
# SPATIAL INEQUALITIES

**Urban Economics**

**GABRIEL M AHLFELDT**

# I COURSE COMPONENTS

the idea

- Block I
  - Introduction to Urban and Regional Economics and Course Overview
  - Topic I: Regional and urban concentration forces
  - Topic II: The empirics of agglomeration
  - Topic III: Costs and benefits of agglomeration
- Block 2
  - Topic IV: Monocentric city I (household location choice)
  - Topic V: Monocentric city II (household location choice)
  - Topic VI: Firm location choice
  - Topic VII: The urban economy in general equilibrium
- Block 3
  - Topic VIII: The vertical dimension of cities
  - Topic IX: Suburbanization and gentrification
  - **Topic X: Spatial inequalities**

# I INTRODUCTION

roadmap

- **Last time: *Suburbanization and gentrification***
  - **1) Determinants of long-run trends**
    - **Relative transport cost by income groups**
    - **The lifecycle of buildings**
    - **Amenities**
    - **Endogenous gentrification**
  - **2) Welfare dimension**
    - **Winners and losers**
    - **Role of mobility costs**
  - **3) Consequences of Gentrification**
    - **Recent evidence**

# I INTRODUCTION

roadmap

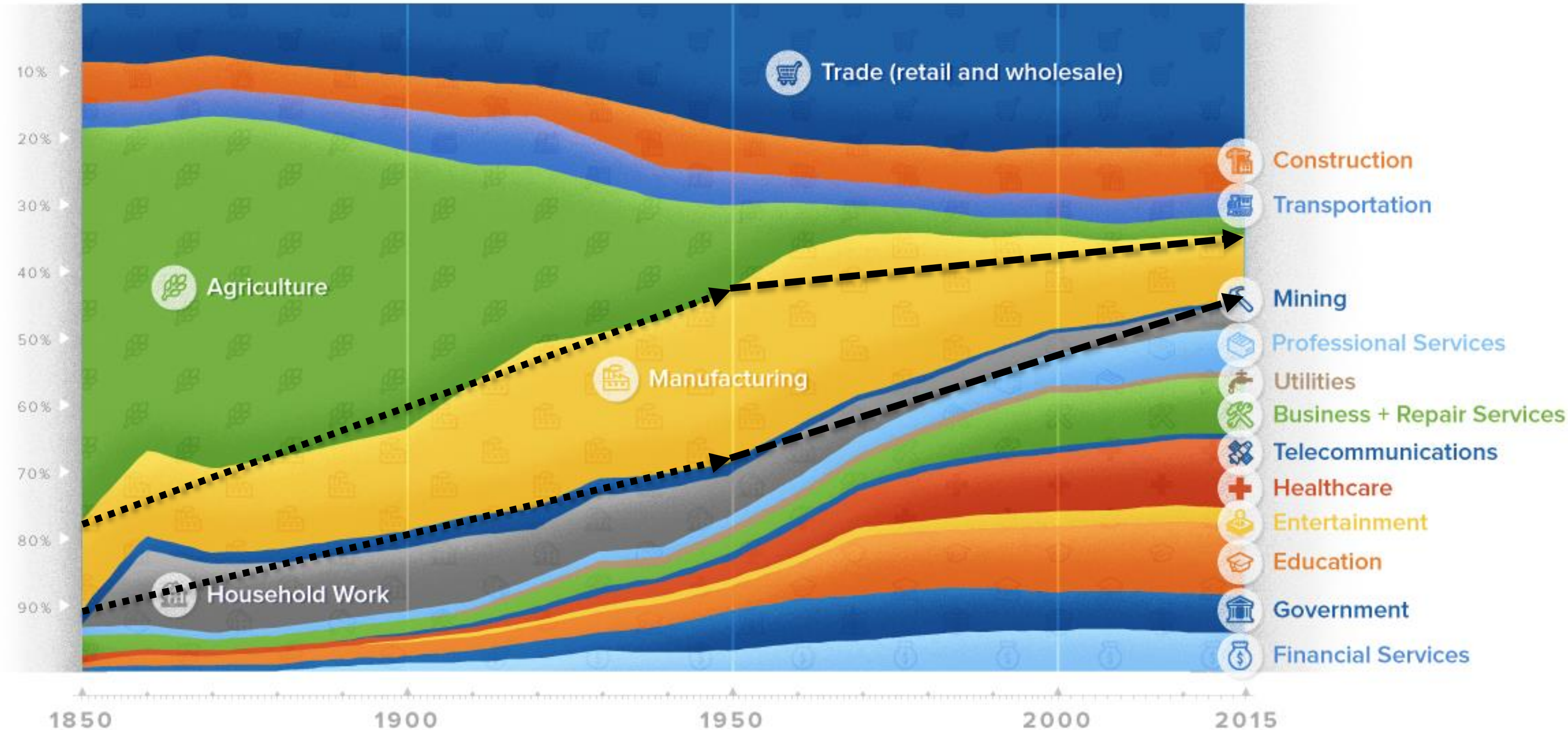
- **This time: *Spatial inequalities***
    - **1) Causes & consequences**
        - **Automation**
        - **Globalization**
        - **Political polarization**
    - **2) Implications**
        - **Dynamic spatial models**
        - **Quality of life**
        - **Spatial incidence**
        - **Place-based policies**

# II SPATIAL INEQUALITIES

**Q: Why do some regions struggle economically?**

# II EMPLOYMENT SECTOR SHARES OVER 150 YEARS

manufacturing decline




Source: IPUMS USA 2017; US Bureau of Labor Statistics, McKinsey Global Institute Analysis

**Decline of manufacturing has implications for regions**

# II MANUFACTURING DISTRIBUTION IN 1900

map

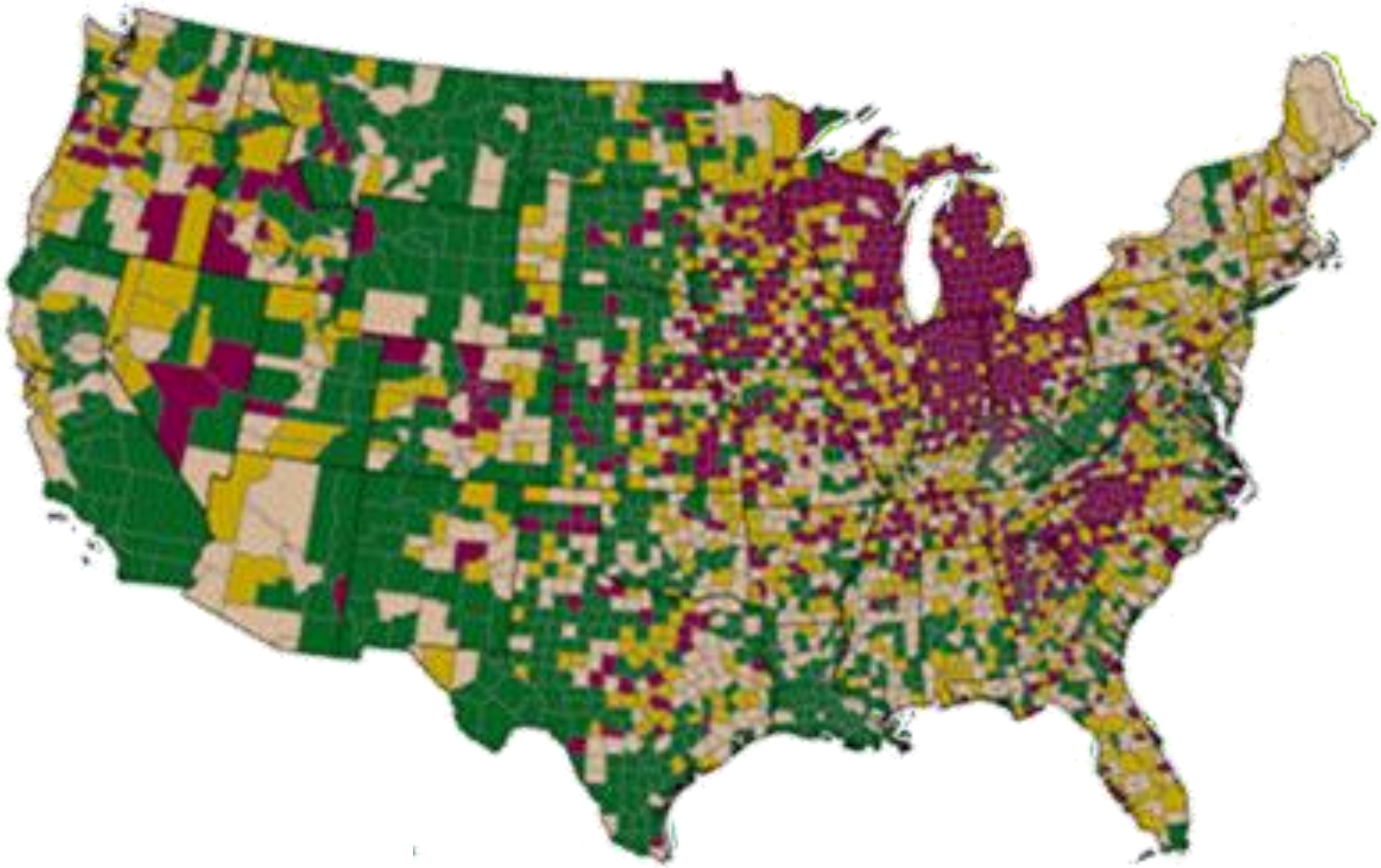
# II MANUFACTURING DISTRIBUTION IN 2000

map

Source: American Community Survey (2005-2009)

