Automation Threat and Labor Market Power

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Cornell University

June 2025

Motivation


The New York Times
What to Know
Key Issues
Effect on the Economy
Biden Scrambles to Contain Fallout
Truckers See Ports Turn Into Ghos
Towns, and Worry About Their F
The strike by longshoremen has halted commerce at
other ports on the East and Gulf Coasts, affecting a
supply-chain workers.
SPORTS ENTERTAINMENT BUSINESS SCIENCE FACT CHECK ODDITIES BE WELL NEWSLETTERS
Matthew Perry death
Longshoremen strike
Royals-Orioles
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strike looms: 'From
By Stephen Sorace, Fox Business
MACHINES DON'T FEED FAMILIES: SUPPORT I WORKER
Reuters
World
US Election
Business
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Sustainability
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Breakingviews
Tech
World at Work | Employee Benefits & Executive Compensation | Worker Rights | Employment | Public Policy
US port workers union backed by Whi
House in strike
By Doyinsola Oladipo and David Shepardson
October 2, 2024 5:49 PM EDT · Updated 3 hours ago
CORPORATE GREED VS. WORKER RIGHTS ILA DEMANDS FAIRNESS
NO WORK WITHOUT A FAIR CONTRACT
NO WORK WITHOUT A FAIR CONTRA
Calculators
Videos
Watch
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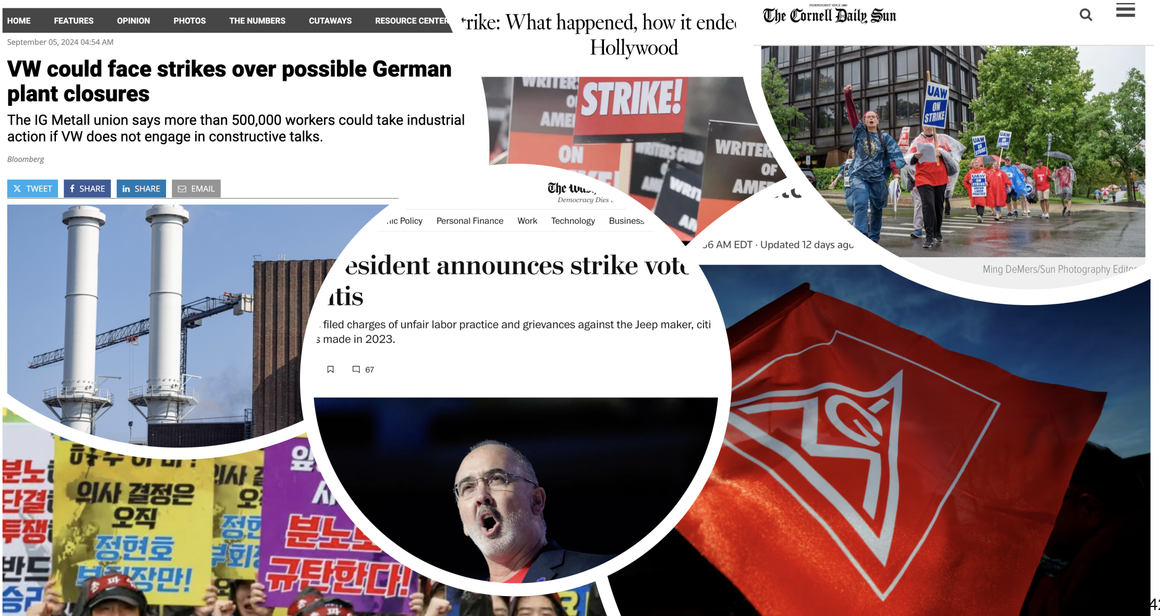
waging a battle against
rest of us may want to take
AM EDT, Wed October 2, 2024
STOP
PROFIT OVER PEOPLE IS UNACCEPTABLE SUPPORT ILA WORKERS
ILA WORKERS OVER MACHINES: DEFEND OUR JOBS AND RIGHTS

Motivation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September 05, 2024 04:54 AM
VW could face strikes over possible German plant closures
The IG Metall union says more than 500,000 workers could take industrial action if VW does not engage in constructive talks.
Bloomberg
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EMAIL
rike: What happened, how it ende
Hollywood
STRIKE!
The Cornell Daily Sun
UAW ON STRIKE
Democracy Dies
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6 AM EDT · Updated 12 days ago
Ming DeMers/Sun Photography Editor
esident announces strike vote
tis
filed charges of unfair labor practice and grievances against the Jeep maker, citi
made in 2023.
67
의사 결정은
오직
정현호
규탄한다!

Motivation

- Significant market power in the labor markets
  - Elasticity of labor supply to an individual firm is finite (e.g., Manning, 2003; Bachmann et al., 2021; Amodio and De Roux, 2021; Bassier et al., 2022; Caldwell and Oehlsen, 2022; Datta, 2023)
  - Wage markdowns: Wage $<$ MRPL (e.g., Berger et al., 2022; Yeh et al., 2022; Hoang et al., 2024)
  - Labor markets are highly concentrated (e.g., Azar et al., 2019; Felix, 2022)

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- Labor reallocation, mobility, collusion, workforce composition $\rightarrow$ Labor market power
  - Trade (e.g., Felix, 2022; Kondo et al., 2022), infrastructure investments (Brooks et al., 2021; Perez et al., 2022), employer collusion (Delabastita and Rubens, 2023), immigration (Amior and Manning, 2025), public works program (Byambasuren et al., 2025)

Motivation

- Automation $\rightarrow$ Employment and wages
  - Perfectly competitive labor market (e.g., Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2022) and labor market imperfection (Chau and Kanbur, 2021; Acemoglu and Restrepo, 2023)

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- RQ1. What is the state and evolution of labor market power in German manufacturing?

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- RQ3. How automation threat can (theoretically) affect the wage bargaining outcomes?

This Paper

- RQ1. What is the state and evolution of labor market power in German manufacturing?
  - Estimate plant-level wage markdowns (MRPL/Wage) and compute evolution of aggregate markdowns: (1) baseline and (2) heterogeneous workers
- RQ2. Does firms' exposure to robots (empirically) affect employer power?
- RQ3. How automation threat can (theoretically) affect the wage bargaining outcomes?

This Paper

- RQ1. What is the state and evolution of labor market power in German manufacturing?

- RQ2. Does firms' exposure to robots (empirically) affect employer power?
  - Estimate the causal impact of exposure to industrial robots on wage markdowns in German manufacturing using shift-share IV design at the (1) LLM and (2) firm level
  - Estimate employment and wage effects

- RQ3. How automation threat can (theoretically) affect the wage bargaining outcomes?

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- RQ1. What is the state and evolution of labor market power in German manufacturing?
- RQ2. Does firms' exposure to robots (empirically) affect employer power?
- RQ3. How automation threat can (theoretically) affect the wage bargaining outcomes?
  - Develop a simple conceptual model to (1) formalize and (2) explore potential mechanisms through which automation threat affects firm's and workers' bargaining position

Preview of Main Findings

- Sizable labor market power in German manufacturing
    - Average worker receives 79 cents on the marginal euro

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- A wage bargaining framework with heterogeneous workers
  - Consistent with the main empirical results
  - Separate bargaining (e.g., via worker group-specific unions) $\Longrightarrow$ Heterogeneous effects of automation threat on firm's bargaining power and markdowns over different workers

Roadmap

1. Context
2. Data
3. RQ1. Markdown Estimates
4. RQ2. Empirical Analysis
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1. **Context**
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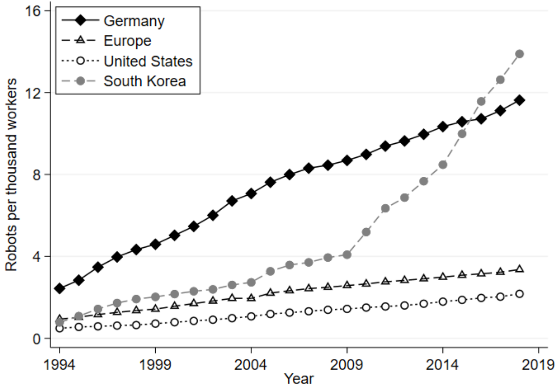
Context: German Manufacturing

- Why Germany?
  - The country is much more automated than any other countries such as the US, except for South Korea since 2016



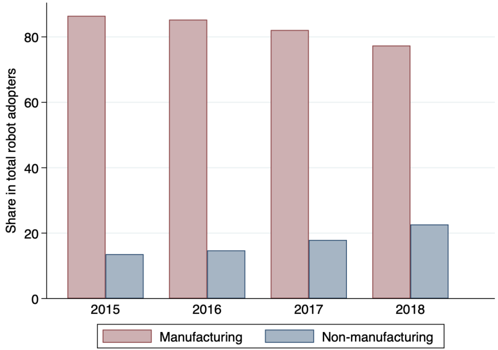
Source: IFR, OECD, BHP or BEH, and own calculations.

Context: German Manufacturing

- Why Germany?
  - Three salient features of the German labor market (Jäger et al., 2022):
    - $\rightarrow$ Collective bargaining at the industry-region level with firm-level negotiations
    - $\rightarrow$ Notable regional differences in the collective bargaining coverage
    - $\rightarrow$ Unions representing different occupation, skill, and experience groups, especially before the 2015 “Unity Law”

Context: German Manufacturing

- Why German manufacturing industry?
  - Robots and robot adopters are highly concentrated in manufacturing ▸ Share of robot adopters



Notes: The figure plots the share of manufacturing and non-manufacturing robot adopters in the total number of robot adopters between 2015-2018 using data from the IAB Establishment Panel (IAB BP). The 2014 data was not presented for compliance with data privacy.

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Data

- IAB Establishment Panel (IAB-BP, 1993-2019)
  - Institute for Employment Research, German Federal Employment Agency
  - Annual nationally representative survey of establishments
  - Information necessary to estimate markdown using production approach
  - Firm-level automation measures (only 2014-2018) Definition of robots

Data

USE OF ROBOTS

77. a) Have you used robots over the last 5 years for operational performance or production?
A robot is any automated machine with multiple axis or directions of movement, programmed to perform specific tasks (partially) without human intervention. This includes industrial robots but also service robots. This excludes machine tools, e.g. CNC-machines.

Yes.............................◯ ⇓ No.............................◯ ⇒ *go to question 81!*

If so,

b) How many robots have you used in total per year over the last five years? An estimate will suffice. If multiple robots are used in one robot cell, please count them individually. Again, please provide an estimate if no exact figure is available.

If "none" enter "0". Please enter "XXX" if there's no information possible to single years.

2014	2015	2016	2017	2018
________	________	________	________	________

If no robot was used in 2018 or no entry, go to question 81.
If at least one robot was used in 2018, go to question 78.

If there was use of at least one robot in 2018:

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- BIBB/BAuA Employment Surveys
  - Federal Institute for Vocational Education and Training
  - Worker-level job tasks (2006, 2012, 2018)

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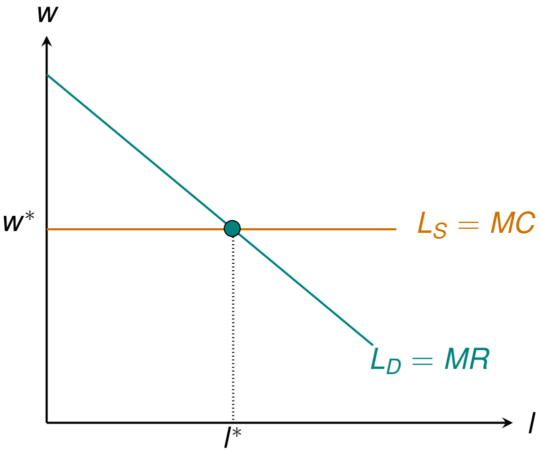
Individual Firm's Labor Market Equilibrium

(a) Perfect competition



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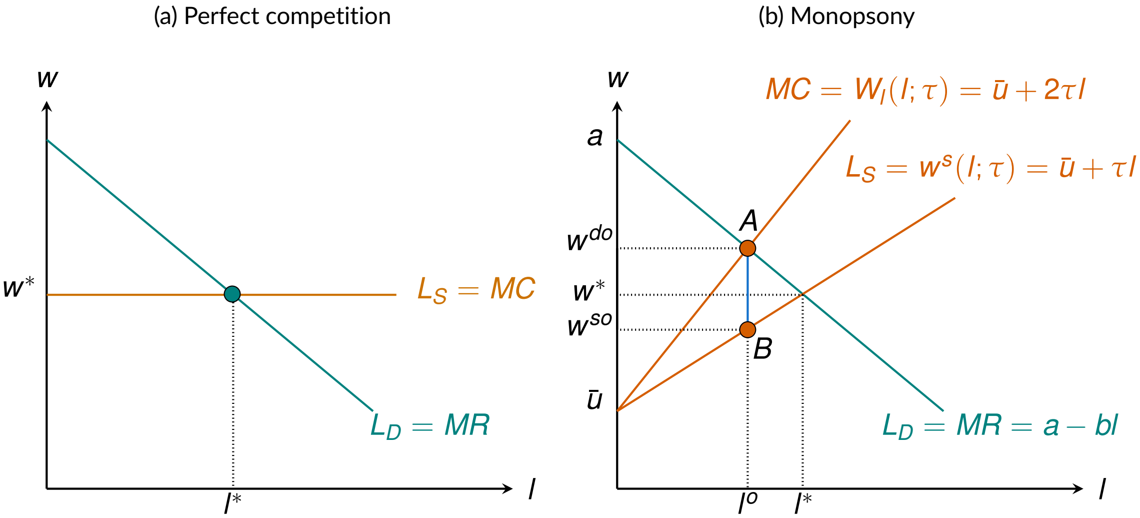

Measuring Labor Market Power: Definition

- The wage markdown, ν, is defined as the ratio of marginal revenue product of labor (MRPL) to wage:

$$\nu = \frac{R_l(l)}{w(l)} = \varepsilon_S^{-1} + 1,$$

where $R_l(l) = \frac{\partial R(l)}{\partial l}$ is the MRPL, $w(l)$ is the wage, and $\varepsilon_S = \frac{\partial l}{\partial w(l)} \frac{w(l)}{l}$ is the elasticity of labor supply.

