Matching in Cities

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The German Labour Market in a Globalised World

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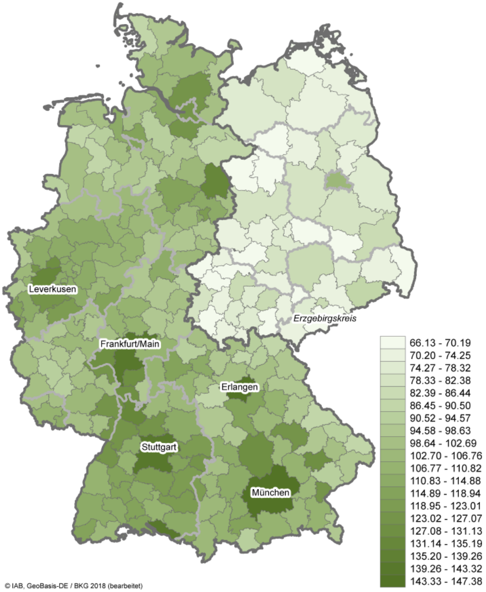
Spatial Wage Disparities

- In most countries, the spatial distribution of economic activity is highly uneven
- Large differences across cities in labor productivity and wages
  (wages in Munich 60% higher than in Uelzen!)
- Governments spend huge amounts of money on "place-based policies" designed to transfer resources from high income areas towards low income areas
- Still, these differences are growing over time



City-level average wages, 2014

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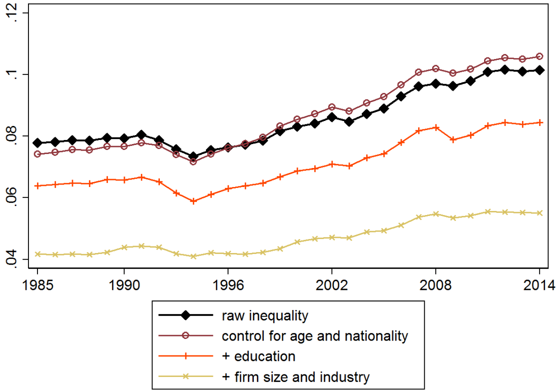
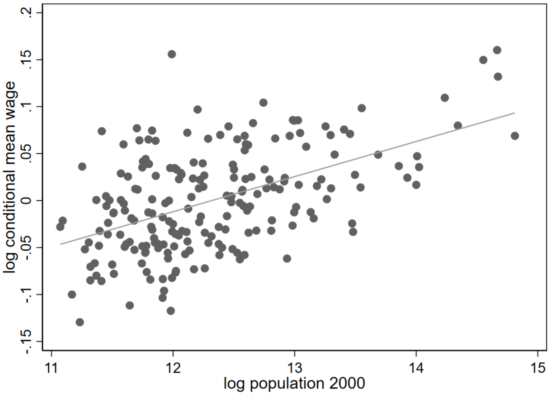


Standard deviation of city-level average wages.

Sources of Wage Disparities



Conditional wages and city size.
Elasticity: 0.037 (s.e. = 0.004)

Geographical wage disparities strongly associated with city size!

- Geographical sorting: Workers in bigger cities have higher (unobserved) ability

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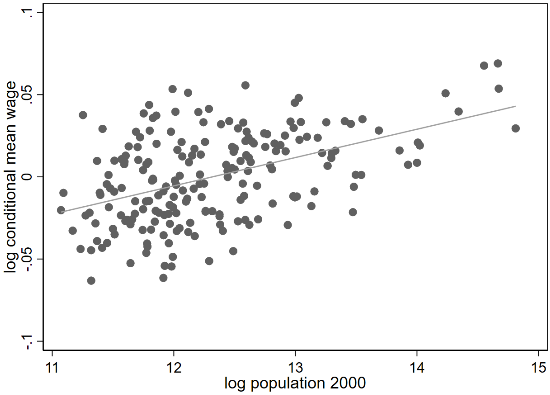

Conditional wages and city size.
Elasticity: 0.017 (s.e. = 0.002)

Geographical wage disparities strongly associated with city size!