# II CAHNGE IN POVERTY RATE 2000-2006/10

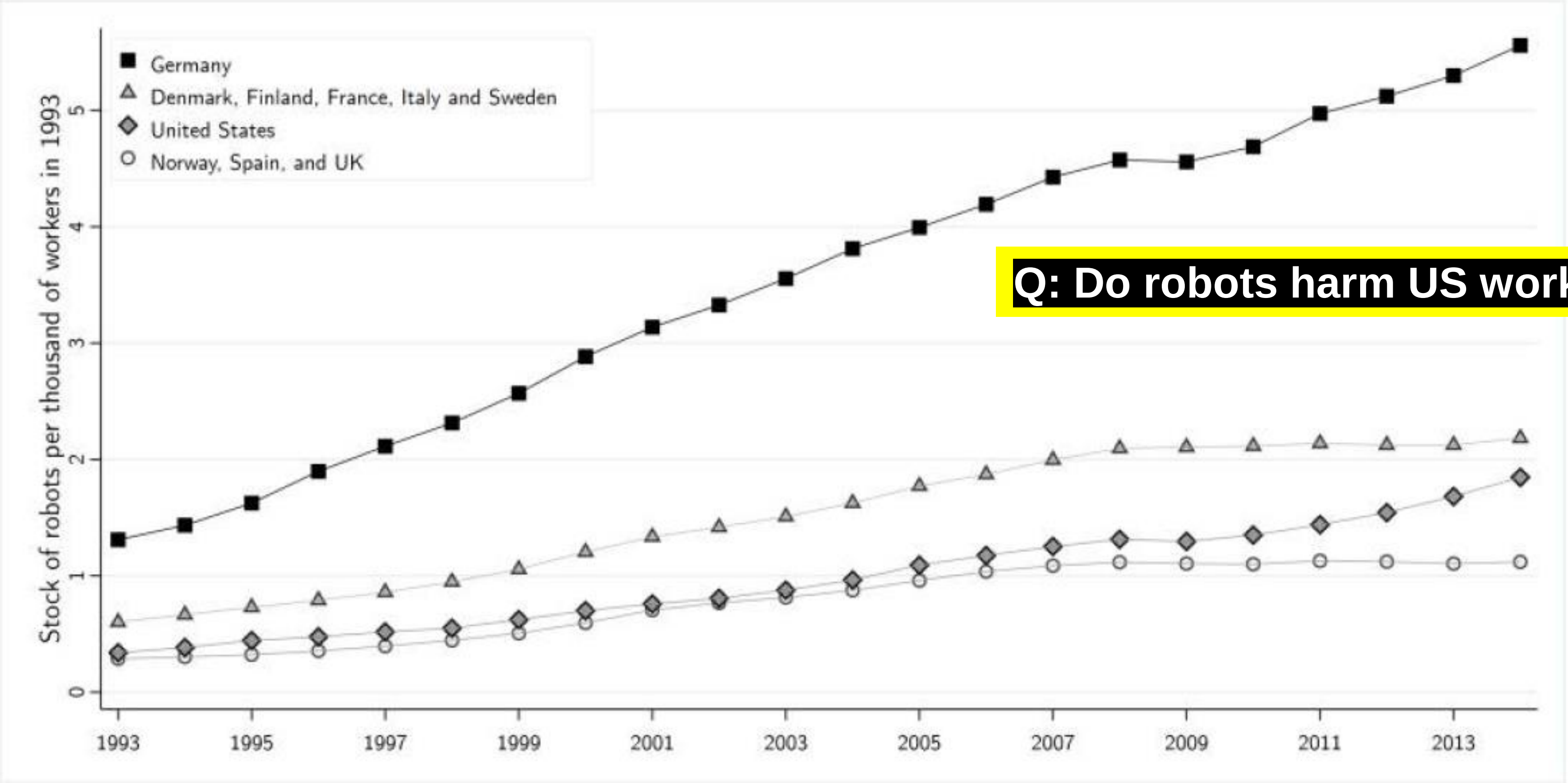
map



Source: American Community Survey (2006-2010)

# II ACEMOGLU & RESTREPO (2019)

rise of the robots




**Q: Do robots harm US workers?**

Acemoglu & Restrepo, 2019

# II EMPIRICAL SPECIFICATION

Acemoglu & Restrepo (2019)

- **Adusted penetration of robots (APR)**
  - increase in robots per employee over the 1993-2007 period in a sector *i*
- Using the sector shares $l_{ci}$ in commuting area *c* gives the **regional exposure**

$$\text{US exposure to robots}_c = \sum_{i \in \mathcal{I}} \ell_{ci} \cdot APR_i,$$

- Use in instrumental variable for **APR based on robot adoption in Europe**

$$d \ln L_c = \beta_L \cdot \text{US exposure to robots}_c + \epsilon_c^L; \quad d \ln W_c = \beta_W \cdot \text{US exposure to robots}_c + \epsilon_c^W$$

**Employment** **Wages** **Long-difference estimation**

# II EFFECTS ON LABOUR MARKETS

Acemoglu & Restrepo (2019)

**Exposure to robots follows "manufacturing map"**

**Exposure to robots not exclusively driven by automotive industry**

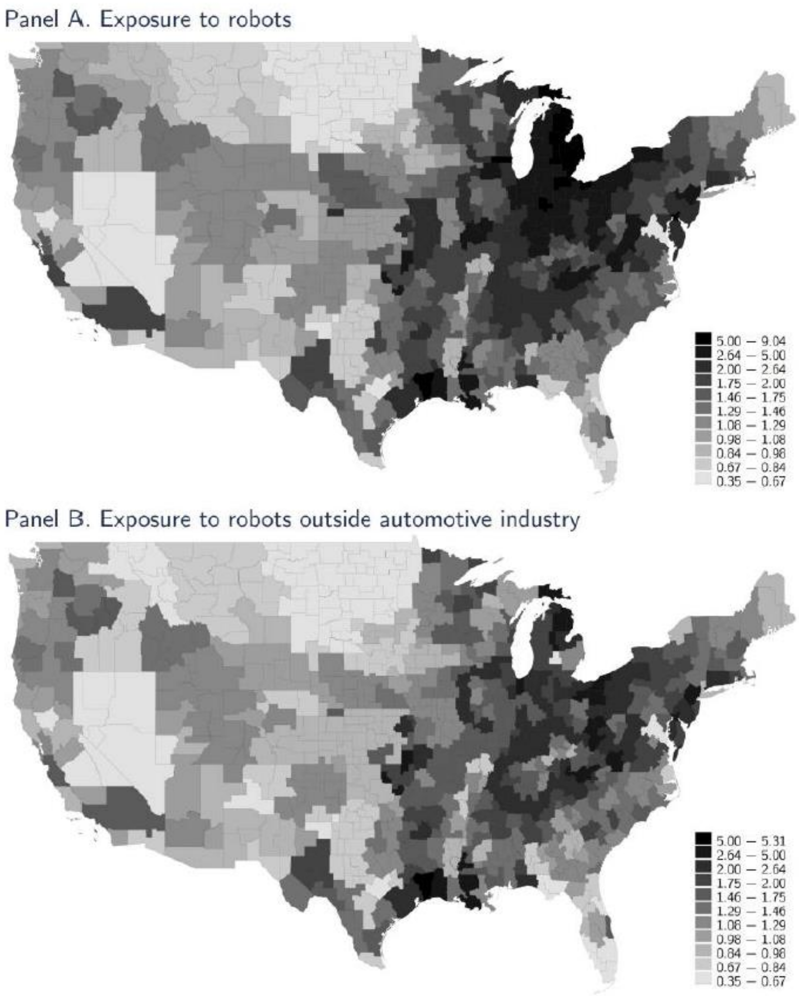



FIGURE 4: GEOGRAPHIC DISTRIBUTION OF EXPOSURE TO ROBOTS 1993-2007
The top panel shows the distribution of exposure to robots. The bottom panel shows the distribution of exposure to robots outside of the automotive industry.

Acemoglu & Restrepo, 2019

# II AUTOMIZATION SHOCK

Acemoglu & Restrepo (2019)

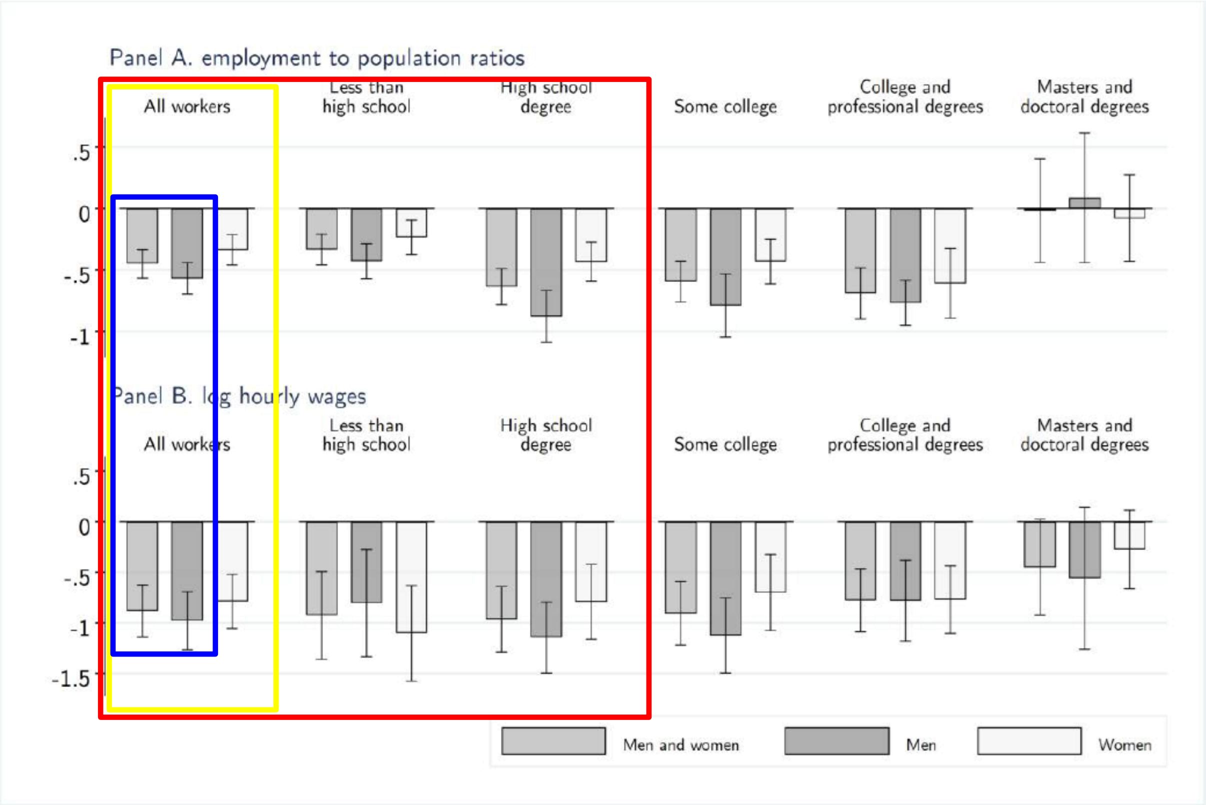



FIGURE 9: EFFECTS OF ROBOTS ON EMPLOYMENT AND WAGES BY EDUCATION AND GENDER. The figure presents estimates of the effects of exposure to robots on changes in the employment to population ratio (top panel) and changes in log hourly wages (bottom panel) for all workers and for men and women with different education levels (less than high school; high school degree; some college; college or professional degree; and masters or doctoral degree). The capped lines provide 95% confidence intervals.