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- In perfectly competitive labor markets: $\nu = 1$

- Employer has market power: $\nu > 1$

Measuring Labor Market Power: Markdown Estimation

- Markdown is defined by (Yeh et al., 2022)

$$\nu_{jt} = \frac{\theta^L_{jt}}{\alpha^L_{jt}} \mu^{-1}_{jt}$$

  - θ^L_{jt}: output elasticity of labor
  - α^L_{jt}: share of labor expenditure in revenue
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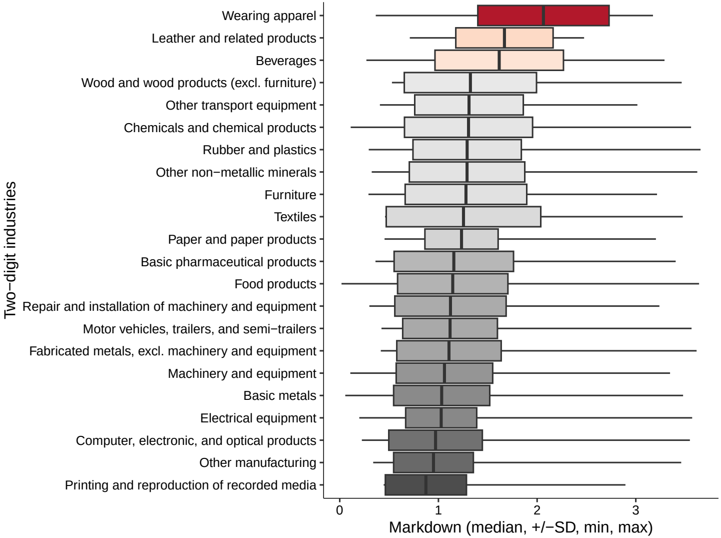
$$\mu_{jt} = \frac{\theta^M_{jt}}{\alpha^M_{jt}}$$

$\rightarrow$ θ^M_{jt}: output elasticity of any flexible input M_{jt} (e.g., materials, energy, etc.)
$\rightarrow$ α^M_{jt}: share of expenditure on input M_{jt} in revenue

Estimation approach · Production function estimation

Estimated Plant-Level Markdowns in German Manufacturing Industry



- Sample size = 12,794
- Sizable variance across industries

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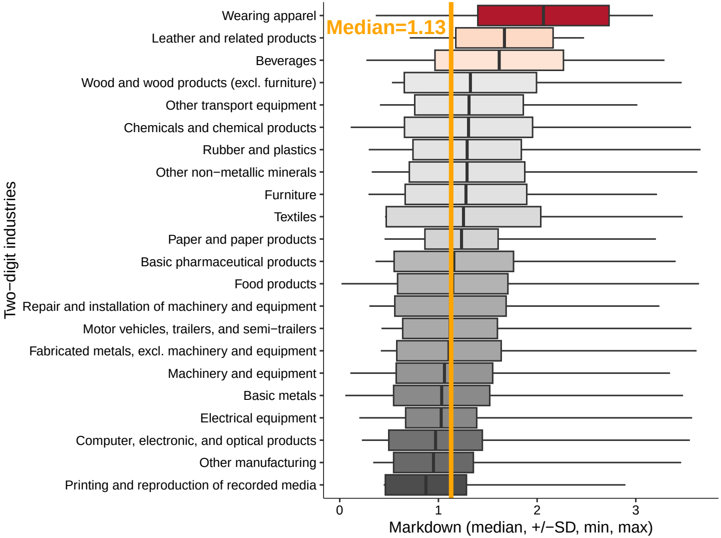

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- Sizable variance across industries
- Most manufacturing plants operate in a monopsonistic market

Firm characters | MD-Size ladders | MD: E/W | E/W specific | MD-Union | Industry specific | HHI

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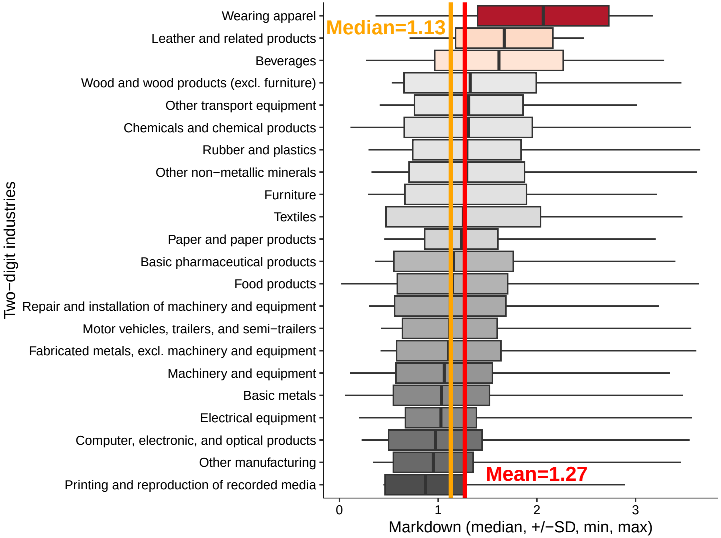

- Sample size = 12,794
- Sizable variance across industries
- Most manufacturing plants operate in a monopsonistic market
- Workers in a German manufacturer earn 79 cents on each euro generated, on average

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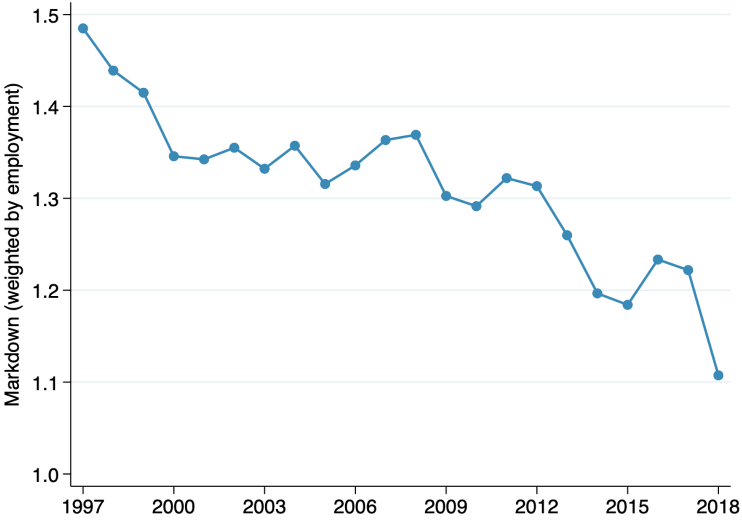
Trend of Aggregate Markdowns



Aggregation approach Cobb-Douglas specification Markup trend

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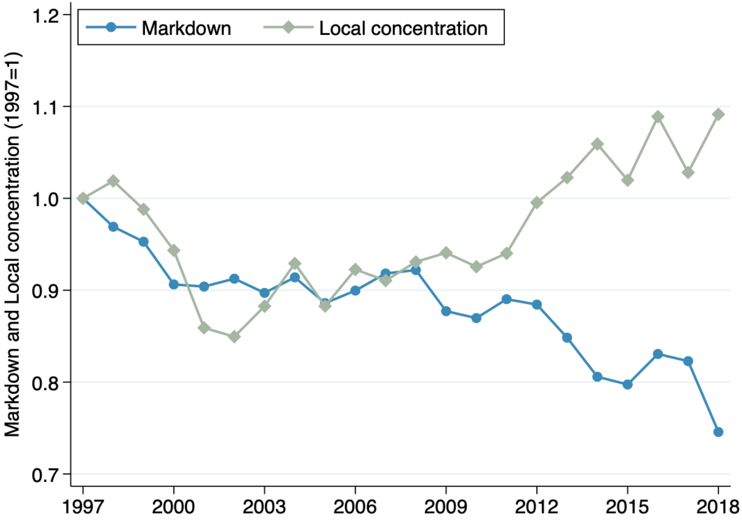

Aggregation approach
Cobb-Douglas specification
Markup trend
Aggregation approach: HHI
Cross-sectional correlation

Defining Routine and Nonroutine Workers

- BIBB Employment Survey provides the worker-level task descriptions with occupation
- Following Autor et al. (2003) and Spitz-Oener (2006), job activities/tasks are classified into three broad task categories k:

	Classification	Tasks
Nonroutine Cognitive	Nonroutine analytic	Researching, analyzing, evaluating and planning, making plans/constructions, designing, sketching, working out rules/prescriptions, and using and interpreting rules
	Nonroutine interactive	Negotiating, lobbying, coordinating, organizing, teaching or training, selling, buying, advising customers, advertising, entertaining or presenting, and employing or managing personnel
Routine	Routine cognitive	Calculating, bookkeeping, correcting texts/data, and measuring length/weight/temperature
	Routine manual	Operating or controlling machines and equipping machines
Nonroutine Manual	Nonroutine manual	Repairing or renovating houses/apartments/machines/vehicles, restoring art/monuments, and serving or accommodating

Defining Routine and Nonroutine Workers

- Following Antonczyk et al. (2009), task intensity (TI) measure is defined as

$$\mathrm{TI}_{ikt} = \frac{\text{number of activities in category } k \text{ performed by } i \text{ at time } t}{\sum_k \text{number of activities in category } k \text{ performed by } i \text{ at time } t},$$

where k indicates routine, nonroutine manual, and nonroutine cognitive category.

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- Combine with LIAB by occupation and normalize the three measures to have mean zero and unit standard deviation

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- Worker i is routine if

$$\max(\mathrm{RTI}_{ijt}, \mathrm{NRCTI}_{ijt}, \mathrm{NRMTI}_{ijt}) = \mathrm{RTI}_{ijt}$$

Estimated Wage Markdowns for Heterogeneous Workers

	Median	Mean	$IQR_{75\text{-}25}$	SD	N
	Panel A. Routine, NRC, and NRM workers				
Routine workers	1.153	1.291	0.669	0.623	3178
Nonroutine cognitive (NRC) workers	1.356	1.613	0.880	0.904	3178
Nonroutine manual (NRM) workers	1.492	1.985	1.508	1.645	3178
	Panel B. High-skilled and low-skilled workers				
High-skilled workers	1.108	1.246	0.592	0.527	4223
Low-skilled workers	1.610	2.198	1.731	2.015	4223

Notes: The distributional statistics are calculated using sampling weights provided in the data.