- Geographical sorting: Workers in bigger cities have higher (unobserved) ability
- Agglomeration economies: Working in bigger cities makes workers more productive
  - Human capital spillovers
  - Specialized intermediate (service) inputs
  - **This paper: Quality of matches between workers and firms**

Assortative Matching

(Positive) assortative matching:
The tendency of high-quality workers to work in high-quality plants

	Munich	**Balingen**	**Cochem**
residents	2,531,068	190,291	64,689
share of top tercile workers working in top tercile plants	17.1%	12.3%	8.5%
share of bottom tercile workers working in bottom tercile plants	17.1%	13.5%	10.9%

Assortative Matching

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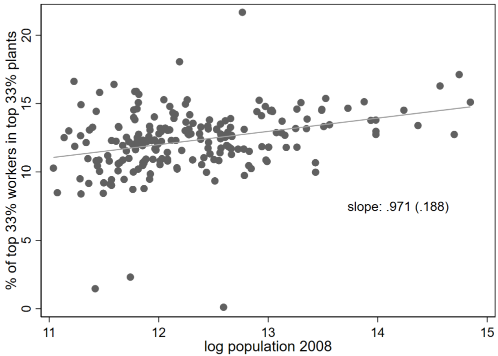
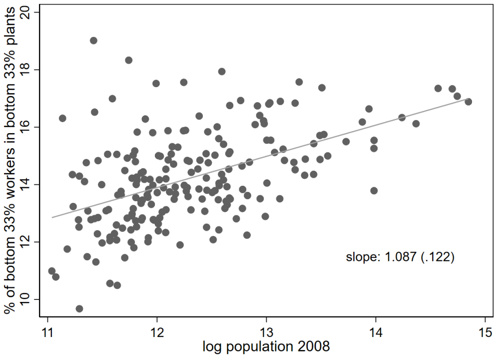


(A) Top Workers and Plants



(C) Bottom Workers and Plants

Assortative Matching

(Positive) assortative matching:
The tendency of high-quality workers to work in high-quality plants

- Importance of assortative matching has long been discussed in labor economics (Becker, 1973; Shimer and Smith, 2000; Shimer, 2005).
  In particular: Has increased nationwide wage inequality in Germany (Card, Heining, Kline; 2013)!
- We study to what extend assortative matching explains spatial wage differences in Germany
- We find that assortative matching increases with city size
  (Existing literature: Andersson, Burgess, Lane, 2007 (+); Figueiredo, Guimaraes, Woodward, 2014 (0); Mion, Naticchioni, 2009 (−); Andini, DeBlasio, Duranton, Strange, 2013 (+))
- This has two consequences:
  - Magnifies wage differences across cities
  - Increases aggregate earnings

Agenda

- Data and Empirical Approach
- Results
  1. Between-City Matching
  2. Within-City Matching
  3. Aggregate Effects
- Conclusion

Data

- IAB Employee History File (BEH)
    - Entire labor market histories of all private sector workers s.t. social security.
    - Focus on male full-time workers aged 20-60
    - Allows to follow individual careers across different workplaces
    - 298,565,604 worker-year-observations of a total of 29,187,865 individuals and 3,252,487 plants.
- Geographical unit of analysis: Travel-to-work areas around 258 German cities
- Main analysis concentrates on 204 West German regions because of vast East/West-Differences

Worker Quality, Plant Quality, and Assortative Matching

- Abowd, Kramarz, and Margolis (1999) approach (henceforth AKM).
  Decomposition of individual (log) wage into worker- and plant-specific pay components:

$$\ln(\text{wage}_{it}) = \mu_i + \Psi_{\mathbf{J}(i,t)} + X_{it}'\gamma + \epsilon_{it}$$

μ_i **"worker effect":** proportional worker specific component, portable across plants

$\Psi_{\mathbf{J}(i,t)}$ **"plant effect":** proportional wage premium (or discount) for all workers of plant J

X_{it} age profiles, year effects

ϵ_{it} error term

Worker Quality, Plant Quality, and Assortative Matching

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- Not a structural model of the labor market
- Worker and plant effects do not necessarily measure true ability or productivity (Eeckhout and Kircher, 2011; Abowd et al., 2004, 2018)
- But consistent with production functions where the plant effect captures plant-specific TFP, e.g. $Y_J \propto \tilde{\mu}_i^a \tilde{\Psi}_{\mathbf{J}(i,t)}^b$
- log wages are additive in worker and plant effects and have no match-specific component
- But multiplicative in levels, and thus, "good" workers (with high μ_i) earn relatively more than "bad" workers (with low μ_i) when working for a "good" plant

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- Estimation issues:
  - Split data into five 7-year time intervals:
    i) 1985-1991, ii) 1990-1996, iii) 1996-2002, iv) 2002-2008, and v) 2008-2014
  - Use nominal wages for baseline results (reflect productivity rather than amenity differences)

Worker Quality, Plant Quality, and Assortative Matching

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$$\ln(\text{wage}_{it}) = \mu_i + \Psi_{\mathbf{J}(i,t)} + X_{it}'\gamma + \epsilon_{it}$$