**Negative effects *overall***

***Hits manufacturing regions***

**1 robot/1,000 workers reduces employment rate by 0.2 pp and wages by 0.42%**

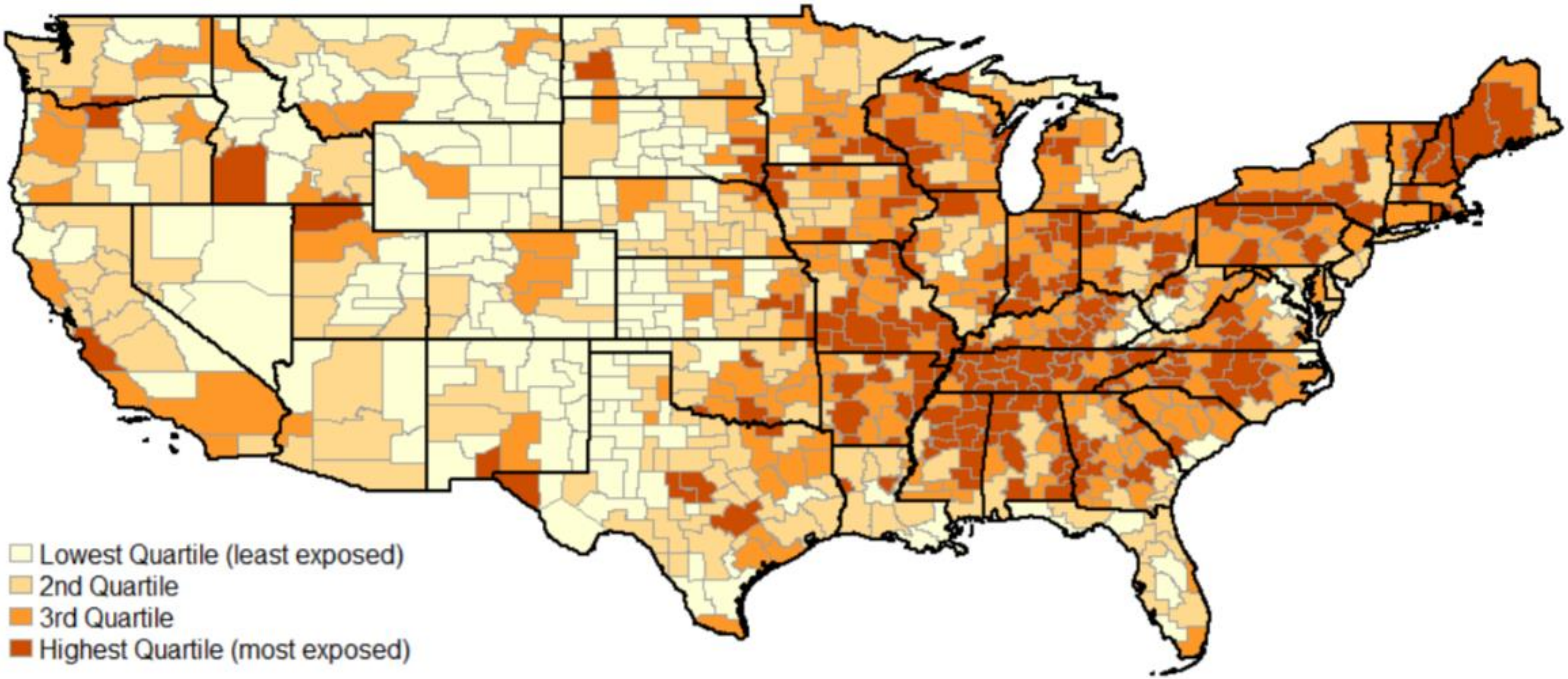
**Hits *low-skilled* more than *high-skilled***

**Hits *men* more than *women***

**Despite greater exposure, automization (and trade shocks) had little effects in Germany (see appendix)**

# II IMPORT EXPOSURE

Autor, Dorn, Hanson (2020)




**Import exposure following China joining WTO the manufacturing map (based on regional sector shares and other countries' imports from China)**

# II RESULTS

## Autor, Dorn, Hanson (2020)

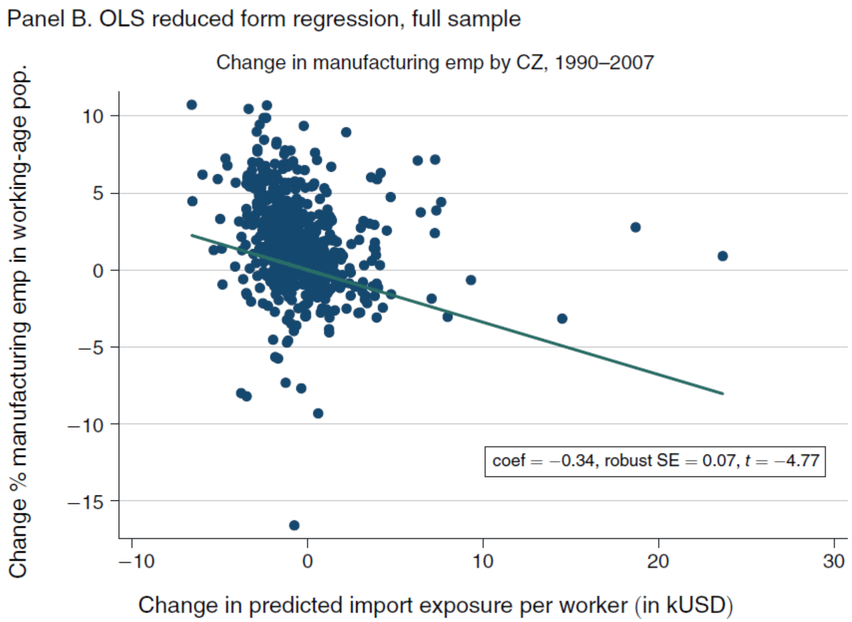



FIGURE 2. CHANGE IN IMPORT EXPOSURE PER WORKER AND DECLINE OF MANUFACTURING EMPLOYMENT: ADDED VARIABLE PLOTS OF FIRST STAGE AND REDUCED FORM ESTIMATES

| | I. By education level | | |
|---|---|---|---|
| | All (1) | College (2) | Noncollege (3) |
| *Panel A. No census division dummies or other controls* | | | |
| (Δ imports from China to US)/worker | −1.031** | −0.360 | −1.097** |
| | (0.503) | (0.660) | (0.488) |
| $R^2$ | — | 0.03 | 0.00 |
| *Panel B. Controlling for census division dummies* | | | |
| (Δ imports from China to US)/worker | −0.355 | 0.147 | −0.240 |
| | (0.513) | (0.619) | (0.519) |
| $R^2$ | 0.36 | 0.29 | 0.45 |
| *Panel C. Full controls* | | | |
| (Δ imports from China to US)/worker | −0.050 | −0.026 | −0.047 |
| | (0.746) | (0.685) | (0.823) |
| $R^2$ | 0.42 | 0.35 | 0.52 |

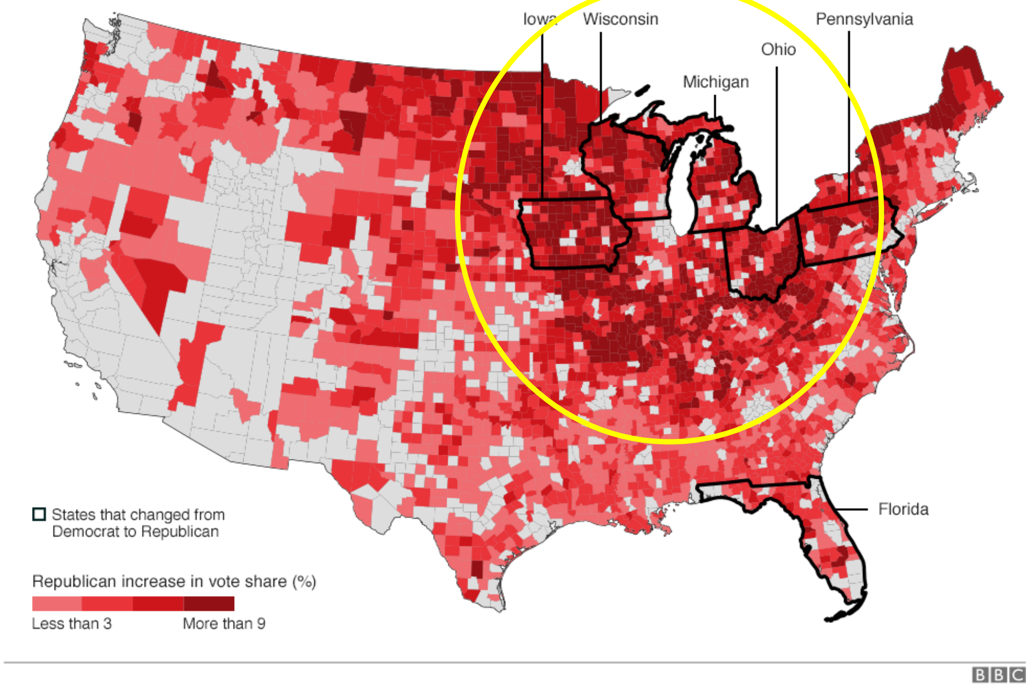
**A $1000-per worker increase in trade exposure predicts a one log-point decline in employment. The effect comes exclusively from noncollege workers**

**See appendix for wage effects**

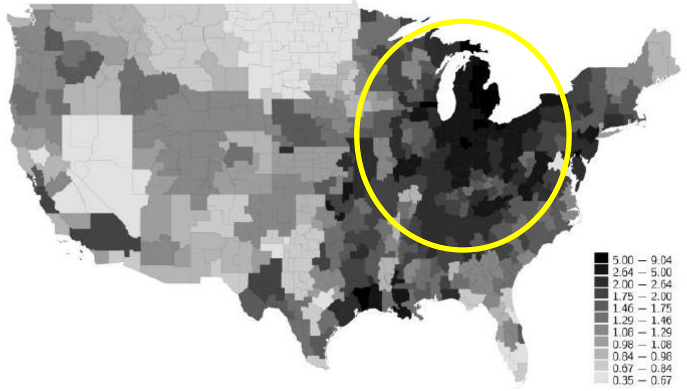
# II EVIDENCE FROM TRUMP

polarization

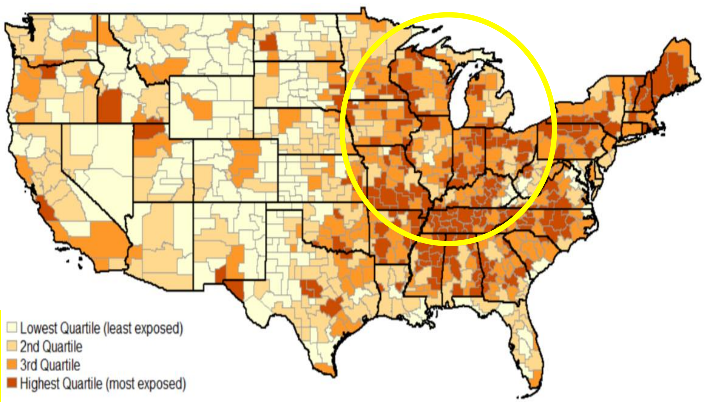
**Where Trump increased Republican votes**




**Exposure to automation**




**Exposure to imports**




Source: Autor et al (2013, 2016)

**More support for a political leader who shifted the party towards anti-globalization positions in areas hit by spatial shocks**