Distribution: Task | Distribution: Skill | Trend: Task | Trend: Skill | Autor and Dorn (2013) | Distribution: Autor and Dorn (2013)

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Motivating Facts

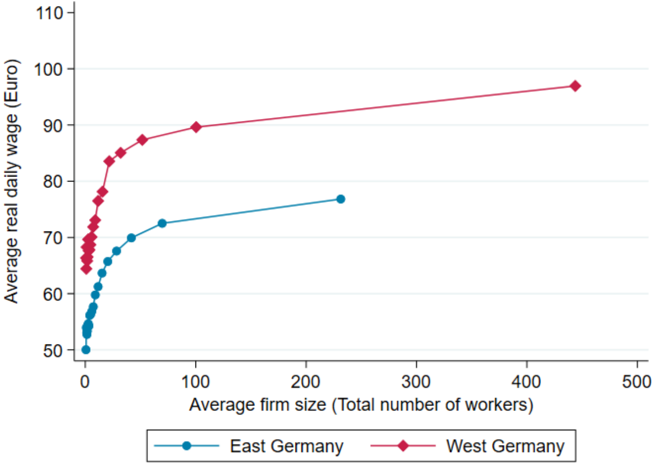
- Fact 1: Robot exposure shock $\neq$ Actual robot adoption

	Dependent variable: Actual robot adoption		
	(1)	(2)	(3)
	Panel A. Robots per 1000 workers		
Robot exposure shock	0.020	0.114	0.072
	(0.020)	(0.181)	(0.173)
Observations	1671	1667	1657
R^2	0.05	0.54	0.56
Year FE	✓	✓	
State FE	✓		
District FE		✓	✓
State-by-Year FE			✓

Firm regression East West Distribution of robots

Motivating Facts

- Fact 2: Wage discount in East Germany (Heise and Porzio, 2023)



▸ Regression specification ▸ Regression table ▸ Union coverage

Motivating Facts

- Fact 3: Workers less protected by trade unions have lower wages

	Dependent variable: Log average real daily wage		
	(1)	(2)	(3)
Union coverage	0.347	0.361	0.420
	(0.137)	(0.146)	(0.148)
Observations	11142	8847	8319
R^2	0.86	0.91	0.93
Firm FE	✓	✓	✓
Year FE	✓		
District-by-Year FE		✓	✓
Industry-by-Year FE			✓

▸ Wage-Union quartiles

Labor Market-Level Analysis

Empirical specification:

$$\Delta Y_{rt} = \alpha_t + \beta \widehat{\Delta \text{Robot exposure}}_{rt} + \gamma \widehat{\Delta \text{Trade}}_{rt} + \delta \widehat{\Delta \text{ICT}}_{rt} + \mathbf{X}'_{rt-1}\psi + \mu_{REG(r)} + \epsilon_{rt}$$

- ΔY_{rt}: Annual change in one of the labor market outcomes at the LLM region r (district or kreise) at year $t \in [1998, 2018]$
- $\widehat{\Delta \text{Robot exposure}}_{rt}$: Annual change in LLM region's "predicted" exposure to robots

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- $\Delta \widehat{\text{Robot exposure}}_{rt}$: Annual change in LLM region's "predicted" exposure to robots
- Potential endogenous dist. of robot exposure across LLM regions (kreise) and time
- Shift-share IV approach (Acemoglu and Restrepo, 2020; Dauth et al., 2021)
  - Germany's robot exposure is instrumented by the shift-share IV that rely on robot exposure of other high-income European countries

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$$\Delta Y_{rt} = \alpha_t + \beta \Delta \widehat{\text{Robot exposure}}_{rt} + \gamma \Delta \widehat{\text{Trade}}_{rt} + \delta \widehat{\Delta \text{ICT}}_{rt} + \mathbf{X}'_{rt-1}\psi + \mu_{REG(r)} + \epsilon_{rt}$$

- ΔY_{rt}: Annual change in one of the labor market outcomes at the LLM region r (district or kreise) at year $t \in [1998, 2018]$
- $\Delta \widehat{\text{Robot exposure}}_{rt}$: Annual change in LLM region's "predicted" exposure to robots
- Potential endogenous dist. of robot exposure across LLM regions (kreise) and time
- Shift-share IV approach (Acemoglu and Restrepo, 2020; Dauth et al., 2021)
  - Germany's robot exposure is instrumented by the shift-share IV that rely on robot exposure of other high-income European countries
- SEs are clustered by LLM regions
  - Regression residuals are likely to be correlated across regions with similar industry shares $\Longrightarrow$ Adjust SEs by allowing the correlation amongst error terms within region-industry share groups (Adao et al., 2019)

Construction of Shift-Share Variables

- Endogenous variable: Annual change in LLM region's "predicted" exposure to robots in Germany (Acemoglu and Restrepo, 2020; Dauth et al., 2021)

$$\Delta \widehat{\text{Robot exposure}}_{rt} = \sum_{k} \frac{L_{krt-1}}{L_{rt-1}} \frac{\Delta \text{Robot stock}_{kt}}{L_{kt-1}}$$

where I focus on $k = \{automotive\}$ in the baseline due to relevance assumption per Olea and Pflueger (2013), but checks robustness by adding other industries

Figures: Automotive and non-automotive

Construction of Shift-Share Variables

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where I focus on $k = \{automotive\}$ in the baseline due to relevance assumption per Olea and Pflueger (2013), but checks robustness by adding other industries

Figures: Automotive and non-automotive

- Instruments: Annual change in robot exposure in other high-income European countries (Autor et al., 2013; Acemoglu and Restrepo, 2020, 2022; Dauth et al., 2021)

$$\Delta \text{Robot} \widehat{\text{exposure}}_{ort} = \sum_k \frac{L_{krt-j}}{L_{rt-j}} \frac{\Delta \text{Robot stock}_{okt}}{L_{kt-j}}$$

where $j = 10$ or use employment levels from the prior decade (following the literature), and $o = \{\text{Spain, France, Italy, Norway, Sweden, UK}\}$

Identification Assumptions

1. Relevance or inclusion restriction ⏩ Details
   - Weak IV test (Olea and Pflueger, 2013) + Traditional test (Staiger and Stock, 1997; Stock and Yogo, 2005; Kleibergen and Paap, 2006)
     $\Longrightarrow$ Endog. regressor and instruments are strongly correlated
2. Independence ⏩ Details
   - Sargan-Hansen test (Sargan, 1958, 1998; Hansen, 1982; Altonji et al., 2005)
     $\Longrightarrow$ "Shifts" or shocks are plausibly orthogonal to unobserved determinants of outcomes (Borusyak et al., 2022)
3. Partial monotonicity ⏩ Details
   - Formal and informal tests (Imbens and Angrist, 1994; Mogstad et al., 2021)
     $\Longrightarrow$ 2SLS estimate is a positively weighted average of LATEs
4. Exclusion restriction
   - Zero-first-stage test (in-progress) (Bound and Jaeger, 2000; Altonji et al., 2005; Angrist et al., 2010; Van Kippersluis and Rietveld, 2018)

Baseline Results: Employment

	Dependent variable: 10×Annual log difference in employment		
	Routine (1)	NRM (2)	NRC (3)
ΔPredicted robot exposure	-0.026	0.014	-0.000
	(0.021)	(0.022)	(0.023)
	[1.069]	[0.403]	[0.953]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	133.16	133.16	133.16
Critical value 2SLS ($\tau = 10\%$)	19.51	19.51	19.51
Hansen's J-stat p-value	0.61	0.64	0.22

Notes: $N = 4599$ local labor market regions-by-year (district-by-year). Number of workers.

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Notes: $N = 4599$ local labor market regions-by-year (district-by-year). Number of workers.

Baseline Results: Wages

	Dependent variable: 10×Annual log difference in wages		
	Routine (1)	NRM (2)	NRC (3)
ΔPredicted robot exposure	0.001	-0.002	-0.020
	(0.011)	(0.006)	(0.018)
	[0.261]	[0.156]	[0.218]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	133.16	133.16	133.16
Critical value 2SLS ($\tau = 10\%$)	19.51	19.51	19.51
Hansen's J-stat p-value	0.72	0.26	0.24

Notes: $N = 4599$ local labor market regions-by-year (district-by-year). Average daily wage.

Baseline Results: Wage Markdowns

	Dependent variable: 10×Annual change in aggregate markdowns		
	Routine (1)	NRM (2)	NRC (3)
ΔPredicted robot exposure	0.091	0.070	-0.035
	(0.059)	(0.074)	(0.049)
	[0.038]	[0.096]	[0.057]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	46.25	46.25	46.25
Critical value 2SLS ($\tau = 10\%$)	21.31	21.31	21.31
Hansen's *J*-stat *p*-value	0.25	0.25	0.56

Notes: $N = 4599$ local labor market regions-by-year (district-by-year).

▸▸ Homogeneous workers: OLS ▸▸ Homogeneous workers: 2SLS

Baseline Results: Wage Markdowns

	Dependent variable: 10$\times$Annual change in aggregate markdowns		
	Routine (1)	NRM (2)	NRC (3)
ΔPredicted robot exposure	0.091 (0.059) [0.038]	$\boxed{0.070}$ $\boxed{(0.074)}$ $\boxed{[0.096]}$	-0.035 (0.049) [0.057]
Montiel Olea-Pflueger weak IV test			
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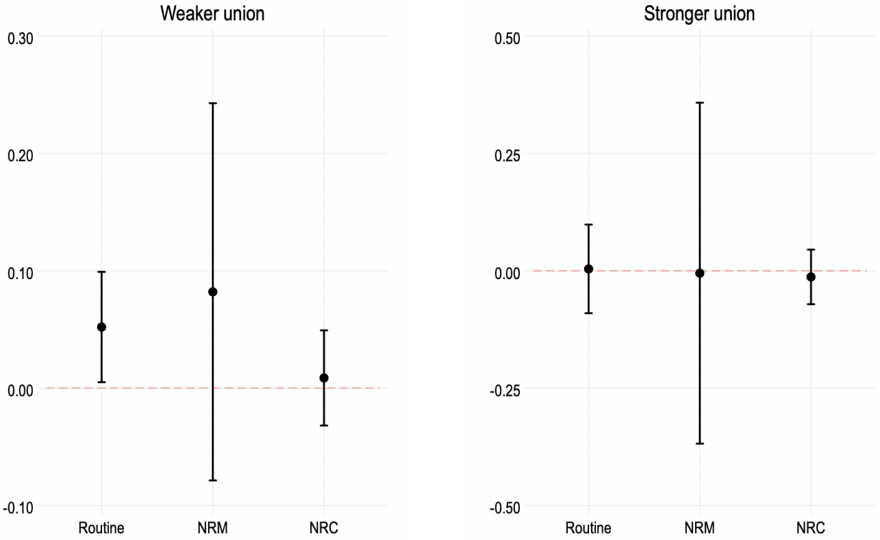
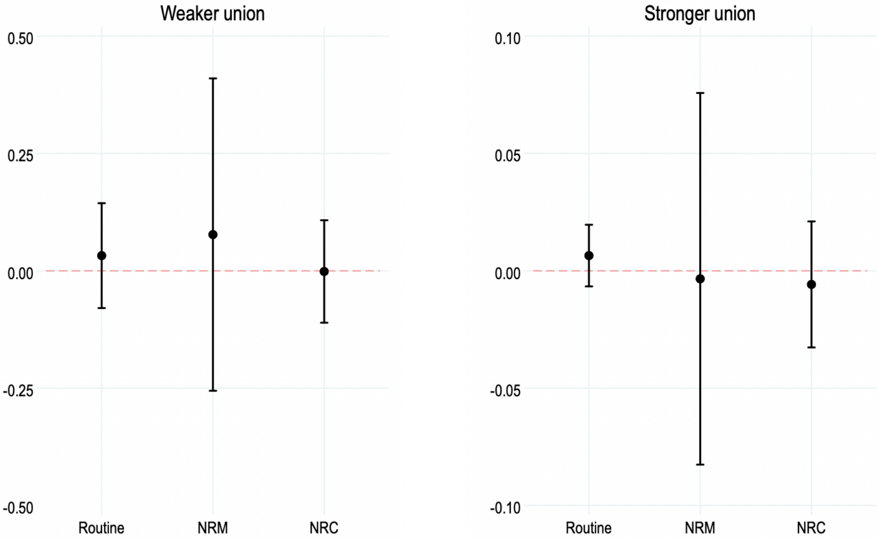
Heterogeneous Effects: Markdowns in **East** Germany by Union



Heterogeneous Effects: Markdowns in **West** Germany by Union



East/West Germany

Robustness Checks

- Common production function for East/West Germany ⏩ East ⏩ West ⏩ East/Union ⏩ West/Union
- Alternative split of union coverage ⏩ Bottom 8 deciles in the East ⏩ Bottom 8 deciles in the West
- Percentage changes of aggregate wage markdowns ⏩ East/Union ⏩ West/Union
- Alternative clusters at the aggregate regions ⏩ Baseline effects
- Adding a treatment of robot exposure in other industries ⏩ East/Union ⏩ West/Union
- Industrial robots in all industries ⏩ Bottom 8 deciles in the East ⏩ Bottom 8 deciles in the West
- Firm-level analysis ⏩ Employment, wages, and wage markdowns

Plant-Level Analysis

Empirical specification:

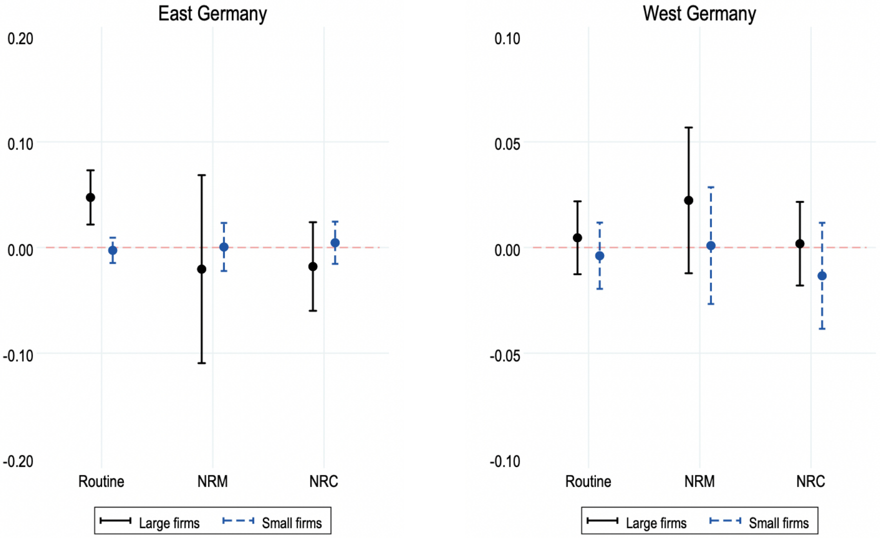
$$\Delta Y_{jt} = \beta \Delta \widehat{\text{Robot exposure}}_{rt} + \mathbf{Z}'_{jt-1}\gamma + \mathbf{X}'_{rt-1}\delta + \phi_j + \mu_{st} + \pi_{kt} + \varepsilon_{jt}$$

- ΔY_{jt}: Annual change in one of the labor market outcomes at firm j in year $t \in [1998, 2018]$
- $\mathbf{Z}'_{jt-1}$: Firm-level controls (incl. dummies for six plant size groups)
- $\mathbf{X}'_{rt-1}$: LLM-level controls (incl. $\Delta \widehat{\text{Trade}}_{rt}$ and $\Delta \widehat{\text{ICT}}_{rt}$)
- ϕ_j, μ_{st}, and π_{kt}: Firm, State-Year, and Industry-Year fixed effects
- SEs are clustered at the LLM region (district or kreis) level

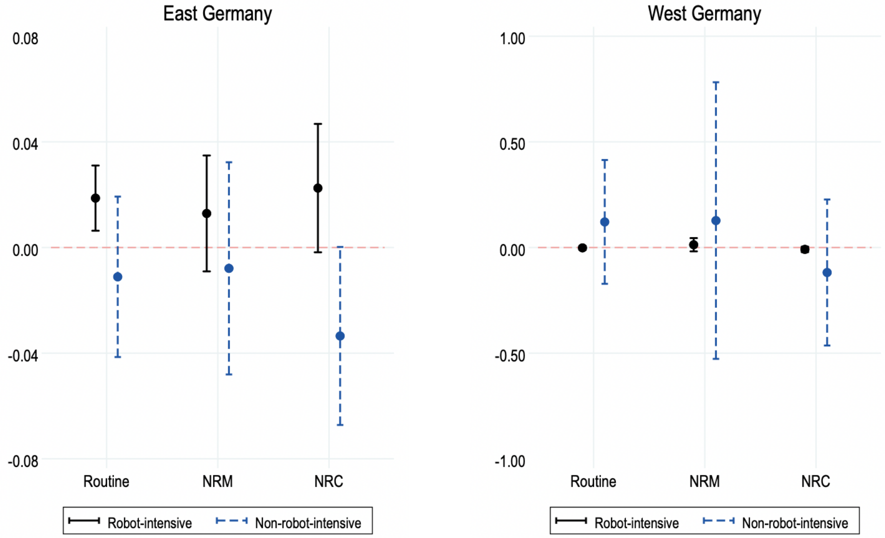
Additional Heterogeneous Effects

- **Firm size** ⏩ Markdowns ⏩ Wages ⏩ Employment
  - Wage markdowns over routine workers $\uparrow$ at large firms in East Germany
  - Routine workers' average wage $\downarrow$ at large firms, but not statistically significant
  - Routine workers' employment $\downarrow$ in West Germany, more significantly at large firms
- **Across industries** ⏩ Markdowns ⏩ Employment
  - Wage markdowns over routine workers $\uparrow$ (weakly $\uparrow$ for NRC workers) in robot-intensive industries in East Germany
  - Routine workers' employment $\downarrow$ more in robot-intensive industries in East Germany
- **Around the global financial crisis (GFC)** ⏩ Markdowns ⏩ Wages
  - Wage markdowns $\uparrow$ before 2009 in East Germany
  - NRC and NRM workers' average wage $\uparrow$ after 2009 in East Germany

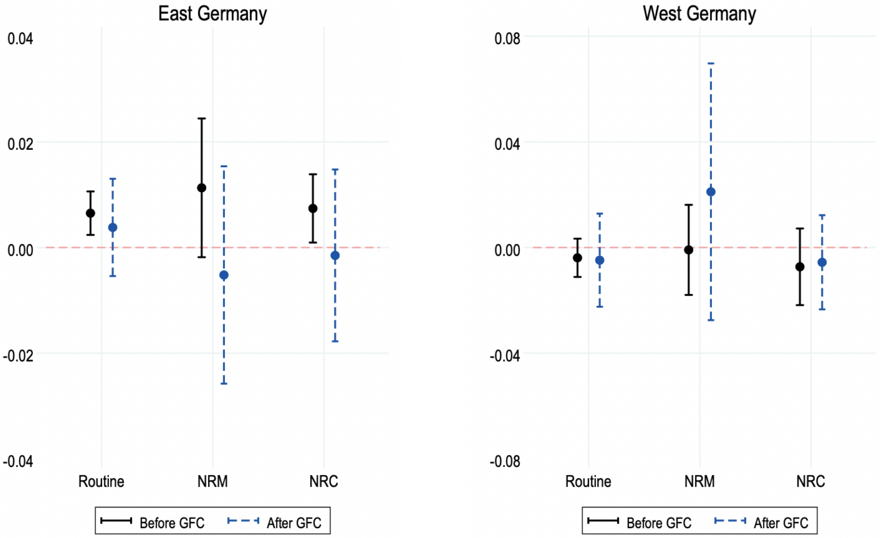
Plant-Level Effects on Markdowns Heterogeneous by Firm Size



Plant-Level Effects on Markdowns Heterogeneous across Industries



Plant-Level Effects on Markdowns Heterogeneous around GFC



Roadmap

1. Context
2. Data
3. RQ1. Markdown Estimates
4. RQ2. Empirical Analysis
5. **RQ3. Model**
6. Conclusion

Setup

- Right-to-manage model of wage bargaining (Nickell and Andrews, 1983)

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- Heterogeneous workers: Routine (L) and nonroutine (H) workers

Setup

- Right-to-manage model of wage bargaining (Nickell and Andrews, 1983)
- Heterogeneous workers: Routine (L) and nonroutine (H) workers
- Separate bargaining

$$\operatorname*{Max}_{w_L} \Big(\overbrace{\boxed{Q - w_L l_L - w_H l_H}}^{\text{firm's profit}} - \overbrace{\boxed{\bar{\pi}_L}}^{\text{threat point}} \Big)^{\overbrace{\boxed{\alpha}}^{\text{bargaining strength}}} \Big(\overbrace{\boxed{w_L}}^{\text{wage paid}} l_L - \overbrace{\boxed{W_L(l_L)}}^{\text{opportunity cost}} l_L \Big)^{1-\alpha}$$

$$\operatorname*{Max}_{w_H} \left(Q - w_L l_L - w_H l_H - \bar{\pi}_H\right)^{\beta} \left(w_H l_H - W_H(l_H) l_H\right)^{1-\beta}$$

- Joint bargaining

$$\operatorname*{Max}_{w_L, w_H} \left(Q - w_L l_L - w_H l_H - \bar{\pi}_{LH}\right)^{1-\gamma_L-\gamma_H} \left(w_L l_L - W_L(l_L) l_L\right)^{\gamma_L} \left(w_H l_H - W_H(l_H) l_H\right)^{\gamma_H}$$

Automation Threat in the Model

- Price of robots (r) $\downarrow \iff$ Automation threat $\uparrow$

Automation Threat in the Model

- Price of robots (r) $\downarrow \iff$ Automation threat $\uparrow$
- Responses of threat points to automation threat

$$\frac{\partial \bar{\pi}_L}{\partial r} < 0, \; \frac{\partial \bar{\pi}_H}{\partial r} = 0, \; \frac{\partial \bar{\pi}_{LH}}{\partial r} < 0$$

Results

- Under separate bargaining, automation threat $\uparrow$ leads to Proposition 1 & 2
  - Routine workers' bargaining outcomes $\downarrow$ and markdowns over $L \uparrow$
  - Nonroutine workers' bargaining outcomes $\uparrow$ and markdowns over $H \downarrow$
  - Firm profit $\uparrow$
- Under joint bargaining, automation threat $\uparrow$ leads to Proposition 3 & 4
  - Routine/nonroutine workers' bargaining outcomes $\downarrow$ and markdowns over L and $H \uparrow$
  - Firm profit $\uparrow$

Results

- Effects of automation threat on bargaining outcomes of different workers

	Bargaining regimes		
	Separate bargaining		Joint bargaining
Nonroutine workers	$\frac{(1-\alpha)(1-\beta)}{1-(1-\alpha)(1-\beta)} > 0$	$\rightarrow$	$-\gamma_H < 0$
Routine workers	$-\frac{1-\alpha}{1-(1-\alpha)(1-\beta)} < 0$	$\rightarrow$	$-\gamma_L < 0$

- Implications of worker *i* on worker *j*'s bargaining outcomes
  - Nonroutine workers' bargaining outcomes worse off due to routine workers in the same union
  - Potential redistributional effect of nonroutine workers on routine workers' bargaining outcomes depends on α, β, and γ_L

Roadmap

1. Context
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5. RQ3. Model
6. **Conclusion**

Conclusion

- Contributions:
  - Provide the comprehensive examination of labor market power in German manufacturing using a “well-established” production approach
  - Establish the first causal evidence on the effect of robot exposure on wage markdowns
  - Offer an alternative and simple bargaining model on automation threat-bargaining power link with new insights

Conclusion

- Main findings:
  - Sizable labor market power in German manufacturing, with average worker receives 79 cents on marginal euro
  - Exposure to industrial robots increases wage markdowns over routine workers, particularly, in regions with low union coverage from East Germany
  - Automation threat $\uparrow \implies$ Markdown over routine (nonroutine) workers $\uparrow$ ($\downarrow$)
    - $\rightarrow$ Mechanism: Separate bargaining

Conclusion

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  - Sizable labor market power in German manufacturing, with average worker receives 79 cents on marginal euro
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  - Automation threat $\uparrow \implies$ Markdown over routine (nonroutine) workers $\uparrow$ ($\downarrow$)
    - $\rightarrow$ Mechanism: Separate bargaining

Threats from automation that has not happened yet have real labor market consequences, which is a contrast to the predictions from simple wage-setting models

Conclusion

- Policy implications:
  - Minimum wage
    - → Need to consider firms' response to higher labor cost
    - → Higher minimum wage $\Longrightarrow$ Robot adoption (Gauthier, 2025)
  - Collective bargaining agreements
  - Sector-specific training programs
    - → Need to consider the effectiveness of the program (e.g., Katz et al., 2022)
  - Any policy improving mobility and reducing labor market frictions

Automation Threat and Labor Market Power

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June 2025

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Appendix

Firm's Actual Robot Adoption and District-Level Exposure Shock

Back

	(1)	(2)	(3)	(4)
	Panel A. Robots per 1000 workers			
Robot exposure shock	0.047	0.065	0.068	0.114
	(0.029)	(0.152)	(0.153)	(0.195)
Observations	6442	6418	6418	6215
R^2	0.02	0.17	0.18	0.75
	Panel B. ΔRobots per 1000 workers			
ΔRobot exposure shock	0.034	-0.148	-0.169	-0.160
	(0.060)	(0.104)	(0.104)	(0.128)
Observations	5275	5256	5256	5050
R^2	0.01	0.11	0.12	0.46
Year FE	✓	✓		
State FE	✓			
District FE		✓	✓	
State-by-Year FE			✓	✓
Firm FE				✓

