The wage elasticity of recruitment

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Context: How much market power do employers have over their workers?

- Simple way to answer this is to try to estimate the wage elasticity of the labour supply curve to individual employers
- Often done in the context of dynamic model in which long-run steady state of employment can be written as:

$$N(w) = \frac{R(w)}{q(w)}$$

- Higher wages make it easier to recruit and reduces quits and elasticity of labour supply curve can be written as:

$$\varepsilon_{Nw} = \varepsilon_{Rw} - \varepsilon_{qw}$$

Big literature on estimating quit elasticity

- Now hundreds of estimates reviewed in meta-study of Sokolova and Sorensen (ILRR, 2021)
- But very few studies of recruitment elasticity
- Most studies rely on result that for job-to-job moves average quit elasticity = - average recruit elasticity if choice between jobs depends on relative wage
- Intuition is that one firm’s quit is another’s recruit
- Would like independent estimates of the recruit elasticity

Existing Studies of Recruitment Elasticity

- Falch (ILRR, 2017) looks at natural experiment from teacher wage changes in remoter parts of Norway
- A number of recent studies on how applications respond to advertised wages – Dal Bo, Finan and Rossi (QJE 2013), Azar, Berry and Marinescu (2019), Dube, Jacobs, Naidu and Suri (AERI, 2019)
- These are interesting but applications are not the same as recruits

Why so few studies of recruitment elasticity?

- Estimating a quit elasticity is relatively simple:
  - Only one current job a worker can leave
  - Usually observe their wage in that job
  - Usual empirical debates about exogeneity, controls etc
- But estimating a recruitment elasticity it is harder:
  - A very large number of firms to which a worker might be recruited
  - Don’t observe the wage that the worker would get if they were to be recruited
- This paper proposes and implements a method to estimate the recruitment elasticity

The econometric model

- Assume that the flow of recruits with characteristics $\mathbf{x}_i$ to firm f that pays wage w_f and has other characteristics $\mathbf{z}_f$ is given by:

$$R_{if} = R\left(w_f, z_f, x_i\right)$$

- Flow of recruits to firm f is then $R_f = \sum_i R_{if}$
- We are interested in the wage elasticity of this function
- We will use AKM estimates of for the wage in each firm:
  - Assumes firms have a wage policy – if pay higher wages to one type of worker then pay higher wages to all
  - Has precedent in the quit elasticity literature e.g. Bassier, Dube and Naidu (JHR 2021)

The recruit probability function

- Suppose we consider a recruit to a set of firms, F. Then the probability that the recruit is to firm f is given by:

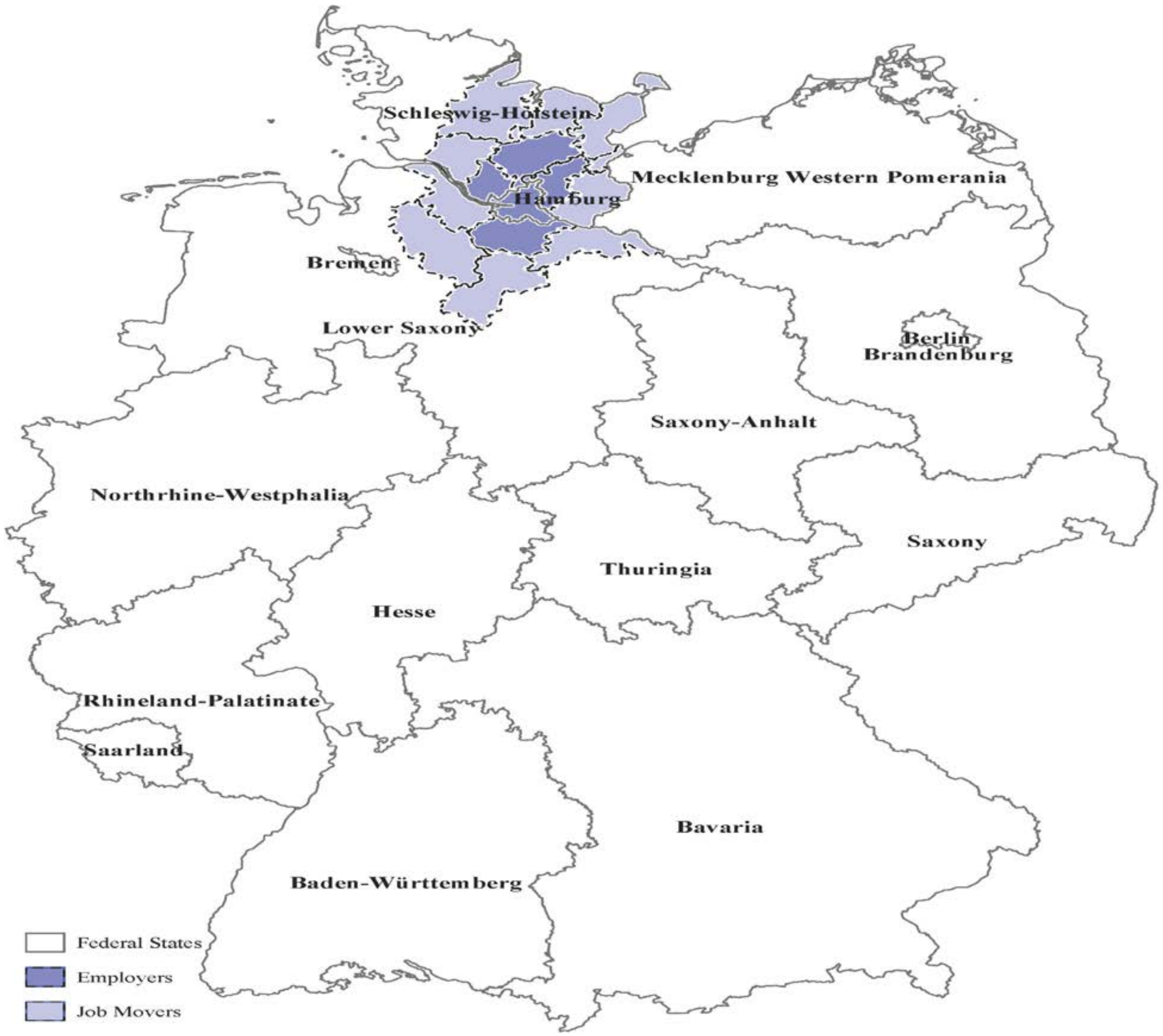
$$p\left(w_f, z_f, x_i\right) = \frac{R\left(w_f, z_f, x_i\right)}{\sum_{f' \in F} R\left(w_{f'}, z_{f'}, x_i\right)}$$

- We call this the recruit probability function – can think of it as coming form competing risks model
- The wage elasticity of recruit probability function is related to the wage elasticity of the recruit function
- We estimate the recruit probability function