- Positive assortative matching: Correlation/Covariance of "worker effect" and "plant effect"

$$Cov(\mu_i, \Psi_{\mathbf{J}(i,t)}) = \underbrace{Cov\left(E_c[\mu_i], E_c[\Psi_{\mathbf{J}(i,t)}]\right)}_{\text{Between}} + \underbrace{E\left[Cov_c(\mu_i, \Psi_{\mathbf{J}(i,t)})\right]}_{\text{Within}}$$

1. **Between-city matching:** High-quality workers tend to locate in cities with many high-quality plants
2. **Within-city matching:** High-quality workers in a city match with high-quality plants in that city

Assortative Matching Between and Within Cities

Between-City Matching

- **Incentives:**
  - If worker quality and plant quality are complements in production, good workers and good plants have an incentive to co-locate
- **Amenities:**
  - Larger cities may offer workers better or more varied consumption amenities and also offer productivity advantages to plants in the form of productive amenities (e.g., transportation infrastructure or other locational advantages)

Assortative Matching Between and Within Cities

Within-City Matching

- **Benefits of Market Thickness:**
  - Larger markets are generally assumed to generate better matches (Diamond 1982, Helsley and Strange 1990)
  - Example: In 2008-2014 633 chemical engineers matched with 361 plants in Munich but only 12 chemical engineers matched with 10 plants in Balingen.

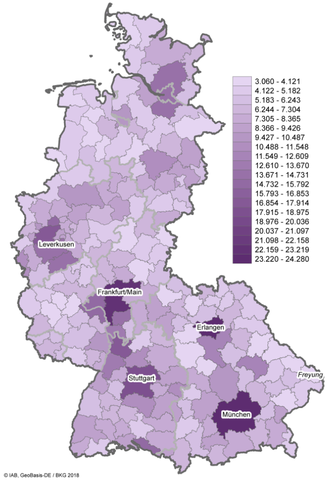
- **Stronger Incentives:**
  - Bigger cities attract more productive workers and plants
  - If worker and plant quality are complements, gains of assortative matching are higher in cities with more productive workers and plants