Actual Robot Adoption and Exposure Shock in East Germany ▸ Back

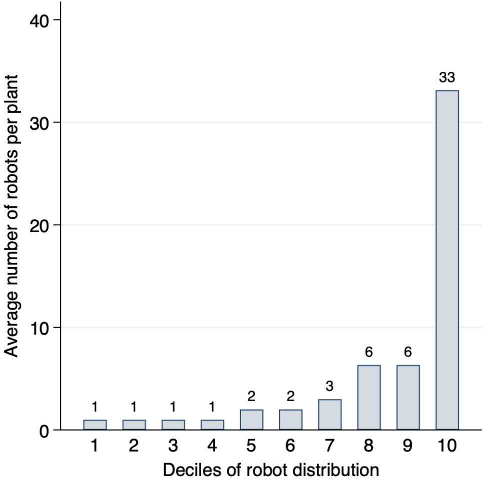
	All industries			Automobile industry		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Robots per 1000 workers					
Robot exposure shock	0.213	0.492	0.373	2.302	4.253	4.605
	(0.087)	(0.844)	(0.867)	(3.448)	(6.332)	(6.315)
Observations	356	356	356	356	356	356
R^2	0.14	0.49	0.53	0.05	0.51	0.54
	Panel B. ΔRobots per 1000 workers					
ΔRobot exposure shock	0.209	1.166	1.130	6.724	2.904	7.905
	(0.858)	(1.737)	(1.720)	(7.407)	(3.614)	(5.873)
Observations	283	282	282	283	282	282
R^2	0.05	0.32	0.34	0.04	0.34	0.39
Year FE	✓	✓		✓	✓	
State FE	✓			✓		
District FE		✓	✓		✓	✓
State-by-Year FE			✓			✓

Actual Robot Adoption and Exposure Shock in West Germany

Back

	All industries			Automobile industry		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Robots per 1000 workers					
Robot exposure shock	-0.014	-0.001	0.007	0.136	-0.221	-0.279
	(0.015)	(0.089)	(0.091)	(0.125)	(0.357)	(0.348)
Observations	1315	1311	1301	1315	1311	1301
R^2	0.03	0.55	0.56	0.02	0.35	0.39
	Panel B. ΔRobots per 1000 workers					
ΔRobot exposure shock	-0.249	-0.234	-0.374	-0.055	-0.154	-0.295
	(0.152)	(0.224)	(0.235)	(0.079)	(0.107)	(0.207)
Observations	1047	1041	1033	1047	1041	1033
R^2	0.02	0.50	0.51	0.01	0.43	0.46
Year FE	✓	✓		✓	✓	
State FE	✓			✓		
District FE		✓	✓		✓	✓
State-by-Year FE			✓			✓

Distribution of Robots (2018, Robot Adopting Firms) ‣ Back



Notes: Based on the IAB Establishment Panel (IAB-BP) data. The figures depict the distribution of the average number of robots per manufacturing plant in 2018. Sampling weights provided in the data are applied.

Fact 2(a): Wage Gap across Regions ▸ Back

Firm-level regression:

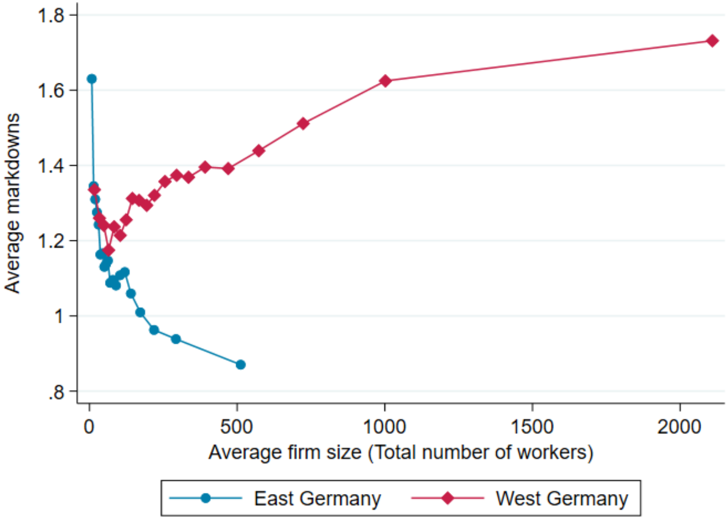
$$Y_{jt} = \beta \mathbb{I}_{j,East} + \mathbf{X}'_{jt}\delta + \gamma_k + \mu_t + \varepsilon_{jt}$$

- Y_{jt} is either (log) average real wage at firm j in year t
- $\mathbb{I}_{j,East}$ is a dummy for whether firm j is located in the East
- $\mathbf{X}'_{jt}$ is a vector firm-level covariates, including workers' average education, female share, and firm size
- γ_k and μ_t are industry and year fixed effects, respectively

Fact 2(a): Wage Gap across Regions
Back

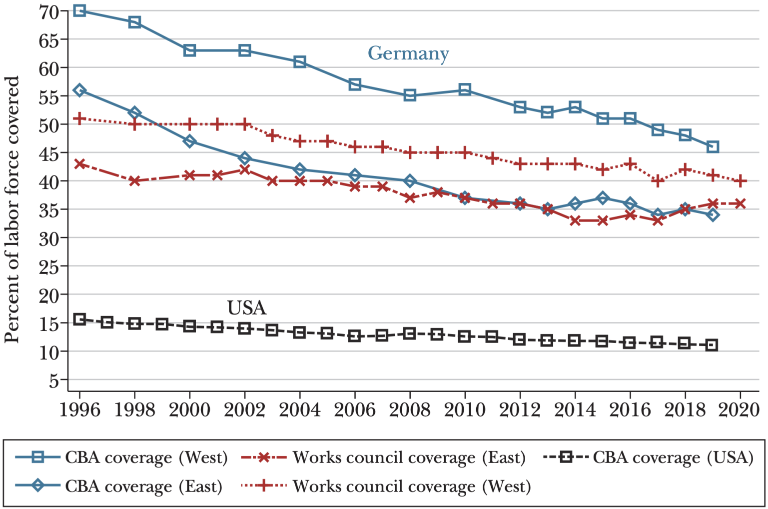
	Dependent variable: Average real daily wage		
	(1)	(2)	(3)
East dummy	-0.173	-0.153	-0.199
	(0.003)	(0.003)	(0.003)
N	207758	207758	207758
R^2	0.04	0.27	0.39
Year fixed effects	✓	✓	✓
Industry fixed effects		✓	✓
Firm characteristics			✓

Markdown Gap between East and West Germany ▸ Back



Fact 2(b): Union Coverage in East and West Germany

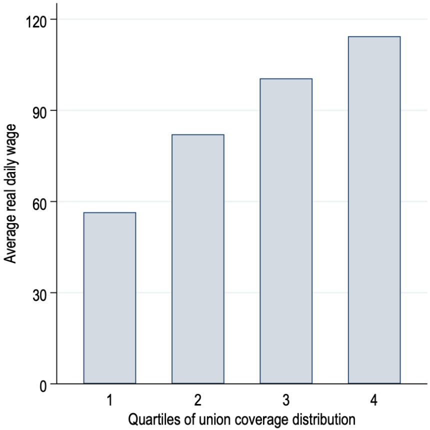
▸ Back



Source: Jäger et al. (2022)

Fact 3: Average Wages along the Distribution of Union Coverage

Back



Notes: Based on the IAB Establishment Panel and the matched employer-employee (LIAB) data. The figure show the average real daily wage per worker at the firm in different quartiles of the union coverage. The firm-level union coverage is measured by the share of workers covered by trade unions in total workers using the IAB establishment panel data. The average daily wage per worker at the firm is calculated using the LIAB data.

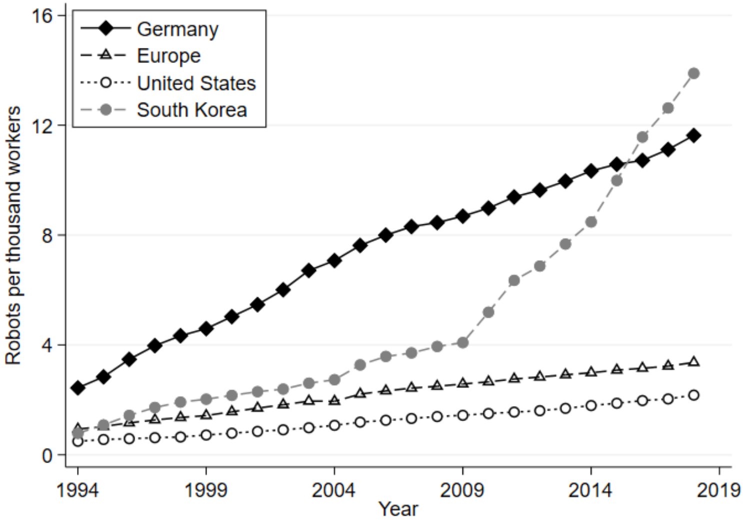
Wage Markdown and Union Coverage

Back

	Median	Mean	SD	Min	Max	N
	Panel A. Union coverage deciles					
First decile	1.258	1.407	0.645	0.416	3.656	1321
Top 9 deciles	1.072	1.178	0.483	0.018	3.641	11485
	Panel B. Union coverage quartiles					
First quartile	1.163	1.308	0.597	0.111	3.656	3229
Top 3 quartiles	1.089	1.206	0.500	0.018	3.641	9577

Notes: The distributional statistics are calculated using sampling weights provided in the data.

Robot Penetration, 1994-2018 ▸ Back



Source: IFR, OECD, BHP or BEH, and own calculations.

Share of Robot Adopters in Manufacturing and Non-Manufacturing

	Weighted (%) (1)	Unweighted (%) (2)	Number of Surveyed Plants (3)
Manufacturing	7.19	12.48	1755
Non-manufacturing	0.96	0.92	6953
Total	1.48	3.25	8708

Notes: Based on the IAB Establishment Panel data in 2018.

Back

IFR: What is a robot – and what is not? ▸ Back

- "**Robot**" defined by International Standards Organization (ISO)
  - IFR members use the definitions contained in the international standard ISO 8373 "Vocabulary" when compiling statistics of industrial robots in particular countries for example. A robot is defined as "a programmed actuated mechanism with a degree of autonomy to perform locomotion, manipulation or positioning".
  - Accordingly, an industrial robot is defined to be an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment."
- **No robots:**
  - software ("bots", AI, Robotic Process Automation-RPA)
  - remote-controlled drones, UAV, UGV, UUV
  - voice assistants
  - autonomous cars
  - ATMs, smart washing machines, etc.

Measuring Labor Market Power: Markdown Estimation

- Estimate plant-level markdowns ν_{jt} using "production" approach following Yeh et al. (2022)
  - Estimate plant-level markup μ_{jt} in the spirit of De Loecker and Warzynski (2012)
  - Estimate production function using "proxy variable" method (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015)
  - Compute output elasticities, under translog production function, as

$$\theta_{jt}^{L} = \hat{\beta}_{l} + \hat{\beta}_{kl} k_{jt} + \hat{\beta}_{lm} m_{jt} + 2\hat{\beta}_{ll} l_{jt}$$
$$\theta_{jt}^{M} = \hat{\beta}_{m} + \hat{\beta}_{km} k_{jt} + \hat{\beta}_{lm} l_{jt} + 2\hat{\beta}_{mm} m_{jt}$$

- Production function estimation
  - General form of production function (in log terms):

$$\begin{aligned} y_{jt} &= f(\mathbf{x}_{jt}; \beta) + \omega_{jt} + \varepsilon_{jt} \\ &= f(\mathbf{v}_{jt}, \mathbf{k}_{jt}; \beta) + \omega_{jt} + \varepsilon_{jt} \end{aligned}$$

    where fully flexible inputs $\mathbf{v}_{jt} = m_{jt}$ and non-fully flexible inputs $\mathbf{k}_{jt} = (k_{jt}, l_{jt})'$.
  - Proxy unobserved productivity ω_{jt} with $\omega_{jt} = g_t(m_{jt}; \mathbf{k}_{jt}, \mathbf{c}_{jt})$ Back

Production Function Estimation

- Three-step process to estimate β vector:
  - **Step 1:** Non-parametric estimation of y_{jt} on $\mathbf{x}_{jt}$

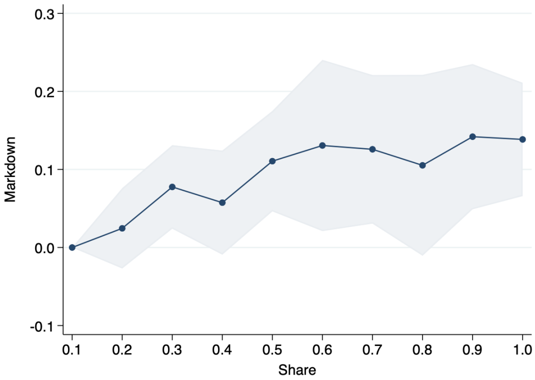
$$\mathbf{x}_{jt} = (k_{jt}, l_{jt}, m_{jt}, k_{jt}l_{jt}, k_{jt}m_{jt}, l_{jt}m_{jt}, k_{jt}^2, l_{jt}^2, m_{jt}^2)'$$