Our empirical application

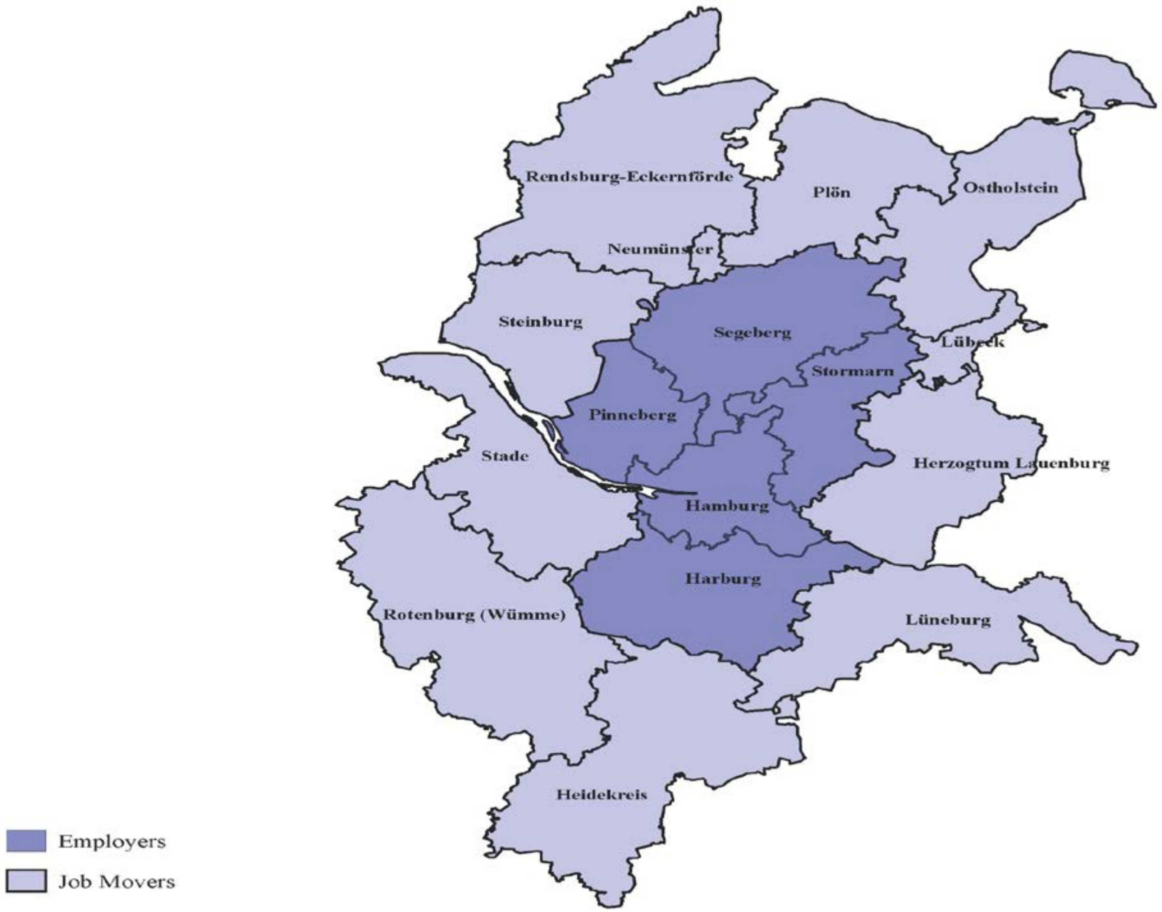
- Recruits between July 1, 2013 and June 30, 2014 who:
  - Live in Hamburg or surrounding areas
  - Were recruited into a firm in Hamburg itself
  - Why Hamburg? – all of Germany infeasible, Berlin unusual, Hamburg 2nd biggest conurbation, relatively self-contained, no international borders nearby
- Data on workers from Integrated Employment Biographies (IEB)
  - Covers 80% of German employment
  - Restrict to workers aged 18-60
- Data on employers comes from Establishment History Panel (BHP)
  - Exclude temporary work agencies
  - Exclude firms with <10 employees
  - Restrict to private sector

The Map



Schleswig-Holstein
Mecklenburg Western Pomerania
Hamburg
Bremen
Lower Saxony
Berlin
Brandenburg
Saxony-Anhalt
Northrhine-Westphalia
Saxony
Thuringia
Hesse
Rhineland-Palatinate
Saarland
Bavaria
Baden-Württemberg
Federal States
Employers
Job Movers

In more detail



Our final sample

- 48,311 recruits
  - 26,168 or 54.2% come from employment
  - 22,143 or 45.8% come from non-employment

- 10,134 plants of which 7,895 recruit at least one worker

- Our model assumes that in principle each of those recruits might have chosen each of those employers