# II EVIDENCE FROM BREXIT

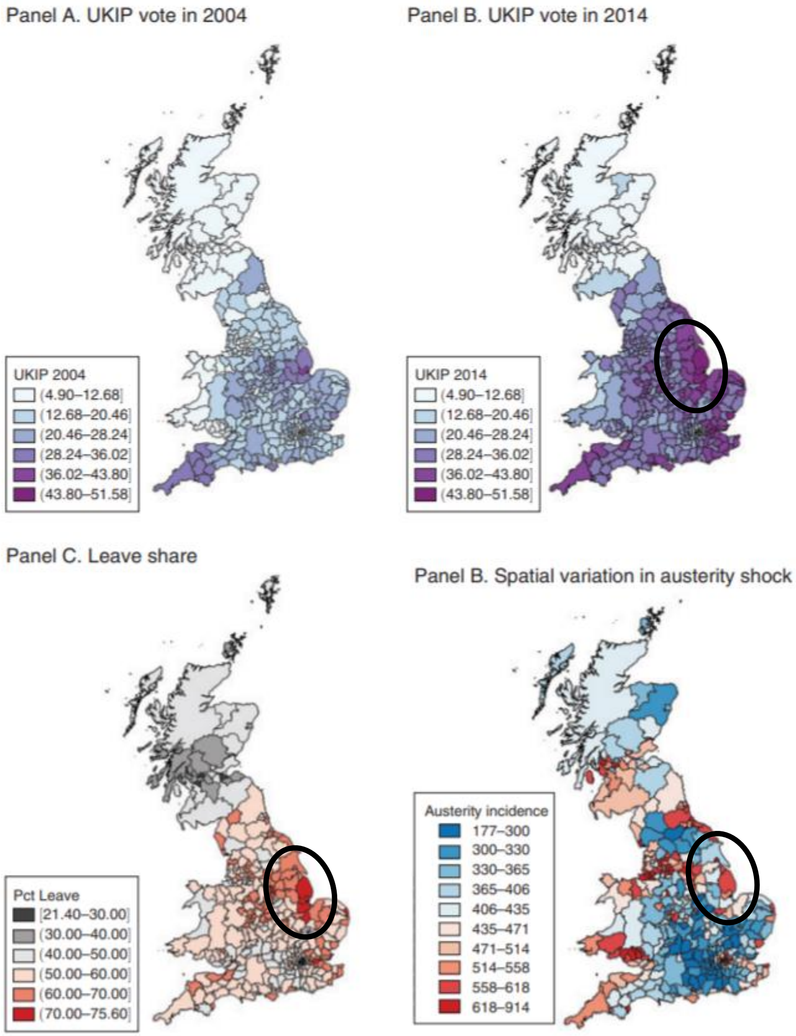
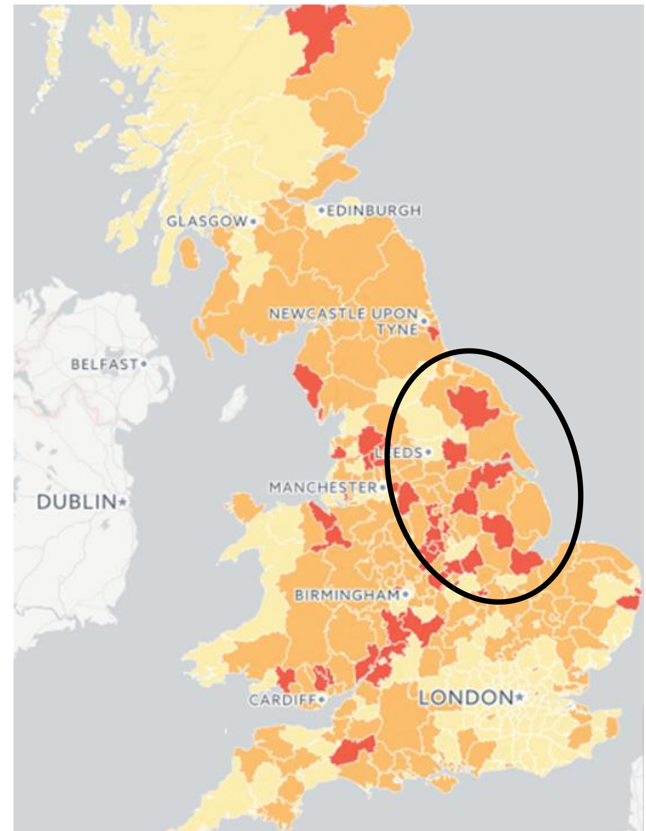



Figure 2. UKIP Vote Share in the EP Elections in 2004, 2014, and the Leave Share in the 2016 European Union Referendum

Source: Fetzer (2019)



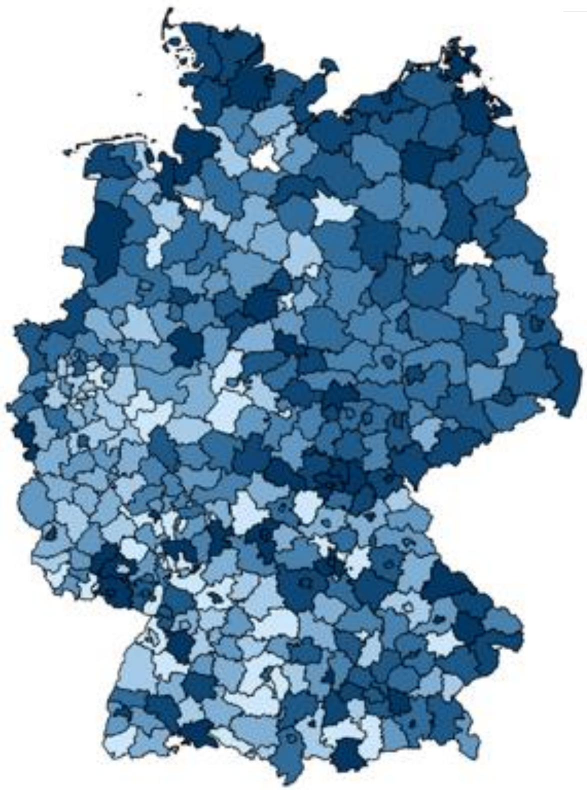

Source: RSA analysis of Business Register and Employment Survey (BRES), 2015

**"Manufacturing map" visible in votes for extreme positions**

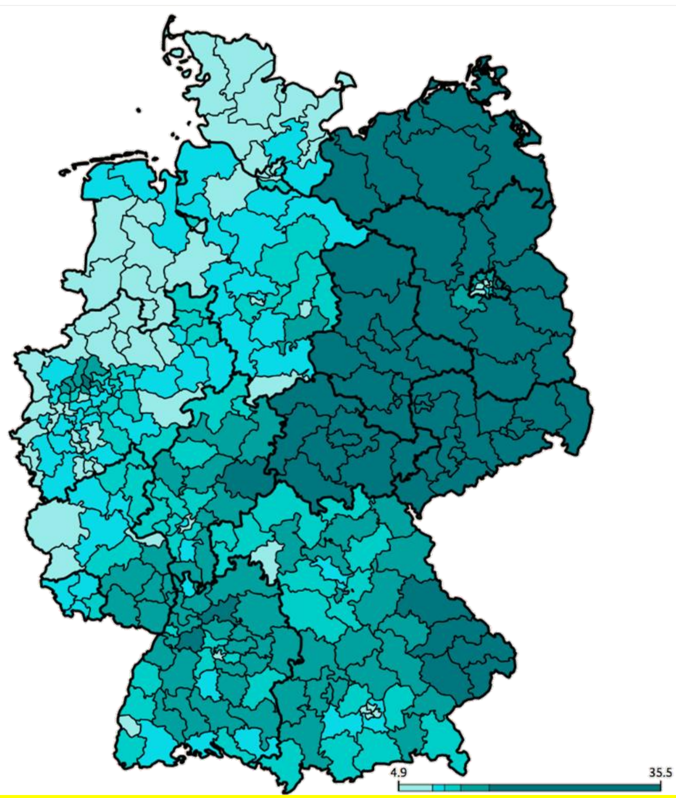
# II EVIDENCE FROM THE AFD IN GERMANY

polarization

**Exposure to trade with Eastern Europe and China**



**Share AFD *2017***




Source: Dippel et al (2017)

**Political party with xenophobic anti-globalization position strongest where exposure to trade was largest**

# III SPATIAL EQILIBRIUM

implications

**Q: How do we rationalize “local” discontent in “competitive spatial equilibrium”?**

# III STANDARD SPATIAL EQUILIBRIUM

spatial frictions

- Standard **spatial equilibrium** framework (Rosen-Roback) assumes
  - zero mobility cost and
  - Homogenous workers
  - Spatially equalized utility owing to perfect mobility

**Spatial shocks do not have local effects, no reason for localized polarization**

- "**Place-based policies**" have limited effects
  - Subsidies, transfers, and public investment **attract workers**
  - But migration leads to **capitalization** in **real estate** prices
  - Renting workers not better off, **gains** appropriated by **landlords**

**Not much policy can do to address polarization**

# III STANDARD SPATIAL EQUILIBRIUM

Notations from Ahlfeldt, Bald, Roth, Seidel (2021)

- Standard **spatial equilibrium** framework (Rosen-Roback)
- Utility of **worker *ω*** of **group *Θ***
  in **region *i*** at **time *t***
  (who was in region k in t-1)

$$U^{\theta}_{i|k,t}(\omega) = \left(\frac{x^{\theta}_{i,t}(\omega)}{\alpha}\right)^{\alpha} \left(\frac{h^{\theta}_{i,t}(\omega)}{1-\alpha}\right)^{1-\alpha} A^{\theta}_{i,t}$$

- Marshallian demand function from optimization (MRS):

$$x^{\theta}_{i,t}(\omega) = \alpha(1-\iota)w^{\theta}_{i,t}(\omega)$$

$$h^{\theta}_{i,t}(\omega) = \frac{(1-\alpha)(1-\iota)w^{\theta}_{i,t}(\omega)}{p_{i,t}}$$

- Constant <u>indirect</u> utility: $V^{\theta}_{i,t} = \left((1-\iota)w^{\theta}_{i,t}\right)^{\alpha} \left(\frac{(1-\iota)w^{\theta}_{i,t}}{p_{i,t}}\right)^{1-\alpha} \mathcal{A}^{\theta}_{i,t} = \bar{U}^{\theta}_{t}$

- Solve for implied quality-of-life differentials: $A^{\theta}_{i,t} = q^{\theta}_{t} \frac{\left(p^{\theta}_{i,t}\right)^{1-\alpha}}{w^{\theta}_{i,t}}$

**Inverse real wage / “compensating differential”**

# III MORETTI (2010)

spatial equilibrium with home attachment

- **Long-run spatial equilibrium framework**
  - Workers are **freely mobile**, prices adjust to maintain spatial equilibrium
  - Workers with **heterogeneous preferences for location**
- **Marginal worker is indifferent between locations**
- **“Inframarginal worker” is not**
  - Derives an idiosyncratic amenity from a location
  - May not migrate even if indirect utility (ignoring amenity) would be higher
- **Spatial incidence**
  - An improvement in a city will lead to less-than-utility-offsetting migration

**Spatial shocks can affect worker utility positively or negatively**

# III DYNAMIC SPATIAL MODELS

spatial equilibrium with migration costs

- **Migration decisions are modelled explicitly**
  - Migration probability depends on push and pull factors
    - Push: High wages, low prices, high quality of life at destination
    - Pull: Migration cost, idiosyncratic taste, utility at origin
- **Equilibrium**
  - Expected **utility is not equalized** across space
  - Equilibrium restored because migration increases house prices
- **Workers can be “trapped” in struggling regions**
  - If migration cost is larger than utility difference
  - Migration akin to investment decision
  - Economically weaker groups may also have larger migration costs