  - **Step 2:** Obtain innovations ξ_{jt} to productivity ω_{jt} using $\omega_{jt} = s_t(\omega_{jt-1}) + \xi_{jt}$
  - **Step 3:** Identify parameters β using GMM-IV with instruments $\mathbf{z}_{jt}$: one-period lagged values of every polynomial term in $f(\mathbf{x}_{jt}; \beta)$ including l_{jt} and m_{jt} but capital at the current period k_{jt}

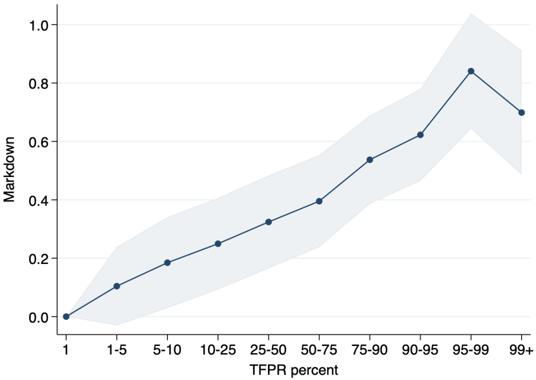
Back

Plant-Level Markdown and Firm Characteristics

(a) Size



(b) Productivity



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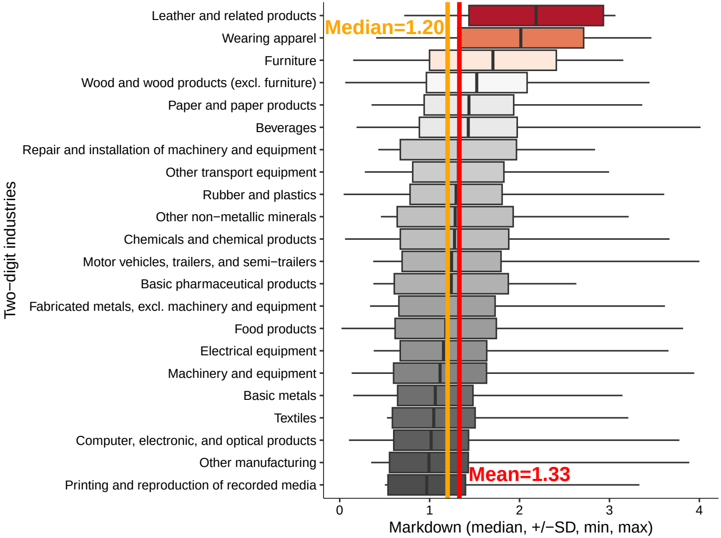
Wage Markdowns Estimated Separate for East and West Germany



- Sample size = 9,431 Back

Markdown Gap between East and West Germany ▸ Back

- Workers in median manufacturer in West (East) Germany earns 85 (80) cents

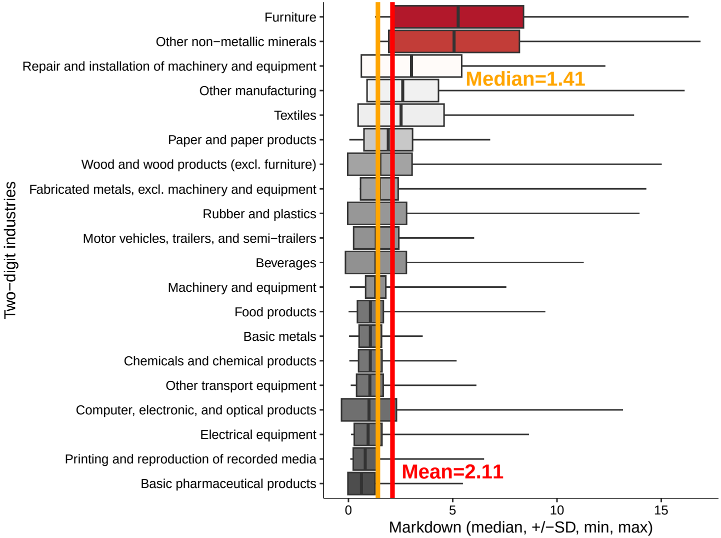
	Median	Mean	$IQR_{75\text{-}25}$	SD	N
East Germany	1.256	1.364	0.687	0.535	4400
West Germany	1.181	1.316	0.702	0.577	4996

Notes: The distributional statistics are calculated using sampling weights provided in the data.

	Dependent variable: Wage markdowns		
	(1)	(2)	(3)
East dummy	0.045	0.026	0.040
	(0.013)	(0.013)	(0.013)
N	9432	9432	9432
R^2	0.02	0.22	0.22
Year fixed effects	✓	✓	✓
Industry fixed effects		✓	✓
Firm characteristics			✓

Notes: Regressions are weighted by sampling weights provided in the data.

Wage Markdowns Estimated Specific across Industries



- Sample size = 12,588 Back

Labor Market Concentration (Manufacturing, 2018)

	Mean	Min	Max	25th Pctile	75th Pctile	fraction moderate conc.	fraction high conc.
	Panel A. By Occupation × Region						
Baseline geographical definition: 141 CZs							
HHI (By 3-digit KldB 1988)	5800	204	10000	2638	10000	0.13	0.76
Alternative occupational definition:							
HHI (By 3-digit KldB 2010)	5285	145	10000	2200	10000	0.15	0.70
HHI (By 2-digit KldB 1988)	4907	183	10000	2000	8828	0.17	0.66
HHI (By 2-digit KldB 2010)	4022	177	10000	1429	5547	0.18	0.55
HHI (By 1-digit Blossfeld)	2871	150	10000	909	3863	0.18	0.38
Alternative geographical definition:							
HHI (By Kreis)	6747	313	10000	3750	10000	0.10	0.86
HHI (By 258 CZs)	6327	253	10000	3333	10000	0.12	0.82
HHI (By 42 regions)	4814	75	10000	1724	9260	0.16	0.63
HHI (By Federal state	4152	75	10000	1250	6250	0.16	0.54

- Average HHI of 5,800 implies that the equivalent number of firms recruiting is only 1.7. By Industry × Region Back

Labor Market Concentration (Manufacturing, 2018)

	Mean	Min	Max	25th Pctile	75th Pctile	% moderate conc.	% high conc.
	Panel B. By Industry × Region						
Baseline geographical definition: 141 CZs							
HHI (By 3-digit ISIC Rev.4)	6003	198	10000	3061	10000	0.11	0.80
Alternative industrial definition:							
HHI (By 2-digit ISIC Rev.4)	4328	162	10000	1746	6250	0.18	0.62
Alternative geographical definition:							
HHI (By Kreis)	7103	284	10000	4400	10000	0.07	0.91
HHI (By 258 CZs)	6645	310	10000	3750	10000	0.09	0.86
HHI (By 42 regions)	4721	113	10000	1911	7278	0.15	0.66
HHI (By Federal state)	4021	69	10000	1511	5702	0.18	0.57

Back

Aggregation Approach: Wage Markdowns

- Following Yeh et al. (2022), I define

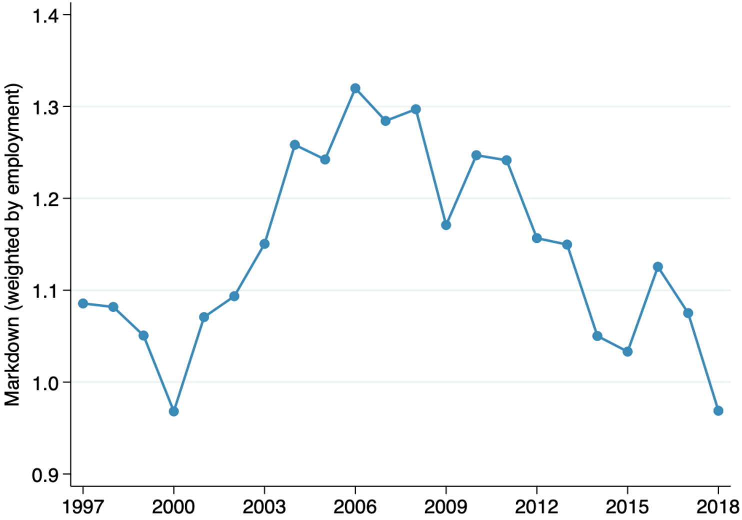
$$\mathcal{V}_t = \sum_{k \in K} \sum_{l \in L} \omega_{klt} \mathcal{V}_{klt}, \tag{1}$$

where ω_{klt} is the employment share of labor market (k, l), and aggregate markdown at the local labor market is

$$\mathcal{V}_{klt} = \frac{\left(\sum_{j \in F_t(k,l)} s_{jt} \cdot \frac{\theta^L_{jt}}{\theta^L_{klt}} \cdot \left(\nu_{jt} \mu_{jt} \right)^{-1} \right)^{-1}}{\left(\sum_{j \in F_t(k,l)} s_{jt} \cdot \frac{\theta^M_{jt}}{\theta^M_{klt}} \cdot \mu_{jt}^{-1} \right)^{-1}}, \tag{2}$$

where θ^L_{klt} and θ^M_{klt} are respectively the average output elasticities of labor and intermediate materials in industry k, location l, and year t. Here $s_{jt} = \frac{p_{jt} y_{jt}}{P_{klt} Y_{klt}}$ are sales weights. Back

Trend of Aggregate Markdowns under Cobb-Douglas Specification



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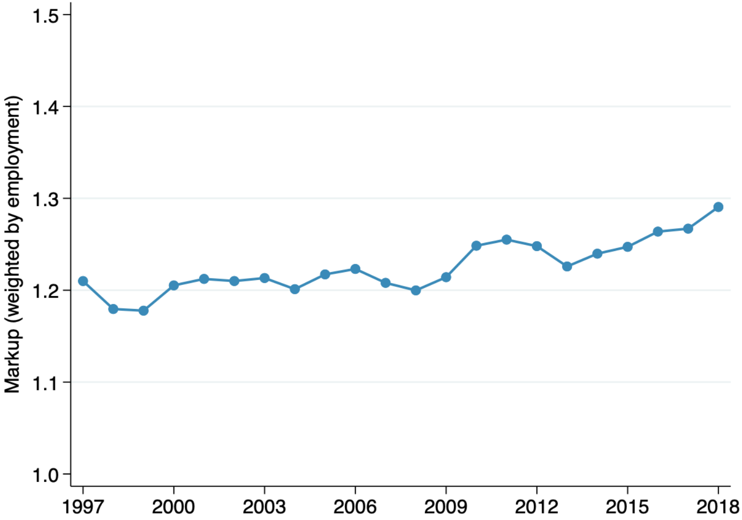
Trend of Aggregate Markups



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Aggregation Approach: Labor Market Concentration

- The average HHI are calculated by weighted average using employment weights:

$$\mathrm{HHI}_t = \sum_{o \in O} \sum_{l \in L} \omega_{olt} \mathrm{HHI}_{olt}, \tag{3}$$

where

$$\mathrm{HHI}_{mt} = \sum_{j=1}^{J} s_{jmt}^2, \tag{4}$$

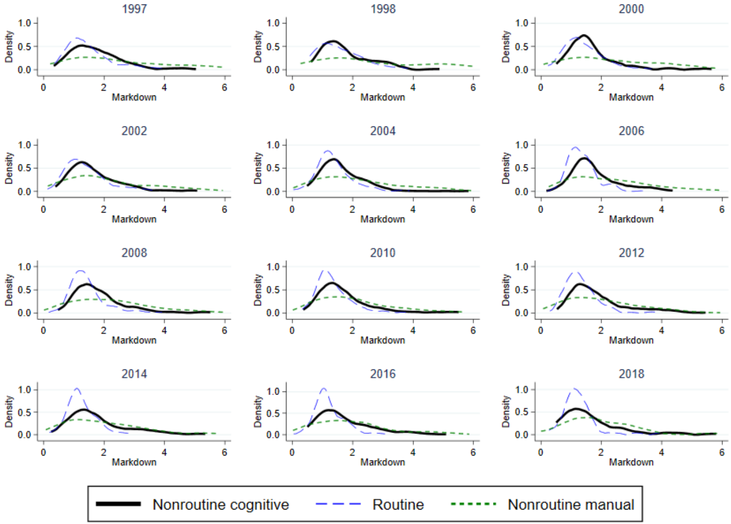
where s_{jmt}^2 is the market share of firm j in market $m = (o, l)$, and o and l denotes occupation and geography index, respectively. Back