Toy model

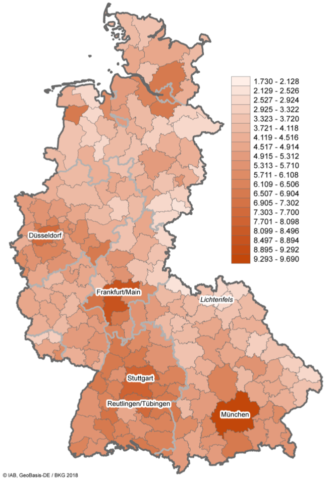
Results

1. Between-City Matching

Spatial Distribution of Top 10%-Workers and Top 10%-Plants

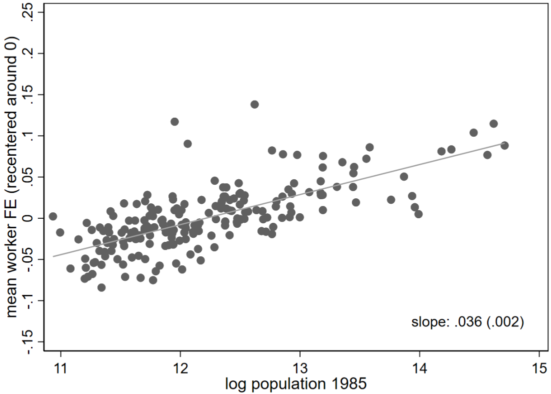


Top decile workers

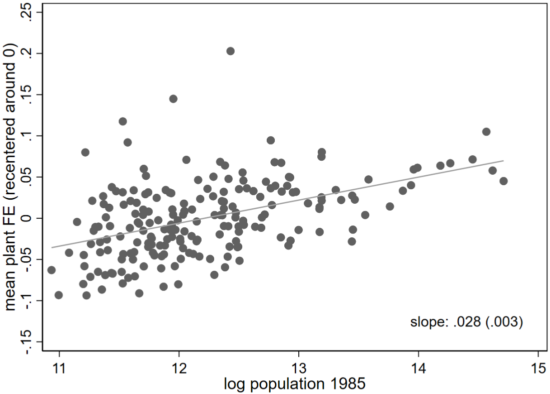


Top decile plants

Average Worker/Plant Effects and City Size

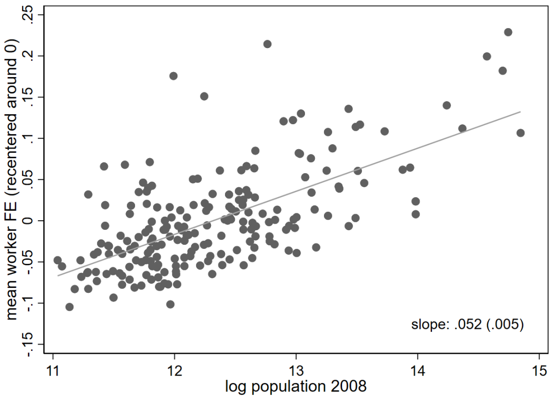


Worker Effects, 1985-1991

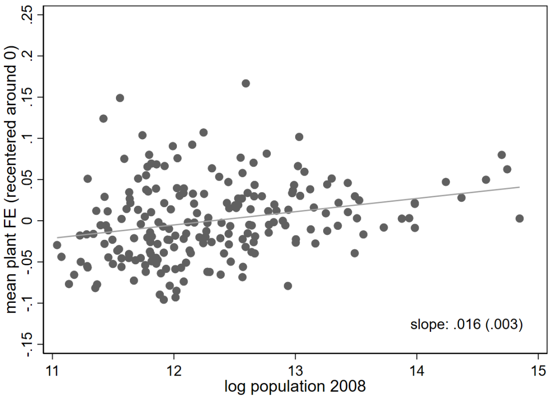


Plant Effects, 1985-1991

Average Worker/Plant Effects and City Size



Worker Effects, 2008-2014

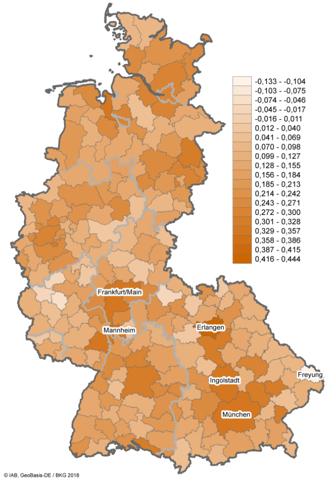


Plant Effects, 2008-2014

Results

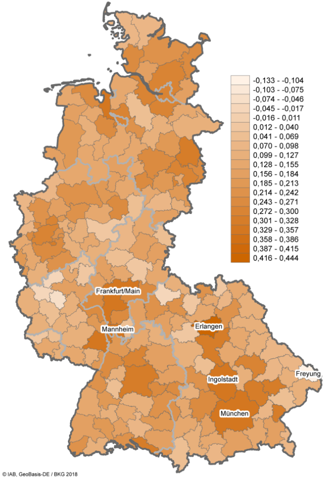
2. Within-City Matching

Assortative Matching and City Size



Degree of Assortative Matching by City, 2008-2014

Assortative Matching and City Size



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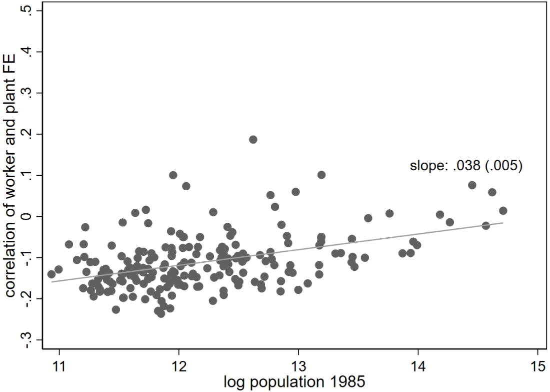

Assortative Matching and City Size, 1985-1991

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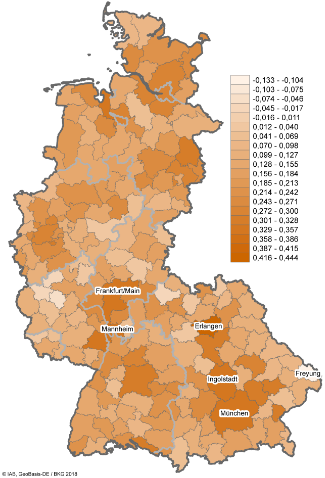

