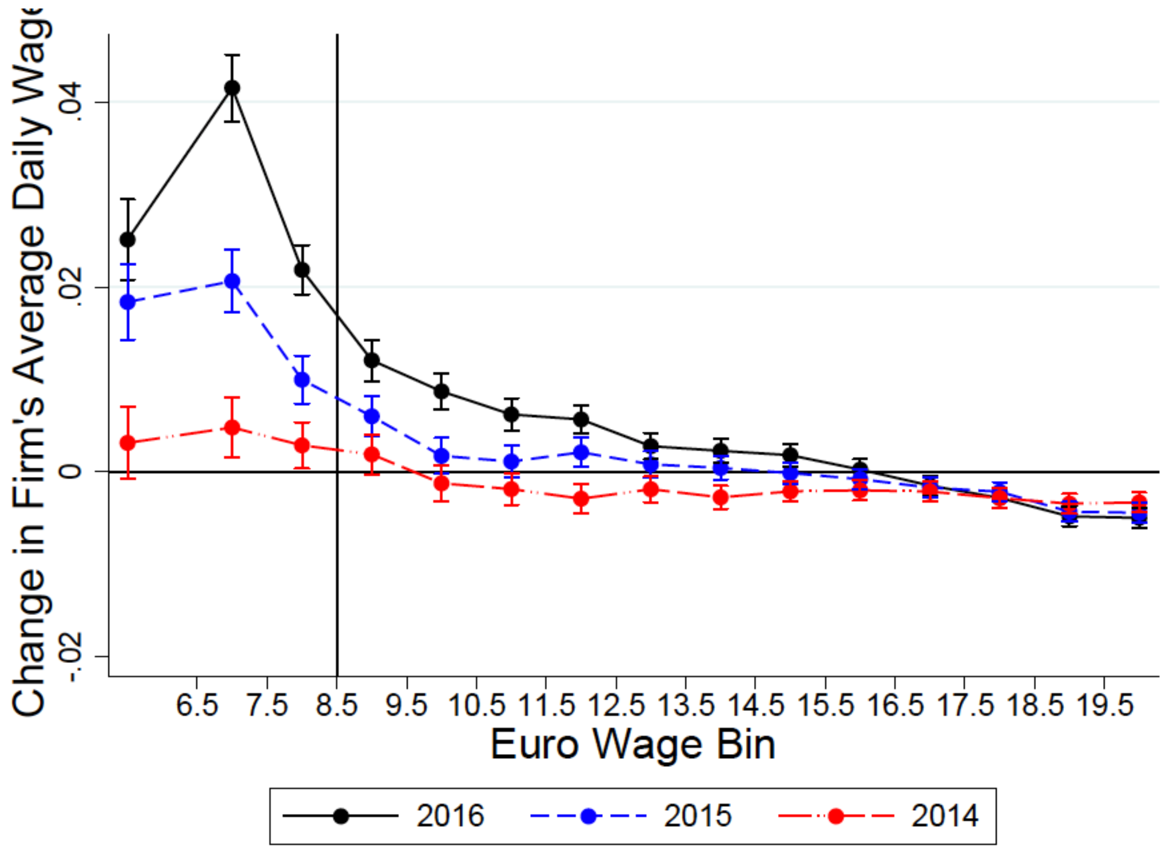
- setting: Jan. 2015 imposition of national min. at 8.50 euro/hr

- at the individual level: change caused wage increases, no loss of employment, and rise in mean firm wage (with some rise in commuting times)