**Can rationalize political polarization in regions hit by negative shocks**

# III DYNAMIC SPATIEL MODELS

spatial equilibrium with migration costs

Table A1: Dynamic and quantitative spatial models

| Authors | Model type | Expectations | Inversion | | Counterfactual |
|---|---|---|---|---|---|
| Ahlfeldt et al. (2020) WP | DSM, GE, MC | PF | P,H,A,bMC | TSE | SSE to SSE |
| Balboni (2019), R&R AER | DSM, GE, MC | PF | P,MA | TSE | TSE to ED |
| Bryan and Morten (2019), JPE | QSM, MC | Static | - | - | - |
| Caliendo et al. (2019b), Ecta | DSM, GE, MC | PF | - | - | TSE to ED |
| Caliendo et al. (2019a), R&R JPE | DSM, GE, MC | PF | - | - | TSE to ED |
| Conte et al. (2020), WP | DSM, GE, MC | Static | P,A,uMC | TSE | TSE to SSE |
| Desmet et al. (2018), JPE | DSM, GE, MC | Static | P,A,uMC | TSE | TSE to SSE |
| Heise and Porzio (2021), WP | QSM, GE, MC | Static | - | - | SSE to SSE |
| Fan (2019), AEJ: Macro | QSM, GE, MC | Static | bMC, TC | SSE | SSE to SSE |
| Monras (2020), JPE | DSM, GE | PF | P,H,A,MR | SSE | TSE to SSE |
| Schubert (2020), WP | DSM, GE, MC | PF | - | - | SSE to SSE |
| Tombe and Zhu (2019), AER | QSM, MC | Static | - | - | - |

Abbreviations:
*Model type*: QSM = Quantitative spatial model; DSM = Dynamic spatial model; GE = General equilibrium; MC = Migration cost
*Expectations*: PF = Perfect foresight
*Inversion*: P = Exogenous productivity; H = Exogenous housing supply; A = Exogenous amenity; uMC = Unilateral migration costs; bMC = Bilateral migration costs; MR: Migration rate; MA = Market access; TC: Trade costs; SSE = Stationary spatial equilibrium; TSE = Transitory spatial equilibrium;
*Counterfactual*: ED = Given end date

Ahlfeldt et al. (2021)

# III DYNAMIC SPATIAL MODEL

## Idiosyncratic utility

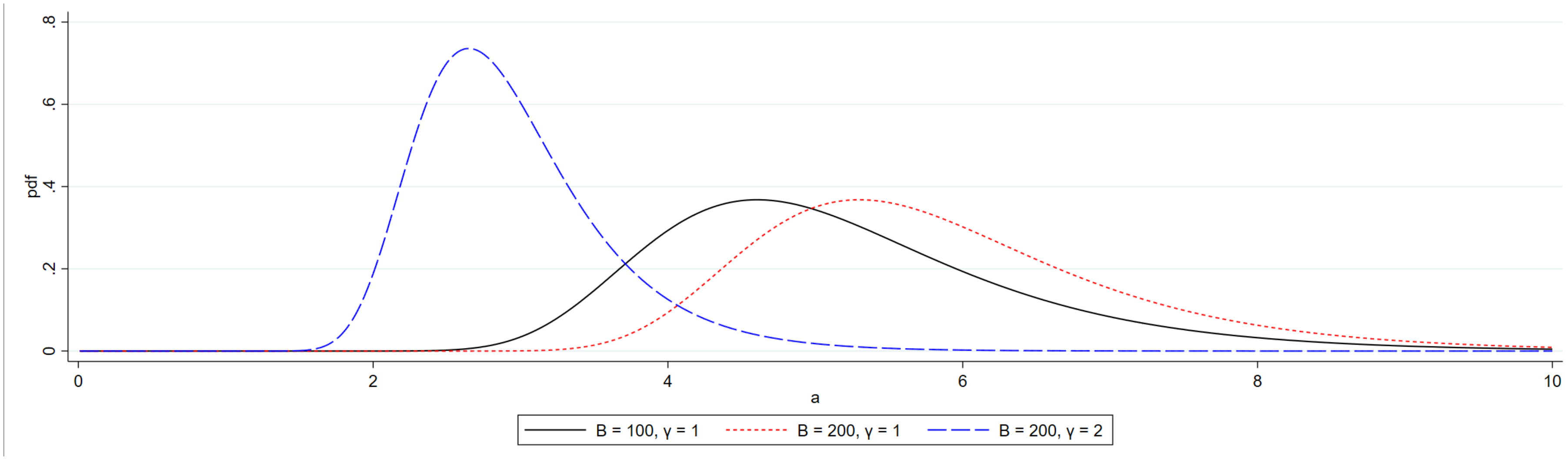
Migration cost

- Utility incorporating "idiosyncratic" taste shock

$$U^{\theta}_{i|k,t}(\omega) = \left(\frac{x^{\theta}_{i,t}(\omega)}{\alpha}\right)^{\alpha} \left(\frac{h^{\theta}_{i,t}(\omega)}{1-\alpha}\right)^{1-\alpha} A^{\theta}_{i,t} \exp\left[a^{\theta}_{ki,t}(\omega) - \tau^{\theta}_{ki}\right]$$

- Idiosyncratic taste shock drawn from Gumbel distribution (CDF)

$$F^{\theta}_{ki,t}(a) = \exp\left(-\tilde{B}^{\theta}_{ki,t} \exp\{-\left[\gamma^{\theta} a + \Gamma\right]\}\right) \qquad \forall \;\; \theta \;\; \text{and} \;\; \gamma^{\theta} > 0$$



# III POPULATION WAGES AND RENT

prices and quantities

- Probability of choosing in location i

$$\chi^{\theta}_{ij|i,t} = \frac{\left(m^{\theta}_{ij} B^{\theta}_{ij,t+1} \mathcal{V}^{\theta}_{j,t+1}\right)^{\gamma^{\theta}}}{\sum_{n \in J} \left(m^{\theta}_{in} B^{\theta}_{in,t+1} \mathcal{V}^{\theta}_{n,t+1}\right)^{\gamma^{\theta}}}$$

- Where $m^{\theta}_{ij} = \exp\left[-\tau^{\theta}_{ij}\right]$ and $\mathcal{V}^{\theta}_{j,t+1} = \exp\left[\ln\left(\frac{(1-\iota) w^{\theta}_{j,t+1} A^{\theta}_{j,t+1}}{p^{1-\alpha}_{j,t+1}}\right) + \mathcal{O}^{\theta}_{j,t+2}\right]$

**Migration cost**

**Migration option value**

- Population is sum over all inflows into i

$$L^{\theta}_{i,t+1} = \sum_{j \in J} M^{\theta}_{ji,t} = \sum_{j \in J} \chi^{\theta}_{ji|j,t} L^{\theta}_{j,t}$$

- Wages depend on population and fundamental labour productivity

$$w^{\theta}_{i,t} = \psi^{\theta}_{i,t} \left(\frac{L_{i,t}}{\bar{T}_i}\right)^{\kappa^{\theta}}$$

$$X_{i,t} = \sum_{\theta} L^{\theta}_{i,t} \varphi^{\theta}_{i,t}$$

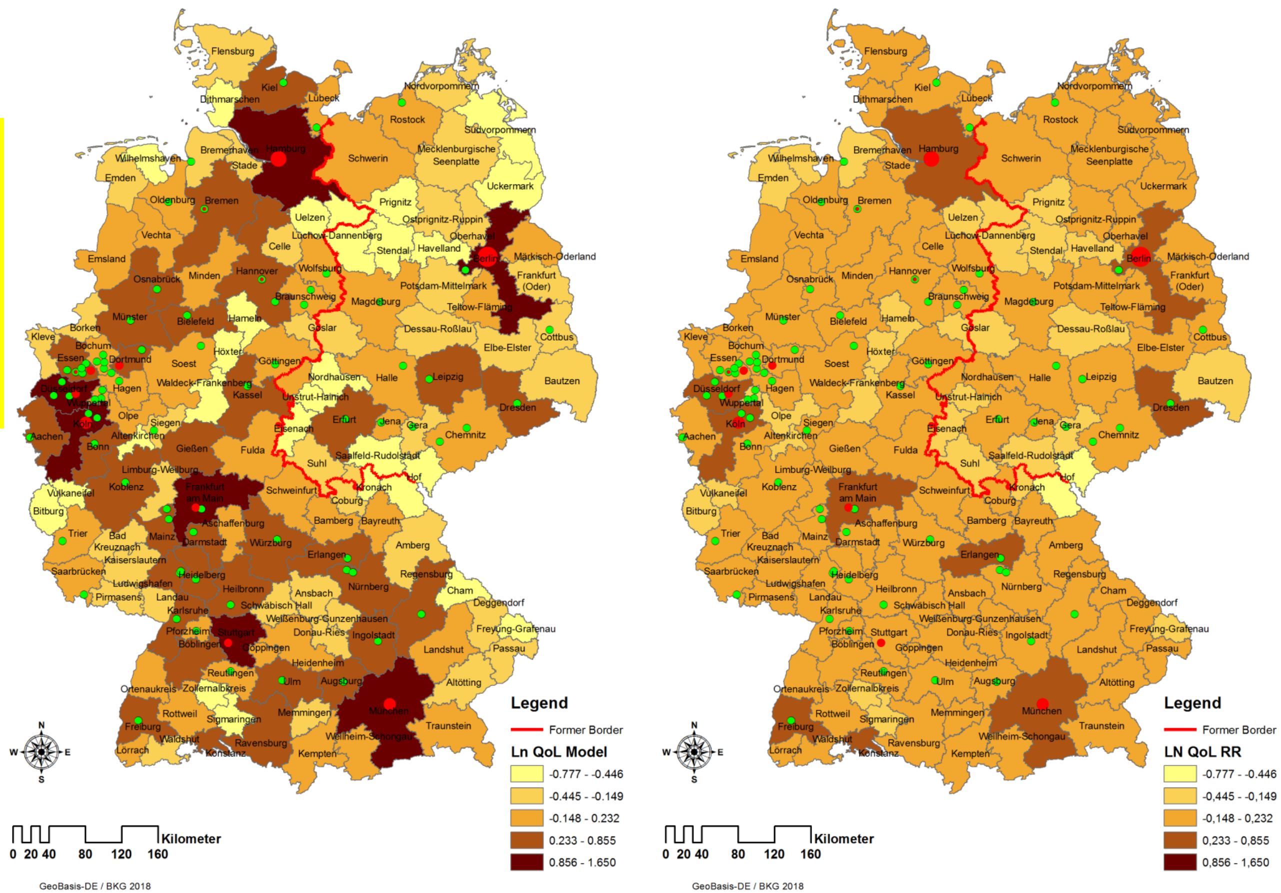
- House prices depend on population and fundamental housing productivity

$$p_{i,t} = \left(\frac{(1-\alpha)\beta(1-\iota) X_{i,t}}{\eta^{\frac{1}{\beta}}_{i,t} \bar{T}_i}\right)^{\beta}$$

# IV RR UNDERSTATES QOL DIFFERENTIALS

Ahlfeldt, Bald, Roth, Seidel (2021)

**QOL inverted from RR and DSM similar, but about 3x as much variation in DSM than in RR**




(a) Dynamic model ($\bar{A}_i$) (b) Rosen-Roback ($\mathcal{A}_i$)

Note: Unit of observation is 141 labour market areas as defined by Kosfeld and Werner (2012). Group adjustment in auxiliary regressions of ln(QoL) against group and region fixed effects, the latter being shown on the maps.