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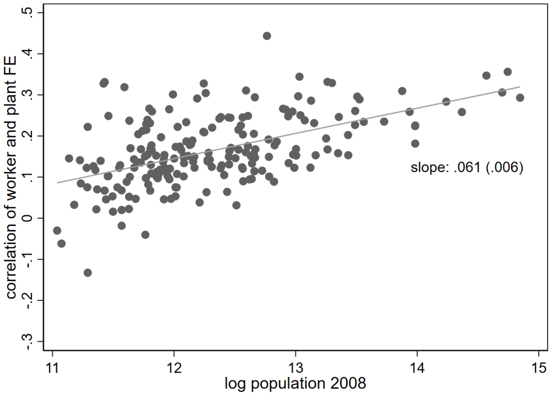
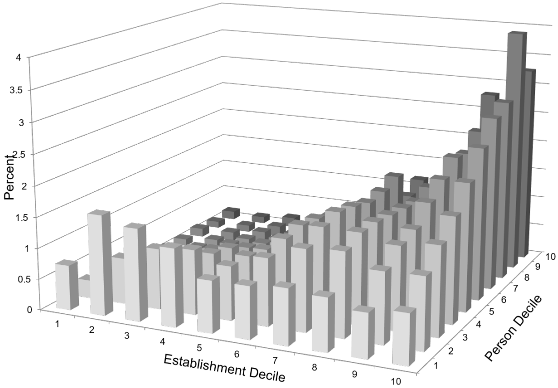
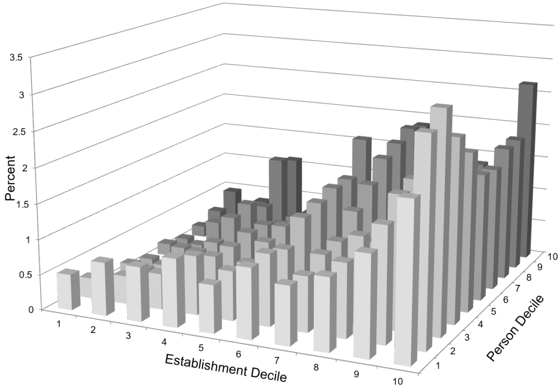


Assortative Matching and City Size, 2008-2014

Illustration: Hamburg and Daun



Hamburg



Daun

Occupation-Specific Local Labor Markets

Increasing returns in matching technology might be specific to narrower definition of occupation-specific labor market cells:

> *A bioengineer and an architect living in the same city may face different market thickness, depending on the local agglomeration of bioengineering firms and architectural firms.*

(Moretti, Handbook of Labor Economics 2011)

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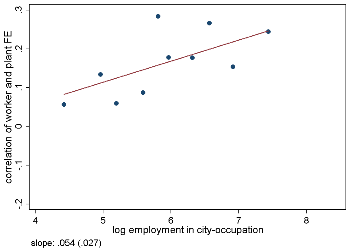

Chemical Engineers

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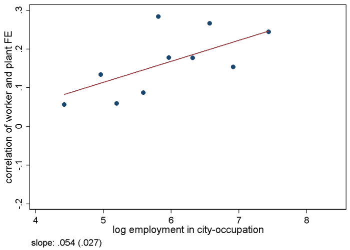

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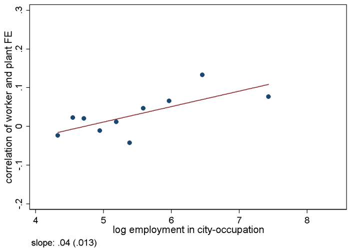

Architects

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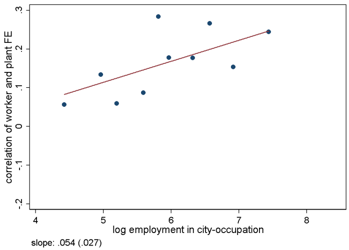

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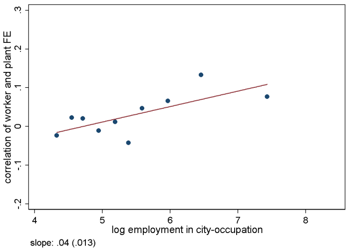

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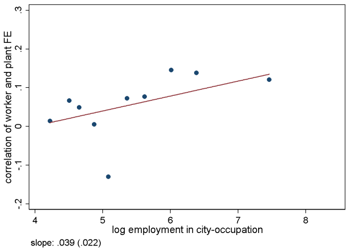

Economists

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(Moretti, Handbook of Labor Economics 2011)

Dependent Variable: Correlation of Worker and Plant FE, 2008-2014	(1)	(2)	(3)	(4)	(5)	(6)
Employment in city	0.0313***		-0.0102***			
	(0.002)		(0.003)			
Employment in city-occupation		0.0645***	0.0681***	0.0682***	0.0388***	0.0305***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
City FE	–	–	–	yes	–	yes
Occupation FE	–	–	–	–	yes	yes
N	10293	10293	10293	10293	10293	10293
R^2	0.016	0.116	0.117	0.160	0.410	0.452