Cross-sectional Correlation between Aggregate Markdown and HHI

Year	$\rho(\mathcal{V}_{jlt}, \text{HHI}_{jlt}^{IAB\text{-}BP})$	$\rho(\text{HHI}_{jlt}^{IAB\text{-}BP}, \text{HHI}_{jlt}^{LIAB})$	$\rho(\mathcal{V}_{jlt}, \text{HHI}_{jlt}^{LIAB})$
1998	0.156**	0.143**	0.203***
2000	0.045	0.149**	0.129**
2002	0.085*	0.213***	0.056
2004	0.055	0.203***	0.103**
2006	0.011	0.220***	0.085*
2008	-0.021	0.237**	0.074
2010	-0.042	0.330***	0.038
2012	0.026	0.266***	0.131**
2014	-0.028	0.223***	0.020
2016	-0.014	0.138**	0.045
2018	0.072	0.258***	0.122
Average	**0.024****	**0.215*****	**0.081*****

Back

Distributions of Markdowns for NRC, Routine, NRM Workers



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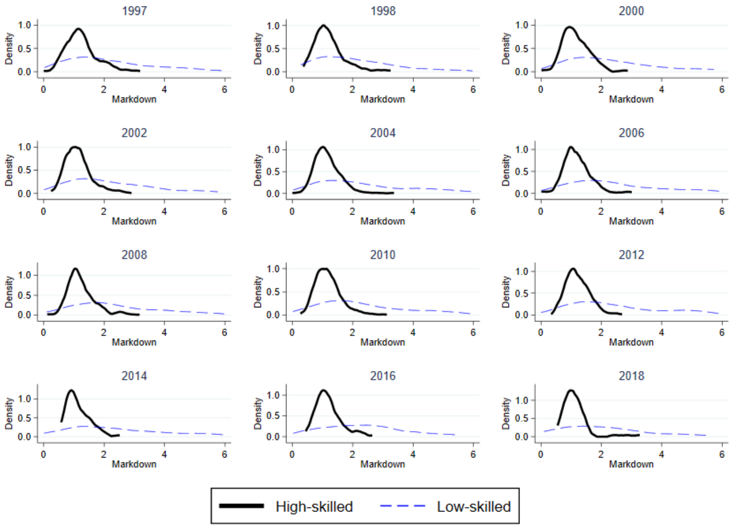
Distributions of Markdowns for High- and Low-Skilled Workers



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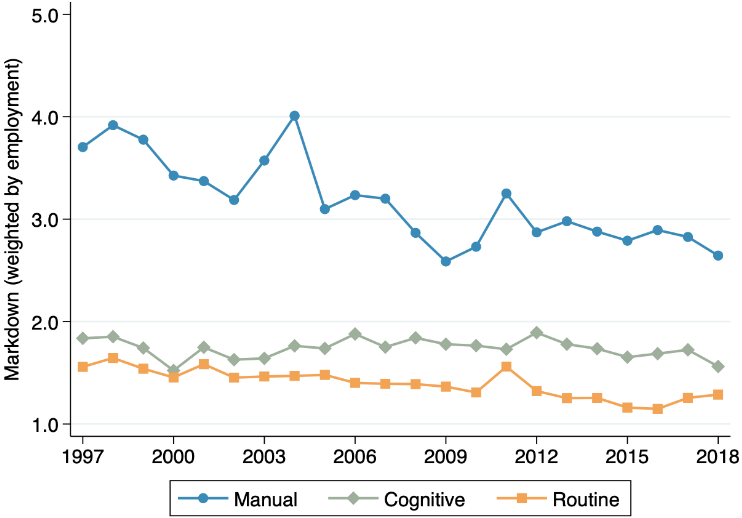
Trend of Aggregate Markdowns for NRC, Routine, and NRM Workers



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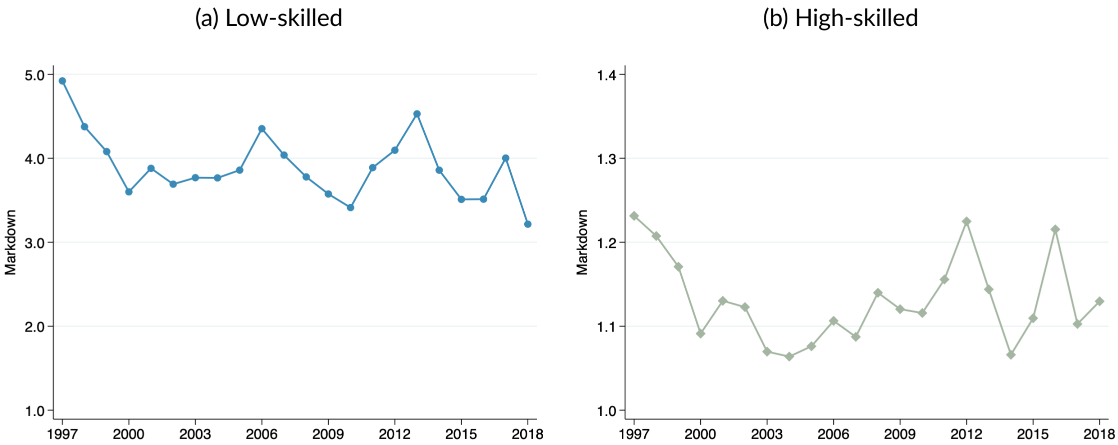
Trend of Aggregate Markdowns for High- and Low-Skilled Workers



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Robustness of Markdowns for Heterogeneous Workers

	Median	Mean	$IQR_{75\text{-}25}$	SD	N
Routine workers	1.075	1.185	0.656	0.566	3779
Abstract workers	1.069	1.280	0.866	0.807	3779
Manual workers	1.634	2.310	1.355	2.354	3779

Notes: Workers are classified based on Autor and Dorn (2013)'s task contents measures that are based on O*NET data. The distributional statistics are calculated using sampling weights provided in the data.

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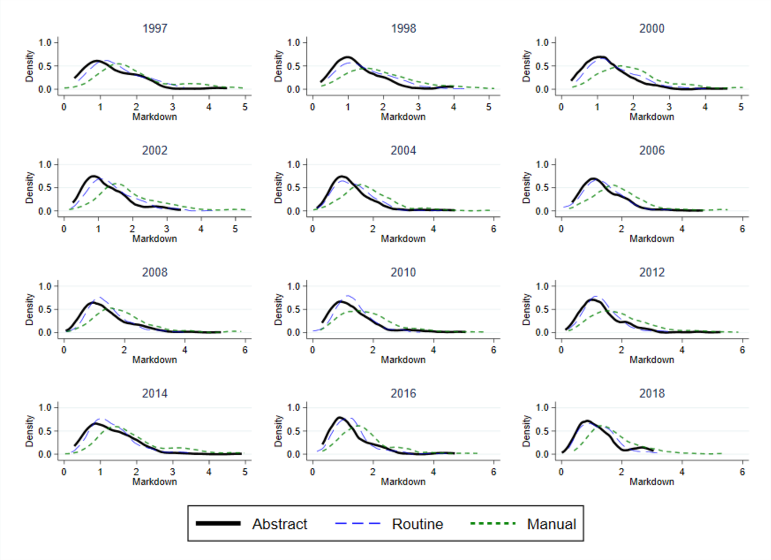
Distributions of Markdowns for Abstract, Routine, Manual Workers



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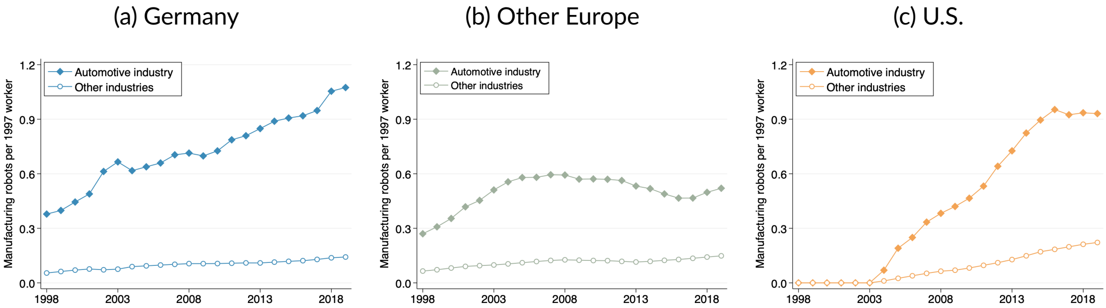
Manufacturing Robots in Automotive and Other Industries



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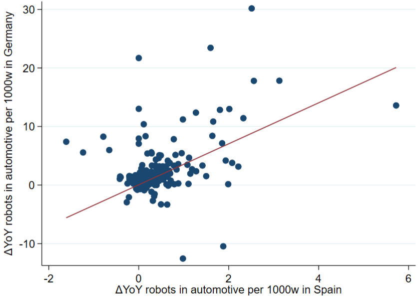
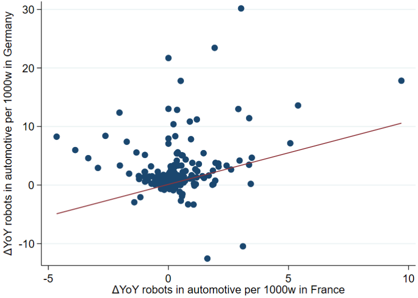
Identification Assumptions ⏩ Back

1. Relevance or inclusion restriction
   - Changes in Germany's robots exposure is strongly correlated with those in other European countries

(a) Spain



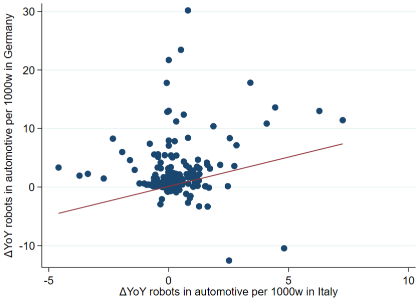
(b) France



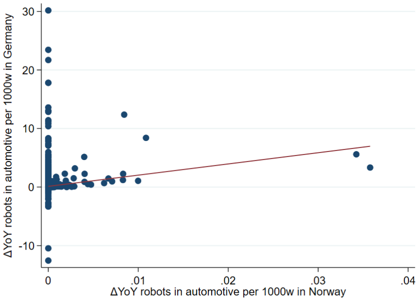
Identification Assumptions ⏩ Back

1. Relevance or inclusion restriction
    - Changes in Germany's robots exposure is strongly correlated with those in other European countries

(c) Italy



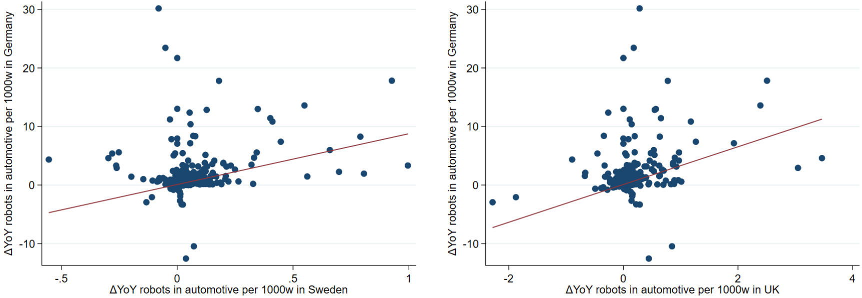
(d) Norway



Identification Assumptions ⏩ Back

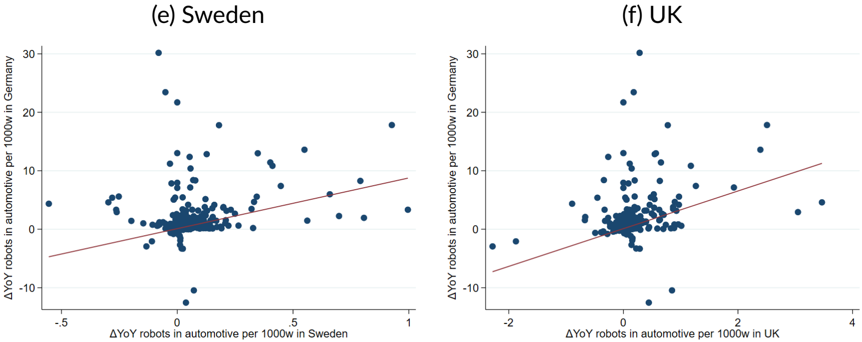
1. Relevance or inclusion restriction
   - Changes in Germany's robots exposure is strongly correlated with those in other European countries

(e) Sweden (f) UK



Identification Assumptions ⏩ Back

1. Relevance or inclusion restriction
   - Changes in Germany's robots exposure is strongly correlated with those in other European countries



   - Overidentified models with a single endogenous variable where SEs are clustered → Weak IV test (Olea and Pflueger, 2013)
   - Montiel Olea-Pflueger test + Traditional test (Staiger and Stock, 1997; Stock and Yogo, 2005; Kleibergen and Paap, 2006) $\implies$ Endog. regressor and instruments are strongly correlated