# IV URBAN QOL PREMIUM

Ahlfeldt, Bald, Roth, Seidel (2021)

**Urban quality of life premium much greater than in RR framework**

**Has significant implications for "urban pull" factors**

DSM-QOL RR-QOL

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Ln($\bar{A}_i^\theta$) | Ln($\bar{A}_i^\theta$) | Ln($\bar{A}_i^\theta$) | Ln($\mathcal{A}_i^\theta$) | Ln($\mathcal{A}_i^\theta$) | Ln($\mathcal{A}_i^\theta$) |
| | All | 2007 | 2017 | All | 2007 | 2017 |
| Ln big data amenity | 0.356*** | 0.114*** | 0.129*** | 0.054** | 0.064*** | 0.058** |
| (residualised) | (0.02) | (0.03) | (0.04) | (0.02) | (0.02) | (0.02) |
| Ln employment | | 0.409*** | 0.455*** | | 0.096*** | 0.123*** |
| | | (0.04) | (0.05) | | (0.02) | (0.02) |
| Near Alps (dummy) | | -0.068 | -0.016 | | -0.009 | 0.054 |
| | | (0.06) | (0.08) | | (0.05) | (0.06) |
| Near coast (dummy) | | -0.090+ | -0.050 | | -0.007 | 0.011 |
| | | (0.06) | (0.06) | | (0.04) | (0.04) |
| East (dummy) | | -0.025 | -0.024 | | 0.037 | 0.008 |
| | | (0.06) | (0.06) | | (0.03) | (0.04) |
| Ln crime per capita | | 0.027 | -0.032 | | -0.032 | -0.063 |
| | | (0.06) | (0.07) | | (0.04) | (0.04) |
| Ln pollution | | -0.302* | -0.402** | | -0.148 | -0.223+ |
| concentration (pm10) | | (0.16) | (0.19) | | (0.10) | (0.13) |
| Housing stock destroyed | | -0.001 | -0.001 | | -0.000 | -0.001 |
| in WWII (%) | | (0.00) | (0.00) | | (0.00) | (0.00) |
| # Opera houses | | 0.059** | 0.051* | | 0.009 | 0.010 |
| | | (0.02) | (0.03) | | (0.01) | (0.02) |
| Ln water area | | 0.063* | 0.064+ | | 0.024 | 0.030 |
| | | (0.03) | (0.04) | | (0.02) | (0.02) |
| Ln area | | -0.072+ | -0.085+ | | -0.005 | -0.035 |
| | | (0.05) | (0.05) | | (0.03) | (0.04) |
| Group effects | - | Yes | Yes | - | Yes | Yes |
| Observations | 27918 | 2538 | 2538 | 27918 | 2538 | 2538 |
| $R^2$ | .593 | .737 | .721 | .0379 | .458 | .459 |

Notes: Unit of observation is group-region. OLS estimation. Ln($\bar{A}_i^\theta$) is the region-group amenity shifter in the DSM developed in this paper. Ln($\mathcal{A}_i^\theta$) is the region-group amenity shifter implied by the Rosen-Roback framework (see section C.4). Standard errors clustered on regions in (1) and (4) and on regions and groups in all other columns. Big data amenity is the log of the number of geotagged photos shared on social media (flick and picasa) residualised in regressions against all other covariates reported in a column. $^+$ $p < 0.15$, $^*$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# IV URBAN PULL


**What’s worse for cities, losing commercial or residential spillovers?**

# IV THOUGHT EXPERIMENT: NO SPILLOVERS

hypothetical permanent lockdown

| (a) No agglomeration economies | All LLM | Large LLM | Small LLM |
|---|---|---|---|
| Population | 1.000 | 0.912 | 1.095 |
| GDP | 0.895 | 0.840 | 0.976 |
| Average wage | 0.895 | 0.893 | 0.904 |
| Average rent | 0.942 | 0.969 | 0.996 |
| High-skilled share | 1.000 | 1.032 | 0.981 |
| Skilled share | 1.000 | 0.981 | 1.010 |
| Average utility | 0.886 | 0.903 | 0.905 |
| (b) No social amenities | | | |
| Population | 1.000 | 0.633 | 1.492 |
| GDP | 0.990 | 0.625 | 1.521 |
| Average wage | 0.990 | 0.988 | 1.019 |
| Average rent | 0.734 | 0.907 | 1.067 |
| High-skilled share | 1.000 | 0.999 | 1.173 |
| Skilled share | 1.000 | 0.967 | 0.977 |
| Average utility | 0.604 | 0.601 | 0.781 |
| (c) Scenarios (a) and (b) combined | | | |
| Population | 1.000 | 0.621 | 1.508 |
| GDP | 0.891 | 0.554 | 1.379 |
| Average wage | 0.891 | 0.893 | 0.914 |
| Average rent | 0.718 | 0.889 | 1.051 |
| High-skilled share | 1.000 | 1.008 | 1.169 |
| Skilled share | 1.000 | 0.961 | 0.979 |
| Average utility | 0.548 | 0.551 | 0.707 |

**If COVID reduced productivity effects from density to zero…**

**If COVID reduced QoL effects from density to zero (no restaurants, pubs, etc)…**

**If COVID eliminated productivity and density effects of density…**

Ahlfeldt et al. (2021)

# V DYNAMIC SPATIAL MODELS

roles of idiosyncratic taste and migration costs

- **DSM differs in two important respects from Rosen-Roback**
  - Taste heterogeneity
  - Migration cost
- **Measurement of quality of life**
  - Static problem, *taste heterogeneity* key to understanding differences
  - Accounting for *migration costs* helps to for transitory deviations from SSE
- **Evaluating spatial shocks or policies**
  - Dynamic problem, *migration costs* play a key role
  - Not all workers will move immediately => gradual adjustments
  - Some workers will never move => “spatial incidence”

**Spatial policies can have spatial effects in DSM**

# V QUALITY-OF-LIFE SHOCK (BETTE AIR QUALITY)

evaluating a spatial policy

**QoL shock**


**7.7%**

**Rent capitalisation**


**6.3%**

**Persistent utility effect**

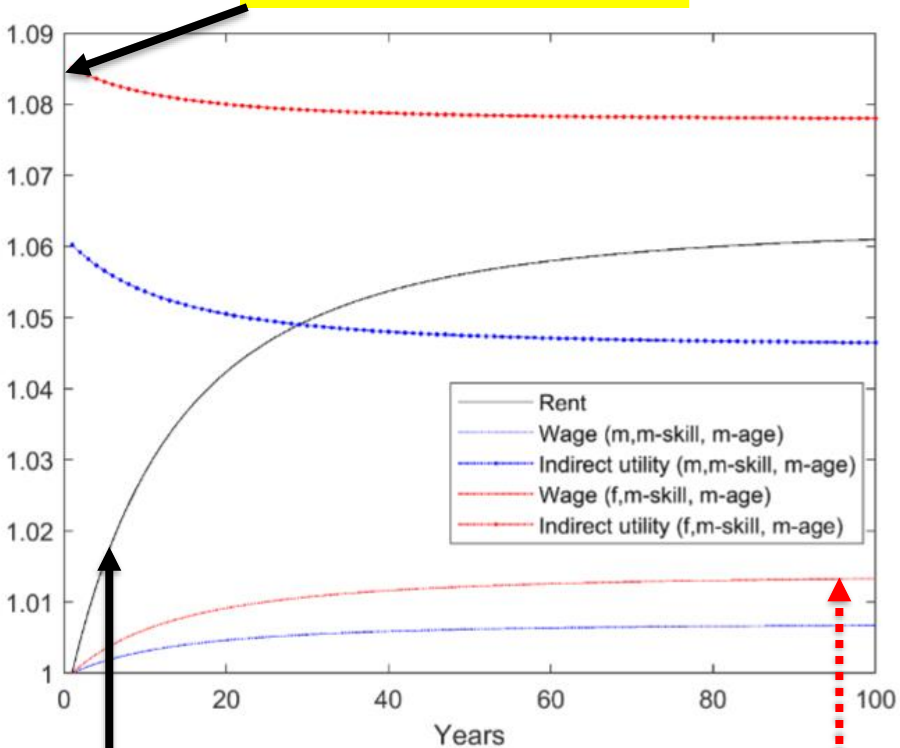

**7.1%**

Ahlfeldt et al. (2020)

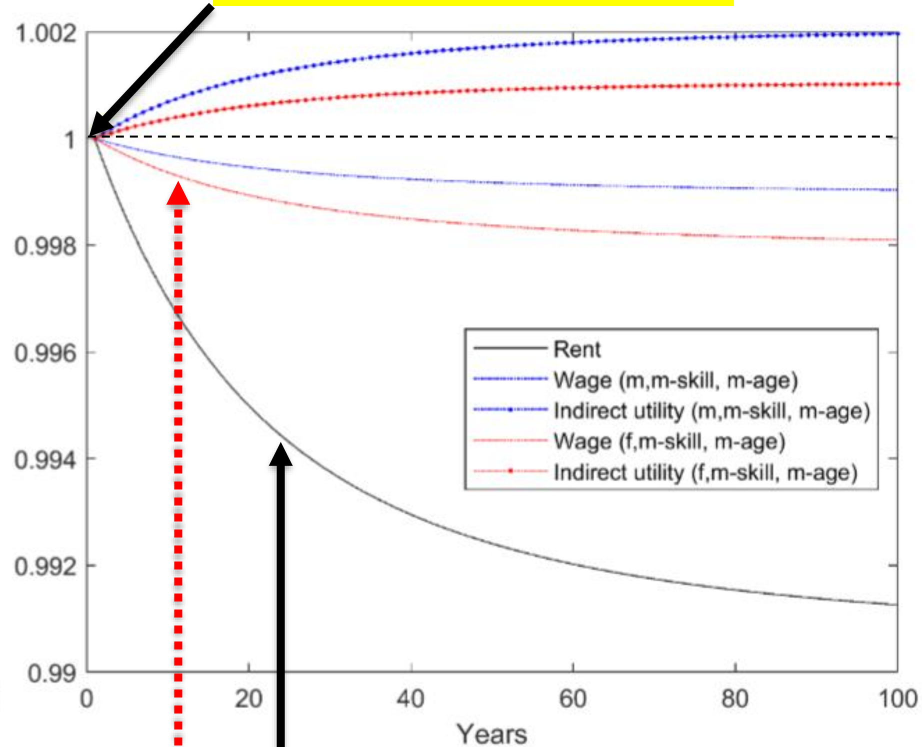
# V QUALITY-OF-LIFE SHOCK (BETTE AIR QUALITY)