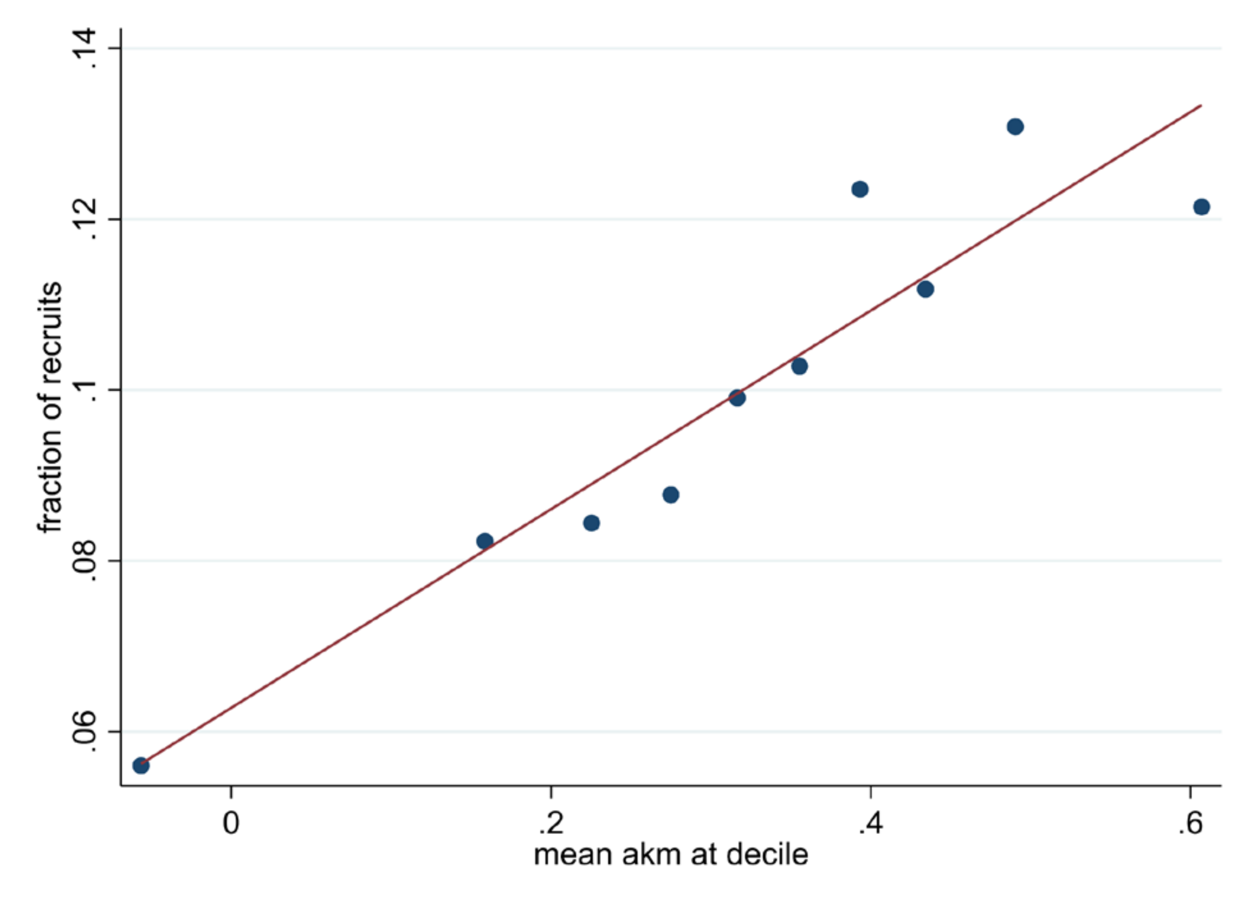
Descriptive statistics for plants

	All plants		Hiring plants	
	Mean	SD	Mean	SD
Hiring plant	0.779	0.415	1.000	0.000
AKM plant wage effect	0.320	0.189	0.324	0.171
Share of male workers	0.603	0.255	0.600	0.252
Share of non-German workers	0.080	0.130	0.075	0.118
Share of workers aged under 30	0.227	0.161	0.238	0.160
Share of workers aged 30–44	0.363	0.139	0.365	0.134
Share of workers aged 45 or older	0.410	0.198	0.396	0.192
Share of low-skilled workers	0.115	0.107	0.115	0.104
Share of medium-skilled workers	0.658	0.218	0.658	0.215
Share of high-skilled workers	0.187	0.215	0.189	0.214
Share of workers on simple tasks	0.133	0.205	0.127	0.194
Share of workers on expert tasks	0.578	0.287	0.581	0.280
Share of workers on specialist tasks	0.162	0.197	0.164	0.194
Share of workers on complex tasks	0.127	0.181	0.128	0.178

Descriptive statistics for recruits

	All recruits	Recruits from employment	Recruits from non-employment
Male	0.605	0.639	0.564
Female	0.395	0.361	0.436
German national	0.926	0.939	0.912
Non-German national	0.074	0.061	0.088
Aged under 30	0.432	0.371	0.504
Aged 30–44	0.377	0.421	0.324
Aged 45 or older	0.192	0.208	0.172
Low-skilled	0.159	0.071	0.263
Medium-skilled	0.567	0.639	0.483
High-skilled	0.274	0.290	0.254
Simple tasks		0.095	
Expert tasks		0.553	
Specialist tasks		0.185	
Complex tasks		0.166	
Recruits	48,311	26,168	22,143

Descriptive Evidence that higher wages lead to higher recruits



Empirical Model

- We use multinomial logit specification:

$$p(w_f, z_f, x_i) = \frac{exp\left(\phi logw_f + \beta_1 z_f + \beta_2 d_{if}\right)}{\sum_{f'} exp\left(\phi logw_{f'} + \beta_1 z_{f'} + \beta_2 d_{if'}\right)}$$

- Can derive from discrete choice model where utility has idiosyncratic component with type 1 extreme value
- Individual characteristics in levels disappear as affect numerator and denominator equally – does not mean flow of recruits does not depend on them, just conditional on being a recruit