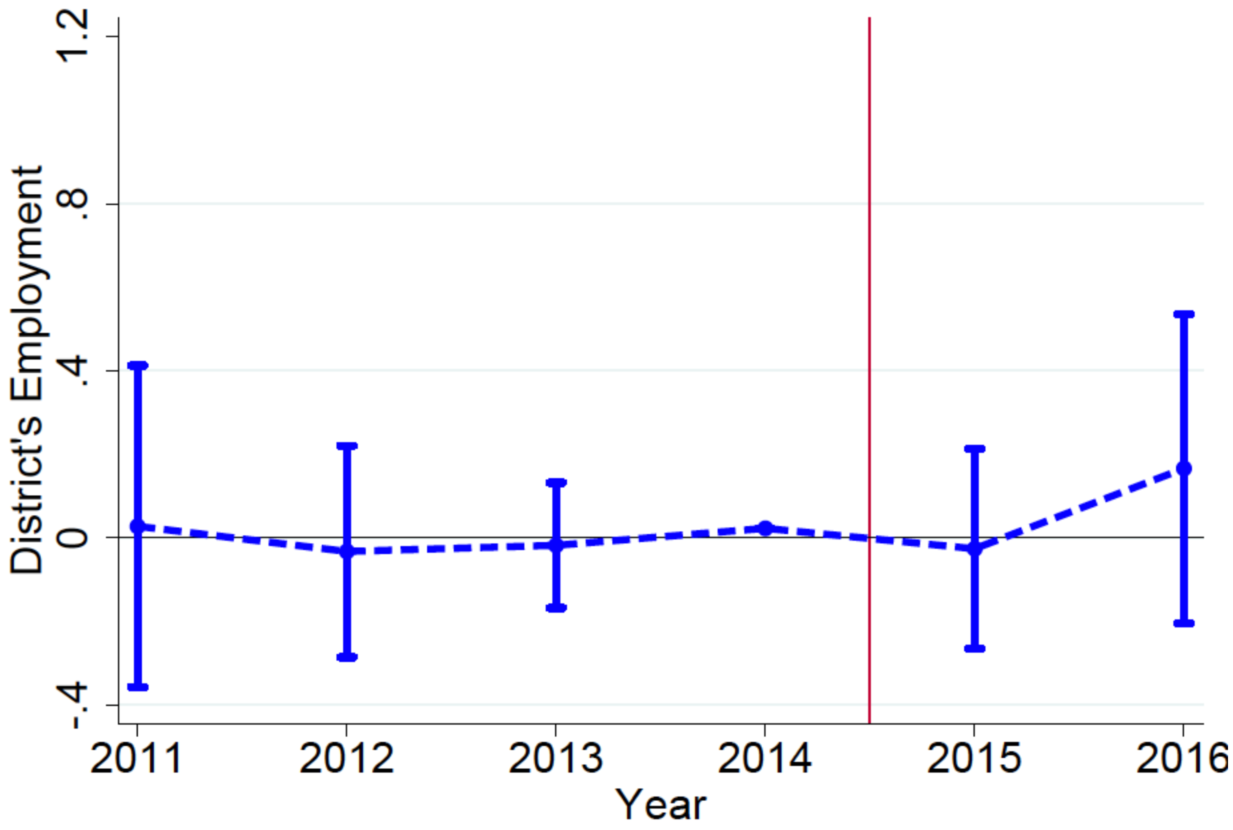
- at the county level: rise in mean AKM firm effect in highly-impacted counties

Re-allocation to higher-wage "firms"

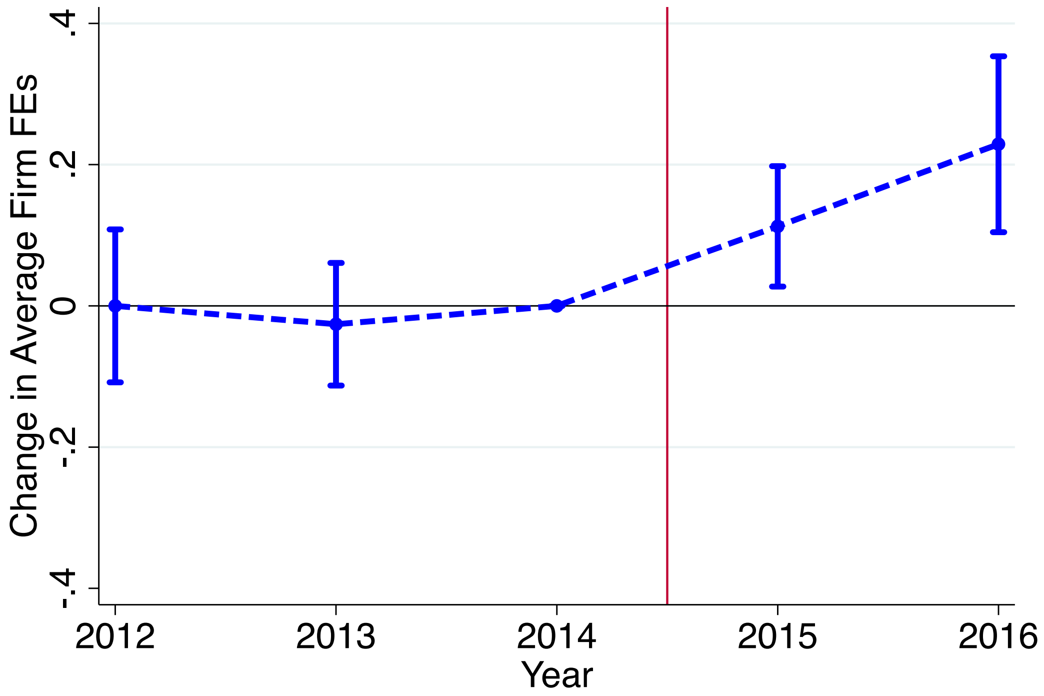
$$q_{j(i,t),i}^{t-2} - q_{j(i,t-2),i}^{t-2} = \sum_w \delta_{wt} D_{w_{i(t-2)}} \times YEAR_t + \sum_w \gamma_{w2013} D_{w_{i(2011)}} + \beta X_{i,t-2} + e_{it}$$



District's Employment – Deviations from Linear Time Trend



Average AKM Firm Fixed Effect (deviations from linear trend)