evaluating a spatial policy

**Bochum (treated)**




**Munich (not treated)**




**In-migration => higher rent**

**In-migration => higher wage**

**Out-migration => lower rent**

**Out-migration => lower wage**

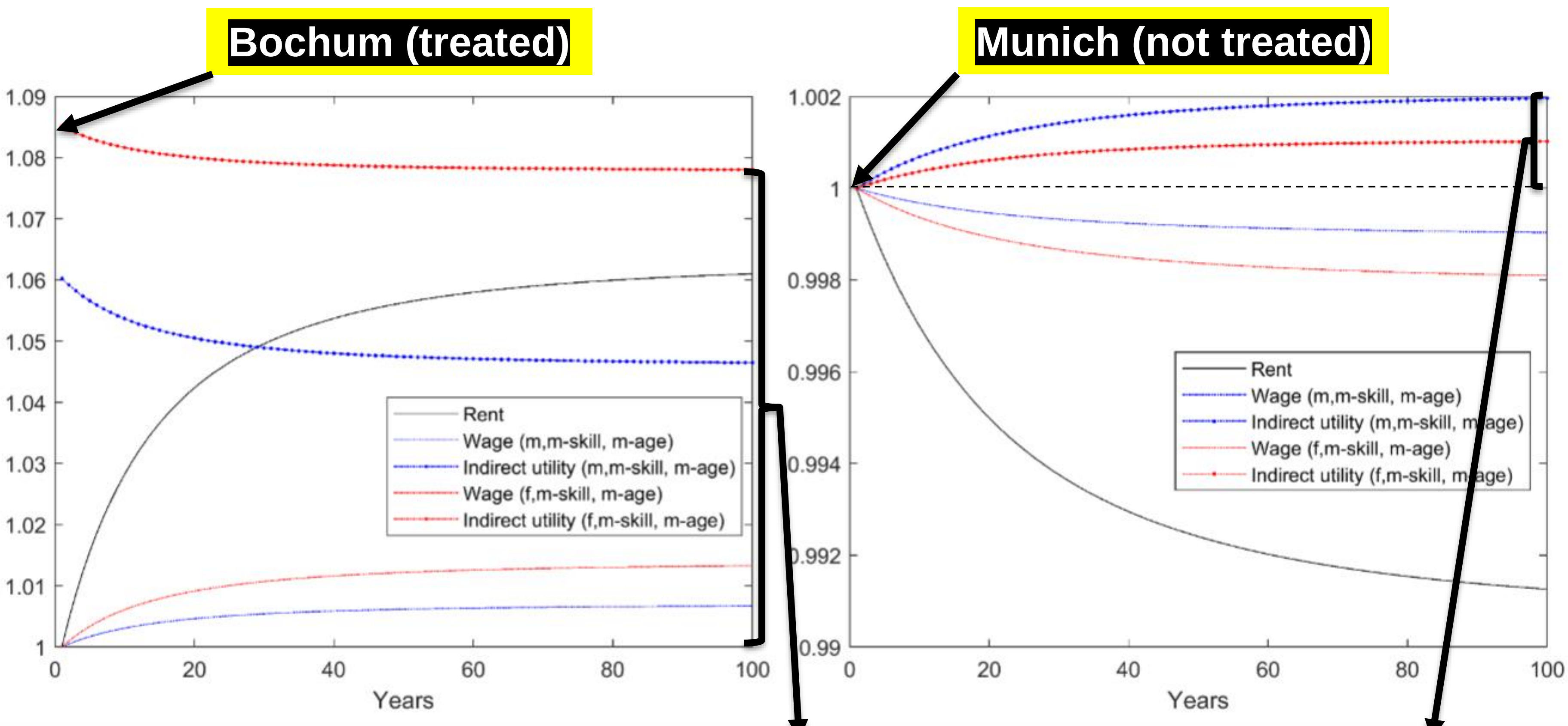




Ahlfeldt et al. (2020)

# V QUALITY-OF-LIFE SHOCK (BETTE AIR QUALITY)

evaluating a spatial policy




**Positive utility due to higher QoL**

**Positive utility due to less competition on housing market**





Ahlfeldt et al. (2020)

# V QUALITY-OF-LIFE SHOCK (BETTE AIR QUALITY)

evaluating a spatial policy

| Outcome | All regions | Treated area | Non-treated area |
|---|---|---|---|
| Population | 1.0000 | 1.0949 | 0.9536 |
| GDP | 0.9991 | 1.0996 | 0.9515 |
| Average wage | 0.9991 | 1.0043 | 0.9978 |
| Average rent | 1.0021 | 1.0175 | 0.9911 |
| High-skilled share | 1.0000 | 1.0109 | 0.9946 |
| Skilled share | 1.0000 | 1.0118 | 0.9976 |
| Average utility | 1.0219 | 1.0350 | 1.0003 |
| Social welfare (inequality adjusted) | 1.0191 | . | . |
| Monetized average utility (bn. €) | 23.1 | . | . |
| Monetized social welfare (bn. €) | 20.2 | . | . |

Relocation

Agg. effect

Dem. shift

Inequality has increased

**Place-based policies help local population since immigration leads to imperfect capitalization (unless some groups have very low migration costs)**





Ahlfeldt et al. (2021)

# V IMPLICATIONS FOR PLACE-BASED POLICIES (PBPs)

spatial incidence

- **Without spatial friction**
  - Place-based policies **capitalize in prices**
- If there is some **home attachment** or **migration cost**
  - Place-based policies **can help local residents**
- Potential **efficiency-equity trade-off**
  - Reduction in spatial inequality may not be welfare enhancing
  - Spatial misallocation of talent (Hsieh and Moretti 2019)
- **Focus on place-based policies**
  - that generate agglomeration economies, ideally in emerging sectors (avoid competition with existing sectors)
  - Promoting access to education usually the best way to help people/regions

**Good news for real estate investors: PBPs usually lead to positive capitalization**

**DSMs can predict capitalization effects accounting for relocation**

# SUMMARY
conclusion

- **Some regions struggle as a legacy of past industry specialization**
  - Automation and globalization have hit the manufacturing sector
- **Leads to poltical polarisation**
  - Strugging regions express discontent in voting
- **Inconsistent with standard spatial equilibrium framework**
  - Utility is equalized in Rosen-Roback framework
  - Needs home attachment or migration cost to rationalize
- **Place-based policies**
  - Need to take into account migration responses
  - The more mobile, the less impactful for local residents
  - Good for investors

# THANKS

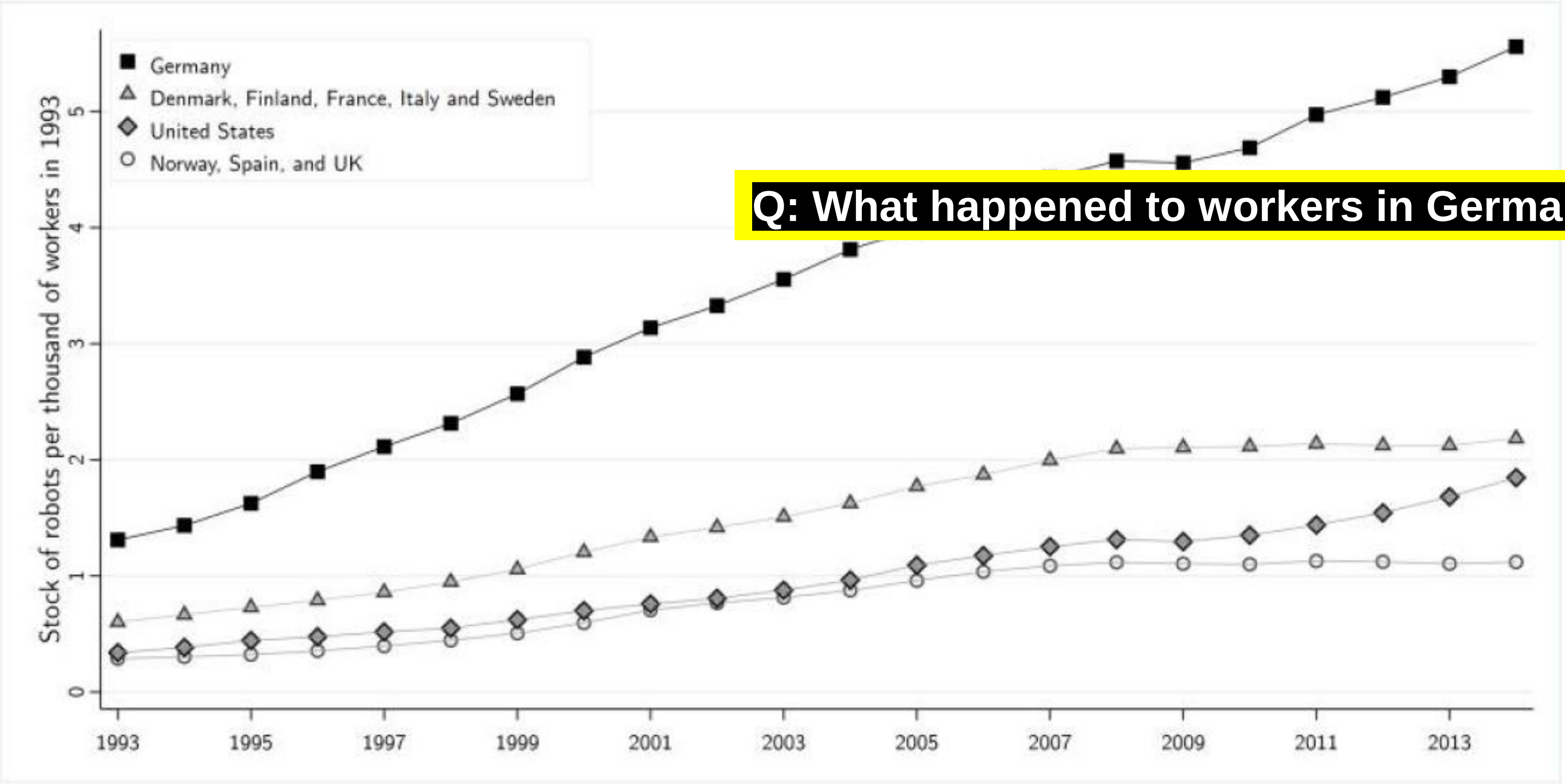
# READING

- Core readings:
  - Autor, Dorn, Hanson (2013): The China Syndrome: Local Labor Market Effects of Import Competition in the United States. American Economic Review 2013, 103(6): 2121–2168
  - Kline, Moretti (2019): People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs. Annu. Rev. Econ. 2014. 6:629–62

- Complementary readings and references:
  - Acemoglu & Restrepo (2020): Robots and jobs: Evidence from US labor markets. Journal of Political Economy, 128(6), 2188-2244
  - Ahlfeldt, Bald, Roth, Seidel (2019): The stationary spatial equilibrium with migration costs. Working paper
  - Autor, Dorn, Hanson (2020): Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure. American Economic Review. 110(10)
  - Baum-Snow, Freedman, Pavan (2019): Why Has Urban Inequality Increased? American Economic Journal: Applied Economics 2018, 10(4): 1–42
  - Dauth, Findeisen, Suedekum (2014) The rise of the east and the far east: German labor markets and trade integration
  - Dauth, Findeisen, Suedekum, Woessner (2019): The adjustment of Labor Markets to Robots. Working paper
  - Desmet, Nagy, Rossi-Hansberg (2018): The geography of development. Journal of Political Economy, 126(3)
  - Hsieh & Enrico Moretti. 2019. Housing Constraints and Spatial Misallocation. American Economic Journal: Macroeconomics, 11 (2): 1-39.
  - Fetzer (2019): Did austerity cause Brexit? American Economic Review, 109(11)
  - Moretti (2010): Local labor markets. Handbook of Labor Economics, Volume 4b.
  - Overman (2019): People, Places and Politics. CEP 2019 election analysis series.