- Include firm characteristics and interactions – ‘distance’

Implementation

- 10k+ possible options (plants) is too many to estimate using multinomial logit directly
- So we use exact equivalence between multinomial logit and fixed effects Poisson
- Each observation is a recruit-plant pair i.e. 48311*10134 observations
- Dependent variable takes value 1 if recruit went to that plant, zero otherwise
- Include recruit fixed effects
- Estimate as Poisson model

Controls

- AKM estimates come from Bellmann, Lochner, Seth and Wolter (202)
- Plant controls are the shares of male and non-German workers, the shares of workers aged under 30 and of workers aged 45 or older, the shares of low-skilled and high-skilled workers, as well as the shares of workers on simple, specialist, and complex tasks.
- Industry and plant location controls comprise 57 dummies for two-digit industry and four dummies for the districts where plants are located.
- Might like to have a measure of firm recruitment activity e.g. vacancies but we do not have this
- Standard errors clustered at recruit level in parentheses.
- Distance is measured ‘as crow flies’ from residence to workplace (robustness later)

Baseline results

Model	(1)	(2)	(3)	(4)
AKM plant wage effect	1.193 (0.023)	1.125 (0.023)	1.276 (0.027)	1.396 (0.029)
Linear distance		–0.102 (0.001)	–0.103 (0.001)	–0.103 (0.001)
Plant controls			✓	✓
Industry and plant location controls				✓

Discussion

- Wage elasticity of recruitment does not vary much with specification
- Not very different from quit elasticity of -1.2 estimated for Hamburg labour market in our previous work
- Distance has a large negative effect
- A 1km increase in distance is equivalent to 9% rise in wages
- Labour markets are very local – this is one reason employers have considerable market power
- Next: look at differences according to whether recruit comes from employment or non-employment