→ Composition of firms in regions with higher exposure to MW improves

Strand 2: Reverse-engineering the AKM model

How could you ever have a model that generates:

$$w_{it} = \alpha_i + \psi_{j(i,t)}$$

Three main ideas (so far):

1. Burdett Mortensen / Manning wage posting model

- original model has identical workers and firms, firms post wages in a job ladder: ψ_j is firm wage rel. to min. wage

- BM is a monopsonistic wage setting model with continuum of firms (firms set wages, but poaching "solves" the Diamond paradox)

- Christensen et al - "homogenize" workers by looking within (broad) occupations, take "wage" at each firm as given

- Bassier, Dube, Naidu - equate wage in BM model with ψ

Problems

i. no model of assortative choice of workers by firms $\Rightarrow$cannot model the rise in sorting

ii. do we really think information is the key problem?

- recent research shows #firms hiring in any given "market" is small (Azar, Marinescu, Steinbaum; Rinz)

e.g., Rinz: typical HHI for CZ*industry = 0.15

$\Rightarrow$ 7 employers (if equal size)

- evidence on "job fairs" etc

2. Differentiated jobs model (CCHK)

Utility at firm j for worker i in group $S \in \{L, H\}$:

$$u_{iSj} = \beta_S \ln(w_{Sj} - b_S) + a_{Sj} + \epsilon_{iSj}$$

Resulting supply function for group S:

$$\ln L_j(W_{Sj}) = constant + \beta_S \ln(w_{Sj} - b_S) + a_{Sj}$$

Firm j technology

$$Y_j = T_j((1-\theta)L_j + \theta H_j)$$

selling price P_j^0. Define $R_j = T_j P_j^0 / b$. Optimal wages:

$$\begin{aligned} \ln w_{Lj} &= \ln \frac{(1-\theta)b}{1+\beta_L} + \beta_L R_j \\ \ln w_{Hj} &= \ln \frac{\theta b}{1+\beta_H} + \beta_H R_j \end{aligned}$$

Problems

i. as in any monopsony model, employers are always 'short of workers.' This seems contrary to reality (except at top of business cycle?)

ii. model can be extended to allow general technology at firm j but in general the approximation to AKM will break down.

iii. model ignores strategic interactions between firms in the same market (each takes the "inclusive value" of being in the market as fixed)

iv. model implies that "very small" firms pay $w \to b$. Equivalent to prediction in consumer demand with logit preferences that price is very high for products with very small shares.

3. Models with ex-post rent-splitting

- many search models assume that after the worker and firm are matched, the wage is determined by a model like:

$$w = (1-\gamma)b + \gamma(R/N)$$

- these models "build in" a wage premium at higher-productivity firms

- examples:

Jorosh, Nimczikm, Sorkin (JNS, 2019)

Helpman, Itskhoki, Muendler, Redding (HIMR, 2017)

Q: where does γ come from? Does it vary across workers? Why don't firms set $\gamma = 0.001$?

Some future topics?

1. In monopsonistic models $w < p$ and firms are willing to hire at the "going wage". How can we break out of that?

- efficiency wages

- quality constraints (HIMR have these in a bargaining model)

2. CCK fit separate AKM models for men/women and show the firm effects are highly correlated but $\psi_j^F \approx 0.9\psi_j^M$. (similar finding in Brazil for NW vs. W). Can we fit separate effects for education or occupation groups and compare the differences across groups?

3. Roca and Puga (2017) show “gains” from experience working in big cities. Is there an equivalent effect for large/profitable/innovative firms? (Serrafinelli). Does this differentially affect men v. women?

4. Network studies (e.g. Saygin et al.) show an effect of having friends at (high-paying) firms. Is this an information effect or some kind of signal of quality effect? Do network effects account for agglomeration effects?

5. Search models with "offer matching" are more popular among theorists than strict wage posting models.

i. in such models, a worker will accept a lower wage to start a job at a more profitable firm (in anticipation of being able to negotiate a higher wage later). Is there any evidence of such "non-monotonicity"? (starting wages are lower at Chicago than Berkeley)

ii. in such models, having an offer from a higher-paying firm can be useful, even if the worker will never move. Is there evidence of strategic offer seeking and reactions to such offers? (Caldwell and Harmon)

6. Evidence from Dustmann et al (German min. wage study) suggests there are significant numbers of workers at low wage firms that could potentially move to higher-wage firms. Why? Lack of information (BM search model) or idiosyncratic preferences for workplaces (CCHK)? *more generally*: what is the explanation for wage variation across firms?

7. Can we isolate firm-specific TFP shocks and see how shocks *at nearby firms* affect wages? (VA nurses study)

7. Do mergers reduce competition for workers and lower wages? (K. Todd; JNS). Do anti-competitive arrangements (e.g., "no raid" deals) reduce wages (Duke-NC Medical case; tech cases). Can we identify strategic interactions between firms with wage setting power?