Robustness I: AKM

- **Interpretation of Assortative Matching:**
  - Firm effects from the AKM model do not capture productivity
  - Hence, the correlation of worker and firm effects does not reflect the strength assortative matching (Lentz and Mortensen (2010), Eeckhout and Kircher (2011) and Bartolucci et al. (2018))
  - Lopes de Melo (2018): measure the intensity of assortative matching by the correlation of worker effects with the average worker effects of their respective co-workers
    Elasticities decline by 25% but remain significant

- **One AKM estimation 1985-2014:**
  - Longer period increases number of observed moves: plant effects more tightly identified
  - Prevents worker and plant effects to change over time
  - Elasticities decline by 10% but remain significant
  - Results now exclusively driven by the allocation of workers and plants, which appears to improve over time.

Robustness II: Limited Mobility Bias

Small number of moves between plants may generate downward bias in the estimated correlation of worker and plant effects. This might be particularly severe in smaller cities!

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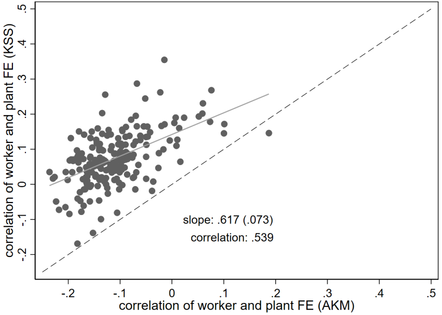
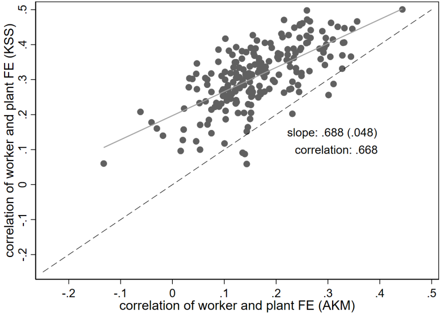
Small number of moves between plants may generate downward bias in the estimated correlation of worker and plant effects. This might be particularly severe in smaller cities!

- **Check 1:** We employ the leave-out estimation by Kline, Saggio, and Solvsten (2020) to obtain unbiased estimates of the variance components



AKM vs. KSS, 1985-1991



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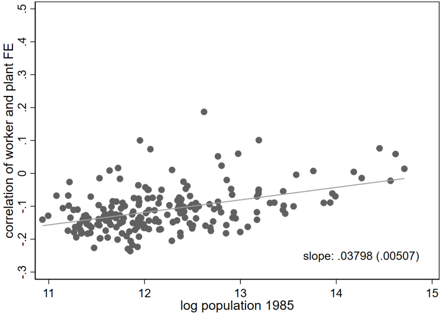
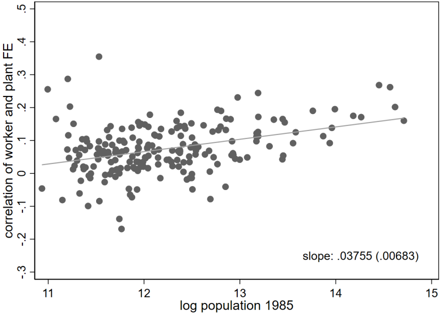


AKM, 1985-1991



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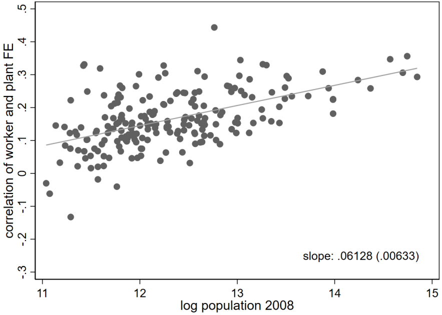
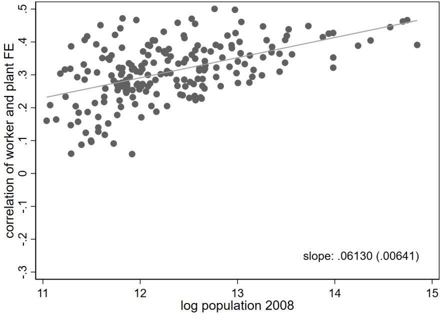


AKM, 2008-2014



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- **Check 2:** We follow Bonhomme, Lamadon, and Manresa (2017a,b) and group ALL German plants into $m = 20, 40$ groups with similar wage structures and re-estimate AKM