# APPENDIX: INDUSTRIAL ROBOTS IN GERMANY

rise of the robots




**Q: What happened to workers in Germany?**

Acemoglu & Restrepo, 2019

# APPENDIX: INDUSTRIAL ROBOTS IN GERMANY

Dauth et al. 2019

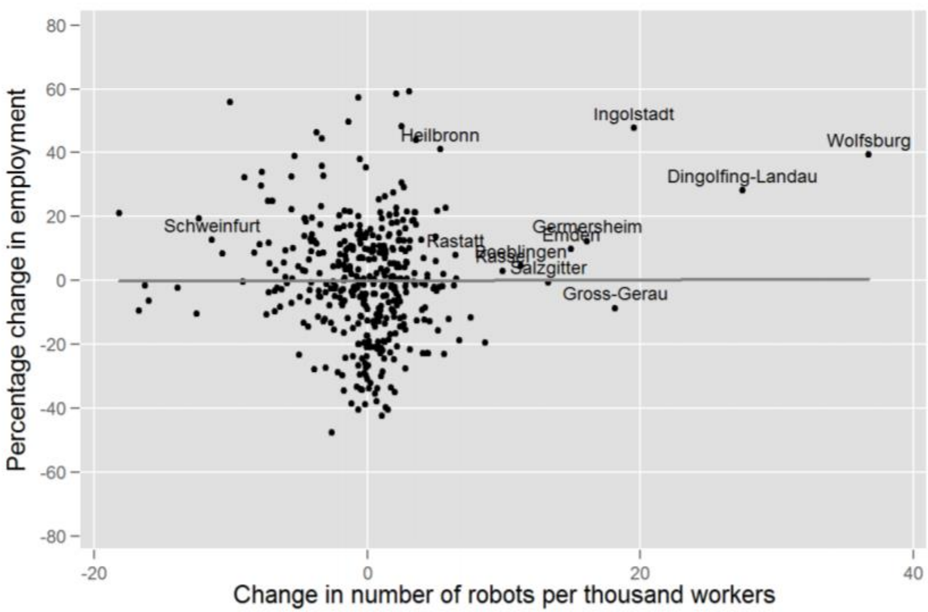



Figure 2: Region-level exposure to robots and employment growth.

*Notes*: The figure displays the correlation of the increase in exposure to robots (conditional on regional employment shares in nine broad industry groups and federal state dummies) and the growth rate of full-time equivalent jobs between 1994 and 2014 at the level of 402 German local labor markets.
Sources: IFR and BEH V10.01.00, own calculations.

**Smaller effects on manufacturing employment, offset by growth of services sector**
***Incumbent workers*** **upgrade to better jobs in the same plant**
***Young workers*** **substitute to higher education**

**Do institutions explain the difference (strong protections for incumbent workers)?**

Dauth et al. 2019

# APPENDIX: TRADE EXPOSURE EFFECTS US

Autor et al. 2020

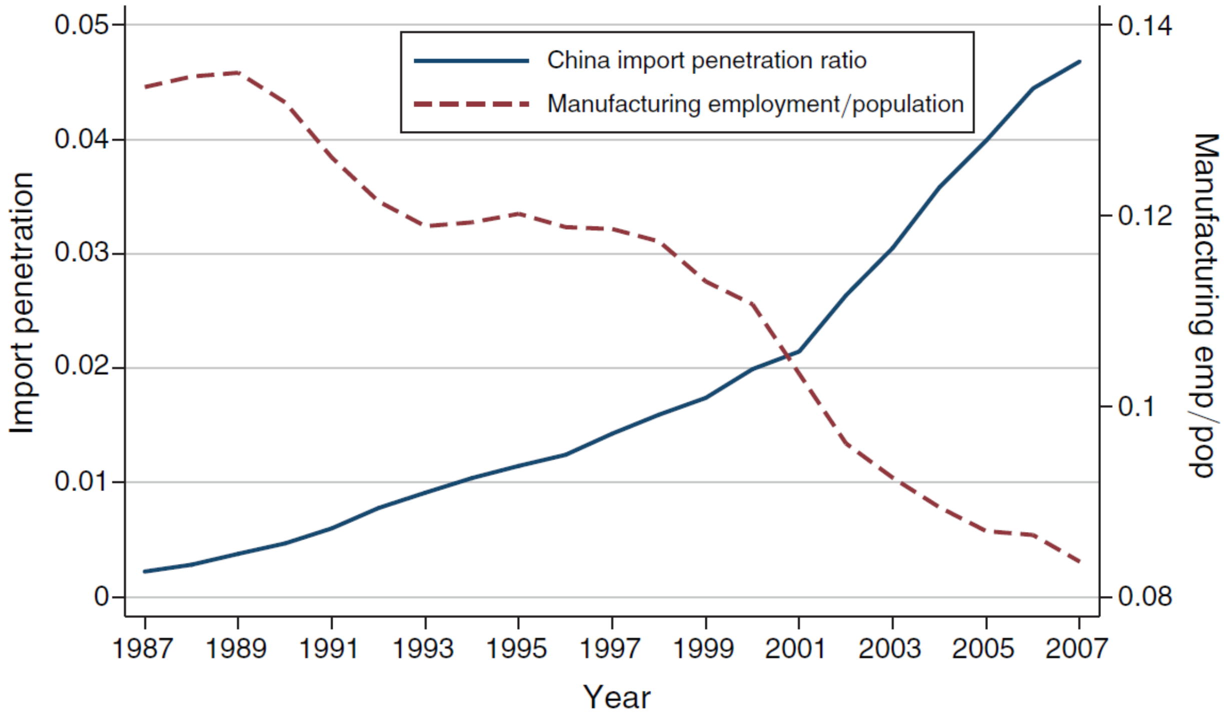



FIGURE 1. IMPORT PENETRATION RATIO FOR US IMPORTS FROM CHINA (*left scale*), AND SHARE OF US WORKING-AGE POPULATION EMPLOYED IN MANUFACTURING (*right scale*)

**Q: Did exposure to Chinese imports harm US workers?**

# APPENDIX: TRADE EXPOSURE EFFECTS US

Autor et al. 2020

- **Import exposure over the 1990-2007 period**
  - Use initial sector shares and changes in imports by sector

$$\Delta IPW_{uit} = \sum_{j} \frac{L_{ijt}}{L_{ujt}} \frac{\Delta M_{ucjt}}{L_{it}}$$

- Create an instrumental variable based on exports of China to 8 other countries

$$\Delta L_{it}^{m} = \gamma_t + \beta_1 \Delta IPW_{uit} + \mathbf{X}_{it}' \beta_2 + e_{it}$$

**Long-difference estimation**

**Employment or wages**

# APPENDIX: TRADE EXPOSURE EFFECTS US

Autor et al. 2020

**Negative wage effects, stronger for *male* than for *female***

**Effects marginally larger for nocollege workers**

**Effects larger for men than women**

*Dependent variable: Ten-year equivalent change in average log weekly wage (in log pts)*

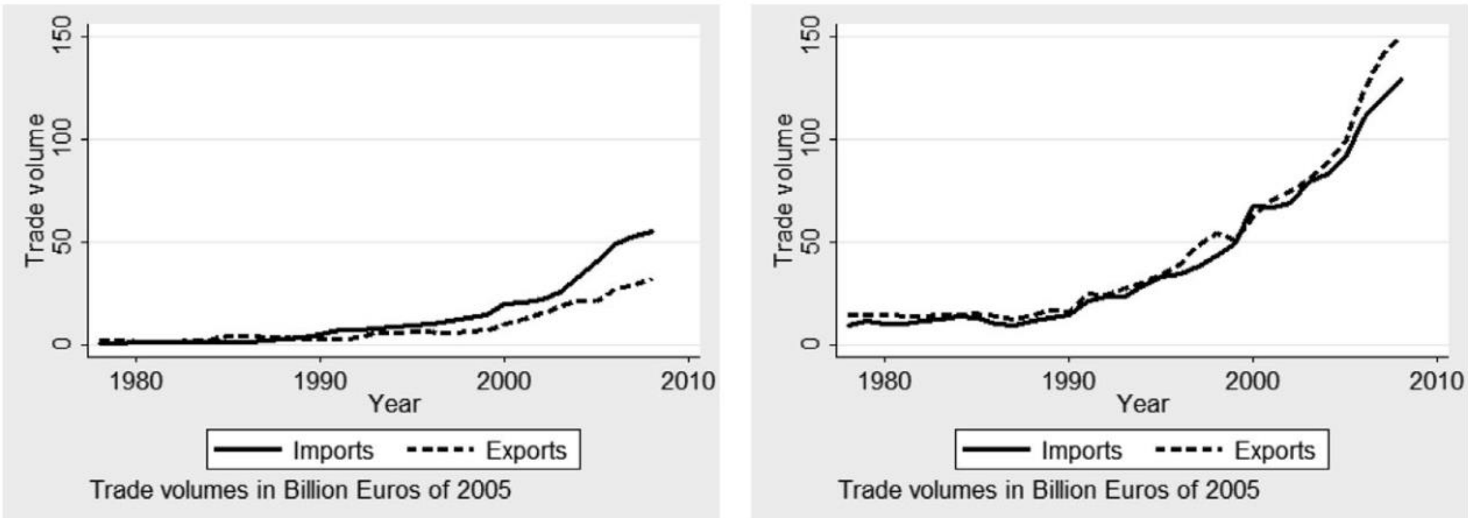
| | All workers (1) | Males (2) | Females (3) |
|---|---|---|---|
| *Panel A. All education levels* | | | |
| (Δ imports from China to US)/worker | −0.759*** | −0.892*** | −0.614*** |
| | (0.253) | (0.294) | (0.237) |
| $R^2$ | 0.56 | 0.44 | 0.69 |
| *Panel B. College education* | | | |
| (Δ imports from China to US)/worker | −0.757** | −0.991*** | −0.525* |
| | (0.308) | (0.374) | (0.279) |
| $R^2$ | 0.52 | 0.39 | 0.63 |
| *Panel C. No college education* | | | |
| (Δ imports from China to US)/worker | −0.814*** | −0.703*** | −1.116*** |
| | (0.236) | (0.250) | (0.278) |
| $R^2$ | 0.52 | 0.45 | 0.59 |

*Notes:* $N = 1{,}444$ (722 CZs × two time periods). All regressions include the full vector of control variables from column 6 of Table 3. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period CZ share of national population.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

# APPENDIX: TRADE EXPOSURE EFFECTS GERMANY

Dauth et al 2014




(a) China (b) Eastern Europe

FIGURE 1. German trade volumes with China and Eastern Europe, 1978–2008.

Dauth et al 2014

**Trade integration also caused job loss in import-exposed industries in Germany**
***But even stronger job gains*** **in export exposed industries and regions**