Differences according to whether recruit is from employment/non-employment

	Panel A: Recruits from employment			
AKM plant wage effect	1.638 (0.031)	1.565 (0.031)	1.584 (0.036)	1.631 (0.038)
Linear distance		–0.099 (0.001)	–0.100 (0.001)	–0.100 (0.001)
	Panel B: Recruits from non-employment			
AKM plant wage effect	0.682 (0.034)	0.624 (0.034)	0.926 (0.040)	1.128 (0.044)
Linear distance		–0.106 (0.001)	–0.107 (0.001)	–0.107 (0.001)
Plant controls			✓	✓
Industry and plant location controls				✓

Discussion

- Wage elasticity for recruits from employment higher than for recruits from non-employment
- Consistent with view that those with a job are going to be more ‘picky’
- Not much difference in the cost of distance
- But coming from non-employment might be correlated with other characteristics – looking at heterogeneity in these is also interest

Heterogeneity by Personal Characteristics

	Sex	Nationality	Education	Age	Together
AKM plant wage effect	1.237 (0.039)	1.524 (0.030)	0.889 (0.034)	1.739 (0.042)	1.394 (0.027)
× male	0.264 (0.047)				0.361 (0.044)
× non-German national		–1.606 (0.083)			–1.552 (0.078)
× low-skilled			–0.291 (0.066)		–0.138 (0.069)
× high-skilled			1.983 (0.048)		1.974 (0.048)
× aged under 30				–0.586 (0.051)	–0.171 (0.051)
× aged 45 or older				–0.465 (0.067)	–0.251 (0.062)

Discussion

- Regressors are centred so main effect can be interpreted as the recruitment elasticity for average recruit
- The variation in recruitment elasticity reflects how well groups do in the labour market:
  - Lower for women, non-Germans, low-educated, younger and older workers
- Suggests that differences in search or market power may be important in explaining wage inequality
- Also see pattern of differentials in ‘cost of distance’ – groups with lower wage elasticity have higher distance effect

And this largely mirrors differences in estimated ‘cost of distance’

	Sex	Nationality	Education	Age	Together
Linear distance	–0.108 (0.001)	–0.103 (0.001)	–0.109 (0.001)	–0.100 (0.001)	–0.102 (0.001)
× male	0.008 (0.001)				0.008 (0.001)
× non-German		–0.013 (0.003)			–0.014 (0.003)
× low-skilled			–0.008 (0.002)		–0.006 (0.002)
× high-skilled			0.031 (0.002)		0.032 (0.002)
× aged under 30				–0.008 (0.002)	–0.001 (0.002)
× aged 45 or older				0.001 (0.002)	0.003 (0.002)

Discussion

- Suggestive of view that some groups are more confined to local labour markets; this gives them a narrower range of employers to choose from and this makes their labour market less competitive
- Find similar patterns if we distinguish between recruits from employment and non-employment
- Also find that those who were previously employed in more complex jobs are more wage elastic and have lower cost of distance
- Can also see how elasticity varies with AKM individual effect

How varies with individual effect

	AKM plant wage	Linear distance
Main effect	1.365 (0.026)	–0.102 (0.001)
× AKM worker wage effect (centred)	1.281 (0.018)	0.020 (0.001)

How varies with AKM plant effect of previous employer (recruits from employment only)

	AKM plant wage effect	Linear distance
× 1st quartile of the distribution of source AKMs	–0.541 (0.058)	–0.104 (0.002)
× 2nd quartile of the distribution of source AKMs	0.232 (0.058)	–0.103 (0.002)
× 3rd quartile of the distribution of source AKMs	2.106 (0.051)	–0.099 (0.002)
× 4th quartile of the distribution of source AKMs	4.289 (0.040)	–0.091 (0.002)

Interpretation: May be competing effects

- If already in a high wage firm may be less likely to move to another firm; this would be the case in search model where only have choice of one other employer at a time but which other employer is randomized
- Those whose decisions are not sensitive to the wage are more likely to end up in plants with low AKM wage effects
- Evidence suggests that the second effect dominates.