		1985-1991			2008-2014	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	worker FE	plant FE	matching	worker FE	plant FE	matching
Panel A: Benchmark						
Log population	0.0365***	0.0279***	0.0380***	0.0523***	0.0161***	0.0613***
	(0.002)	(0.003)	(0.005)	(0.005)	(0.003)	(0.006)
R^2	0.505	0.213	0.188	0.419	0.067	0.286
Panel B: 20 groups defined by 20 wage quantiles			[1985-1991: 97.98%; 2008-2014: 97.83%]			
Log population	0.0339***	0.0173***	0.0317***	0.0487***	0.0028	0.0380***
	(0.003)	(0.004)	(0.007)	(0.007)	(0.006)	(0.007)
R^2	0.453	0.099	0.133	0.359	0.002	0.169

Notes: City level regressions. N=204. All regressions have a constant. Robust standard errors in parentheses. The numbers in brackets are the share of the between plant variance that is captured by the group dummies.

Further Robustness Checks

- **Endogeneity:** We instrument city size with 1952 population
- **Local industry mix:** We use residual plant effects, purged by 2-digit industry
- **Real Wages:** We deflate wages with regional price levels (BBSR 2009)
- **Density vs. Size:** Rankings change but results not.
- **Aggregation:** Results stay stable when we use 325 counties, 108 larger CZ, 8277 municipalities
- **East Germany:** Similar results when only focusing on East Germany
- **Spurious Correlation:** Include ad-hoc control variables, include federal state fixed-effects, and stack periods and include city fixed-effects. Key conclusions remain fairly robust!

Discussion

Assortative matching is significantly stronger in larger cities. Even stronger association when we define a local labor market to be a city-occupation pair, rather than the city as a whole.

- Consistent with previous theoretical papers, where labor market size is an important agglomeration advantage (Labor Market Pooling)
- Consistent with stronger incentives for assortative matching in larger cities
- Learning externalities?
  - Workers in bigger cities learn faster and become more productive over time (De La Roca and Puga, 2017). Faster wage growth in larger cities might generate higher worker fixed-effects.
    But results intact when estimated over long time period.
  - Wage growth is faster in large cities as workers ascend the "firm quality" ladder.
    Divide our sample based on job order. Correlation of worker and plant FE increases monotonously as workers climb up the job ladder. But no evidence that the elasticity of assortative matching with respect to city size increases as workers climb up the job ladder.
- Denser and larger cities reduce search costs. In the cross-section and conditional on industry FE, city size is negatively correlated with the probability that a plant faces difficulties in filling a vacancy.

Results

3. Aggregate Effects

Quantitative Importance of Assortative Matching

Assortative matching potentially matters for two reasons:

- Magnifies spatial wage disparities
- If worker and plant quality are complements, assortative matching increases aggregate productivity, output, earnings

But by how much? $\rightarrow$ Counterfactual exercises!

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Average log wage in city c:

$$E_c[\ln wage_{it}] = E_c[\mu_i + \Psi_{\mathbf{J}(i,t)} + X_{it}'\gamma].$$

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Average log wage in city c:

$$E_c[\ln wage_{it}] = E_c[\mu_i + \Psi_{\mathbf{J}(i,t)} + X'_{it}\gamma].$$

Assuming joint log-normal distribution of $\mu_i, \Psi_{\mathbf{J}(i,t)}, X'_{it}$:

$$E_c[w] = \exp\left(\bar{\mu}_c + \bar{\Psi}_c + \bar{X}_c\gamma\right)$$
$$\times \exp\left[\left(\frac{1}{2}\left(\sigma^2_{\mu(c)} + \sigma^2_{\Psi(c)} + \sigma^2_{X\gamma(c)}\right)\right) + \left(\underbrace{cov_c(\mu_i, \Psi_{\mathbf{J}(i,t)})}_{AssortativeMatching} + cov_c(\mu_i, X'_{it}\gamma) + cov_c(\Psi_{\mathbf{J}(i,t)}, X'_{it}\gamma)\right)\right]$$

Counterfactual Exercises: Effects on Geographical Wage Differences

	(1)	(2)	(3)
Spatial differences of log average wage across cities	90-10	75-25	s.d.
(1) Observed across city dispersion of average wages	0.28	0.15	0.11
	% Difference to observed dispersion:		
(2) Random matching of workers within cities (corr=0)	-5.24	-5.60	-4.75
(3) Matching of workers within cities as in median city (Steinfurt)	-4.62	-3.83	-3.98
(4) Zero elasticity of city size and sorting	-2.21	-1.21	-1.75
(5) 1985 matching of workers within cities	-5.26	-4.73	-2.44
(6) No spatial sorting of workers across cities	-55.27	-54.68	-54.56

Counterfactual Exercises: Effects on Aggregate Earnings

	(1) Average daily wage	(2) %-diff.	(3) Δ Billions
(1) Observed	117.30		
(2) Perfect matching of workers within cities (corr=1)	123.97	5.68	84.37
(3) Reverse sorting of workers within cities (corr=-1)	107.16	-8.65	-128.39
(4) Matching of workers within cities as in median city (Steinfurt)	116.54	-0.65	-9.70
(5) Zero elasticity of city size and sorting	116.70	-0.51	-7.62
(6) 1985 matching of workers within cities	114.83	-2.11	-31.32

The last column reports the implied absolute change in the total compensation of employees according to the national accounts in 2014 in billion Euros.

Conclusion

- Large and persistent geographical disparities lead to concerns about rising inequality
- Crafting appropriate place-based policies requires knowledge of economic sources of disparities

- This paper: Improved matching of workers and plants is an important productivity advantage
  - Wages in large cities are higher not only because of the higher quality of their labor force
  - In bigger cities, "high quality workers" are more likely to work in "good firms"
  - Higher assortative matching in larger cities increases geographical wage inequality but also increases aggregate earnings!

- Implications for place-based policies (Germany: around 1bn Euros per year):
  - Policies designed to subsidize labor demand or labor supply in small struggling communities create a previously unrecognized efficiency loss due to a decline in match quality
  - Alternative strategy: Facilitate job search specifically in small labor markets.

Thanks!

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APPENDIX

Why Should there be Assortative Matching?

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$$\ln(\text{wage}_{it}) = \mu_i + \Psi_{\mathbf{J}(i,t)} + X_{it}'\gamma + r_{it}$$

- Log wages have no match component. But are multiplicative in levels.
- Consider a production function where the output generate by the match of worker i and plant J is proportional to:

$$Y_J \propto \tilde{\mu}_i^a \tilde{\Psi}_{\mathbf{J}(i,t)}^b$$

- Example:
  - Production function: $Y_J = \tilde{\mu}_i \tilde{\Psi}_{\mathbf{J}(i,t)}$
  - Two types of workers: $\tilde{\mu}^* = \{11, 9\}$, two types of firms: $\tilde{\Psi}^* = \{110, 90\}$
  - Rent-sharing rule for wages: $w = (\tilde{\mu}^* \times \tilde{\Psi}^*)/2$
  - Wage / profit generated by match:
    good/good: $w = 605$; good/bad or bad/good: $w = 495$; bad/bad: $w = 405$

Robustness Checks and Alternative Specifications

Back

- **Limited Mobility Bias:** Small number of moves between plants may generate downward bias in the estimated correlation of worker and plant effects.
  This might be particularly severe in smaller cities!
  - We drop cities with highest and smallest turnover
  - We follow Bonhomme, Lamadon, and Manresa (2020) and group ALL German plants into $m = 20, 40$ groups with similar wage structures and re-estimate akm
  - We employ the leave-out estimation by Kline, Saggio, and Solvsten (2020) to obtain unbiased estimates of the variance components
- **East Germany:** Similar results when only focusing on East Germany
- **Endogeneity:** We instrument city size with 1952 population
- **Local industry mix:** We use residual plant effects, purged by 2-digit industry
- **Real Wages:** We deflate wages with regional price levels (BBSR 2009)
- **Density vs. Size:** Rankings change but results not.
- **Aggregation:** Results stay stable when we use 325 counties, 108 larger CZ, 8277 municipalities

Stronger Incentives for Assortative Matching in Larger Cities

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Example

- Production function: $Y_J = \tilde{\mu}_i \tilde{\Psi}_{\mathbf{J}(i,t)}$
- Rent-sharing rule for wages: $w = (\tilde{\mu}^* \times \tilde{\Psi}^*)/2$

Large City

- Two worker types: $\tilde{\mu}^* = \{11, 9\}$,
- Two plant types: $\tilde{\Psi}^* = \{110, 90\}$
- Wage / profit generated by match:
  good/good: $w = 605$;
  good/bad or bad/good: $w = 495$;
  bad/bad: $w = 405$
- **Gain of a good firm replacing a bad with a good worker: 110**

Small City

- Two worker types: $\tilde{\mu}^* = \{6, 4\}$,
- Two plant types: $\tilde{\Psi}^* = \{60, 40\}$
- Wage / profit generated by match:
  good/good: $w = 180$;
  good/bad or bad/good: $w = 120$;
  bad/bad: $w = 80$
- **Gain of a good firm replacing a bad with a good worker: 60**