Different ‘cost of distance’; whether same occupation or industry

AKM plant wage effect	**1.424** **(0.042)**
Linear distance	–0.097 (0.001)
Plant belongs to the same industry as previous employer	2.311 (0.018)
Plant employs workers in the same occupation as previous job	2.923 (0.021)

Different measures of cost of distance

	Linear distance at hiring	Linear distance before hiring	Street distance	Commuting time
AKM plant wage effect	1.631 (0.038)	1.631 (0.038)	1.647 (0.038)	1.647 (0.038)
Distance measure	–0.100 (0.001)	–0.100 (0.001)	–0.079 (0.001)	–0.094 (0.001)

Employer Selection

- The model we have used so far has assumed that recruitment decisions are entirely driven by worker decisions – employers are passive accepting all those who want to work
- But perhaps employers don't accept all applicants for jobs
- Suppose R(w) is flow of people who want to work for firm but employer accepts a fraction θ(w) of applicants
- In this case we have estimated $\varepsilon_{Rw} + \varepsilon_{\theta w}$
- What elasticity would we want to estimate in this case in order to measure market power?

A Simple Model of Employer Selection

- Suppose employer accepts a fraction θ of applicants
- They will only do this if productivity depends on θ - p(θ)
- Profits can then be written as:

$$\pi = \left[p(\theta) - w \right] \theta \frac{R(w)}{q(w)}$$

- And firm will want to choose (θ,w) to maximize this

The German Vacancy Survey

- A repeated cross-sectional survey of plants, focusing on vacancies and hires
- Can be linked to other data sets – so can merge in AKM firm effect
- We use surveys for 2013/14 but for all Germany (sample too small if restrict to Hamburg)
- Asks for the total number of hires in the previous twelve months and, for plants that hired a worker, the number of applicants for the latest filled position in total and by gender.

Check; high wage plants have more hires (in line with earlier findings)

Model	(1)	(2)	(3)	(4)
AKM plant wage effect	1.685 (0.208)	1.832 (0.214)	1.966 (0.156)	1.665 (0.181)
Plant controls		✓	✓	✓
Industry and plant location controls			✓	✓
Observations	9,269			

High-wage firms have more applicants for each vacancy suggesting more selection

Model	(1)	(2)	(3)	(4)	(5)
AKM plant wage effect	1.242 (0.136)	1.023 (0.133)	0.829 (0.128)	0.565 (0.357)	0.616 (0.202)
Occupation dummies		2-digit	3-digit	3-digit	3-digit
				One hire	weighted

Implications

- If we think that the numbers hired is uncorrelated with the wage (e.g. if each vacancy leads to one hire) then this elasticity needs to be added to our previous elasticity to get relevant measure of market power
- We get similar elasticity if we restrict sample to plants with only one hire in previous year
- Earlier we showed lower recruitment elasticity for women; this could be driven by a gender gap in employer selection.
- This does not seem to be the case; probability of hiring a women reflects female share of applicant pool

The probability of hiring a woman

Model	(1)	(2)	(3)	(4) weighted
Share of women among applicants	1.070 (0.028)	0.947 (0.051)	0.950 (0.051)	1.067 (0.075)
AKM plant wage effect			0.094 (0.077)	0.193 (0.128)
3-digit occupation controls		✓	✓	✓
Observations		2,436		2,263

Conclusion

- Have presented a method for estimating wage elasticity of recruitment
- Estimated elasticity approximately 1.6 – robust to different specifications
- Broadly consistent with quit elasticities suggest common practice of assuming two are equal may not be so bad
- Also show variation with disadvantaged groups having a lower estimated wage elasticity