Identification Assumptions ⏩ Back

2. Independence
   - Shocks to the robot adoption in other European countries are unrelated to changes in local economic conditions in Germany (Borusyak et al., 2022)
   - Overidentified model (# instruments $>$ # endog. variables) $\implies$ Overidentifying restrictions test (i.e., all IVs are uncorrelated to ϵ_{rt}) (Sargan, 1958, 1998; Hansen, 1982; Altonji et al., 2005)
   - Sargan-Hansen test $\implies$ “Shifts” or shocks are plausibly orthogonal to unobserved factors that determine the outcomes

Identification Assumptions ⏩ Back

3. Partial monotonicity

   - Monotonicity: The choice behavior or Germany's robot adoption is homogeneous, i.e., the 2SLS estimate is a positively weighted average of LATEs (Imbens and Angrist, 1994)

   - 2SLS estimates can be a positively weighted average of LATEs under a weaker and verifiable condition of "partial" monotonicity (Mogstad et al., 2021)

     $\rightarrow$ Indirect test $\Longrightarrow$ 2SLS weights are positive ⏩ Continuous variables ⏩ Binary variables

     $\rightarrow$ Formal test $\Longrightarrow$ Partial monotonicity assumption is plausible ⏩ Binary variables

Testing for Positive 2SLS Weights

	Germany's exposure to robots (1)	Spain's exposure to robots (2)
	Panel A. Continuous treatment and continuous instruments	
France's exposure to robots	1.010***	0.385***
	(0.281)	(0.033)
Italy's exposure to robots	0.913***	0.348***
	(0.226)	(0.071)
Norway's exposure to robots	149.839***	14.775***
	(43.861)	(4.265)
Sweden's exposure to robots	7.669***	1.654***
	(1.104)	(0.477)
UK's exposure to robots	2.928***	0.694***
	(0.323)	(0.192)
Spain's exposure to robots	3.285***	1.000
	(0.232)	–

Back

Testing for Positive 2SLS Weights

	Germany's exposure to robots (1)	Spain's exposure to robots (2)
	Panel B. Binary treatment and binary instruments	
France's exposure to robots	0.546***	0.763***
	(0.044)	(0.029)
Italy's exposure to robots	0.547***	0.712***
	(0.045)	(0.029)
Norway's exposure to robots	0.412***	0.411***
	(0.057)	(0.060)
Sweden's exposure to robots	0.592***	0.637***
	(0.047)	(0.031)
UK's exposure to robots	0.618***	0.699***
	(0.045)	(0.023)
Spain's exposure to robots	0.650***	1.000
	(0.042)	–

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Formal Test for Partial Monotonicity

	p-value: positive weights (1)	p-value: negative weights (2)
	Panel A. Exposure to robots in Spain and another country	
France's exposure to robots	1.000	0.000
Italy's exposure to robots	1.000	0.000
Norway's exposure to robots	1.000	0.000
Sweden's exposure to robots	1.000	0.000
UK's exposure to robots	1.000	0.000
	Panel B. Exposure to robots in France and another country	
Italy's exposure to robots	1.000	0.000
Norway's exposure to robots	1.000	0.000
Sweden's exposure to robots	1.000	0.000
UK's exposure to robots	1.000	0.000

Continued

Formal Test for Partial Monotonicity

	p-value: positive weights (1)	p-value: negative weights (2)
	Panel C. Exposure to robots in Italy and another country	
Norway's exposure to robots	1.000	0.000
Sweden's exposure to robots	1.000	0.000
UK's exposure to robots	1.000	0.000
	Panel D. Exposure to robots in Norway and in another country	
Sweden's exposure to robots	1.000	0.000
UK's exposure to robots	1.000	0.000
	Panel E. Exposure to robots in Sweden and in another country	
UK's exposure to robots	1.000	0.000

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Baseline Results: Wage Markdowns (OLS)

	Dependent variable: Annual change in aggregate markdowns			
	(1)	(2)	(3)	(4)
ΔPredicted robot exposure	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Year FE, $\mu_{REG(r)}$, Demographics	✓	✓	✓	✓
Manufacturing share	✓			
Broad industry shares		✓	✓	✓
ΔNet exports			✓	✓
ΔICT equipment				✓

Notes: $N = 4599$ local labor market regions-by-year (district-by-year).

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Baseline Results: Wage Markdowns (2SLS)

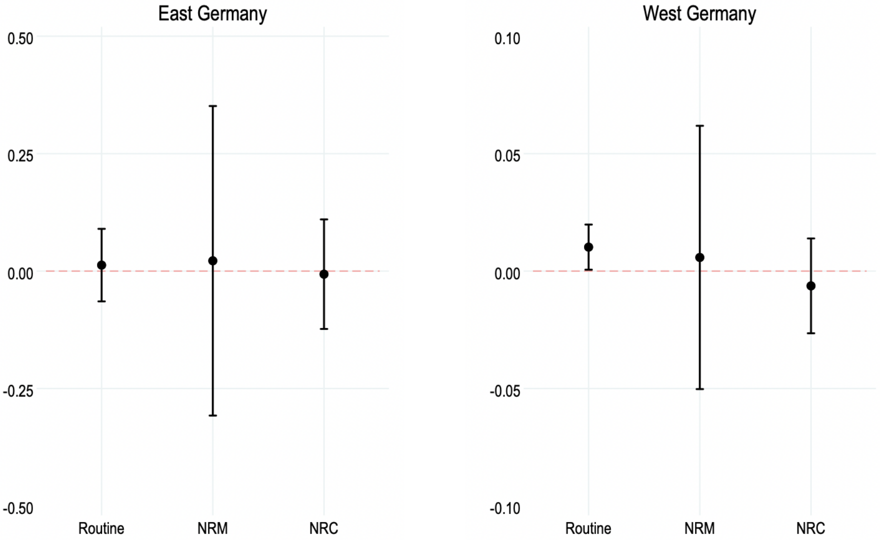
Back

	Dependent variable: Annual change in aggregate markdowns			
	(1)	(2)	(3)	(4)
ΔPredicted robot exposure	0.0007	-0.0000	0.0000	0.0001
	(0.0180)	(0.0164)	(0.0242)	(0.0038)
Montiel Olea-Pflueger weak IV test				
Effective F-statistic ($\alpha = 5\%$)	43.97	46.21	46.23	46.25
Critical value 2SLS ($\tau = 10\%$)	21.23	21.31	21.31	21.31
Hansen's *J*-stat *p*-value	0.36	0.36	0.36	0.36
Year FE, $\mu_{REG(r)}$, Demographics	✓	✓	✓	✓
Manufacturing share	✓			
Broad industry shares		✓	✓	✓
ΔNet exports			✓	✓
ΔICT equipment				✓

Notes: $N = 4599$ local labor market regions-by-year (district-by-year).

Heterogeneous Effects: Markdowns in East/West Germany

Back



Common Production: Markdowns for Hetero. Workers in the East

	Dependent variable: Annual change in aggregate markdowns		
	Routine	NRM	NRC
	(1)	(2)	(3)
ΔPredicted robot exposure	0.024	0.035	-0.015
	(0.024)	(0.053)	(0.020)
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	71.08	71.08	71.08
Critical value 2SLS ($\tau = 10\%$)	23.04	23.04	23.04
Hansen's J-stat p-value	0.56	0.81	0.52
N	1449	1449	1449
R^2	0.03	0.03	0.02

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Common Production: Markdowns for Hetero. Workers in the West

	Dependent variable: Annual change in aggregate markdowns		
	Routine (1)	NRM (2)	NRC (3)
ΔPredicted robot exposure	0.005	0.000	-0.003
	(0.005)	(0.022)	(0.009)
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	86.86	86.86	86.86
Critical value 2SLS ($\tau = 10\%$)	22.69	22.69	22.69
Hansen's *J*-stat *p*-value	0.36	0.43	0.68
N	3150	3150	3150

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Common Production: Markdowns for Hetero. Workers in the East

	Dependent variable: Annual change in aggregate markdowns					
	Union: Below the median			Union: Above the median		
	Routine	NRM	NRC	Routine	NRM	NRC
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPredicted robot exposure	0.109	0.086	0.050	0.000	0.010	-0.036
	(0.026)	(0.071)	(0.028)	(0.072)	(0.153)	(0.085)
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	14.94	14.94	14.94	256.97	256.97	256.97
Critical value 2SLS ($\tau = 10\%$)	21.98	21.98	21.99	22.34	22.34	22.34
Critical value 2SLS ($\tau = 20\%$)	14.23	14.23	14.23	14.46	14.46	14.46
Hansen's J-stat p-value	0.48	0.77	0.91	0.70	0.91	0.42
N	527	527	527	922	922	922

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Common Production: Markdowns for Hetero. Workers in the West

	Dependent variable: Annual change in aggregate markdowns					
	Union: Below the median			Union: Above the median		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
ΔPredicted robot exposure	0.005	-0.000	0.001	0.005	0.009	-0.005
	(0.031)	(0.078)	(0.062)	(0.011)	(0.021)	(0.012)
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	13.53	13.53	13.53	33.50	33.50	33.50
Critical value 2SLS ($\tau = 10\%$)	21.11	21.11	21.11	22.37	22.37	22.37
Critical value 2SLS ($\tau = 20\%$)	13.51	13.51	13.51	14.48	14.48	14.48
Hansen's J-stat p-value	0.36	0.38	0.59	0.86	0.54	0.69
N	1660	1660	1660	1490	1490	1490

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Alternative Union Split: Markdowns for Hetero. Workers in the East

	Dependent variable: Annual change in aggregate markdowns		
	Routine (1)	NRM (2)	NRC (3)
ΔPredicted robot exposure	0.023	0.059	-0.026
	(0.008)	(0.029)	(0.008)
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	9.40	9.40	9.40
Critical value 2SLS ($\tau = 10\%$)	22.84	22.84	22.84
Critical value 2SLS ($\tau = 20\%$)	14.85	14.85	14.85
Critical value 2SLS ($\tau = 30\%$)	11.85	11.85	11.85
Hansen's J-stat p-value	0.34	0.76	0.75
N	1238	1238	1238

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Alternative Union Split: Markdowns for Hetero. Workers in the West

	Dependent variable: Annual change in aggregate markdowns		
	Routine (1)	NRM (2)	NRC (3)
ΔPredicted robot exposure	0.014	0.010	-0.016
	(0.133)	(0.306)	(0.150)
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	6.59	6.59	6.59
Critical value 2SLS ($\tau = 10\%$)	22.85	22.85	22.85
Critical value 2SLS ($\tau = 20\%$)	14.86	14.86	14.86
Critical value 2SLS ($\tau = 30\%$)	11.86	11.86	11.86
Hansen's J-stat p-value	0.36	0.34	0.46
N	2590	2590	2590

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Percent Changes: Markdowns for Hetero. Workers in the East

	Dependent variable: Annual change in aggregate markdowns					
	Union: Below the median			Union: Above the median		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
ΔPredicted robot exposure	14.908	27.304	2.607	0.274	5.273	-7.025
	(7.588]	(14.185)	(7.431)	(15.674)	(26.129)	(14.982)
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	5.04	5.04	5.04	243.88	243.88	243.88
Critical value 2SLS ($\tau = 10\%$)	22.29	22.29	22.29	21.66	21.66	21.66
Critical value 2SLS ($\tau = 20\%$)	14.44	14.44	14.44	13.93	13.93	13.93
Critical value 2SLS ($\tau = 30\%$)	11.49	11.49	11.49	11.05	11.05	11.05
Hansen's J-stat p-value	0.71	0.76	0.83	0.53	0.46	0.74
N	527	527	527	922	922	922

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Percent Changes: Markdowns for Hetero. Workers in the West

	Dependent variable: Annual change in aggregate markdowns					
	Union: Below the median			Union: Above the median		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
ΔPredicted robot exposure	7.224	5.281	0.656	0.964	0.020	-0.660
	(14.955)	(22.188)	(9.452)	(2.129)	(5.986)	(2.145)
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	18.10	18.10	18.10	44.67	44.67	44.67
Critical value 2SLS ($\tau = 10\%$)	19.73	19.73	19.73	22.45	22.45	22.45
Critical value 2SLS ($\tau = 20\%$)	12.48	12.48	12.48	14.55	14.55	14.55
Critical value 2SLS ($\tau = 30\%$)	9.81	9.81	9.81	11.58	11.58	11.58
Hansen's *J*-stat *p*-value	0.71	0.77	0.26	0.77	0.90	0.74
N	1660	1660	1660	1490	1490	1490

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Alternative Clusters: Wage Markdowns

	Dependent variable: Annual change in aggregate markdowns			
	All workers	Heterogeneous workers		
		Routine	NRM	NRC
	(1)	(2)	(3)	(4)
ΔPredicted robot exposure	0.0001	0.0091	0.0070	-0.0035
	(0.0038)	(0.0038)	(0.0096)	(0.0057)
Montiel Olea-Pflueger weak IV test				
Effective F-statistic ($\alpha = 5\%$)	43.00	43.00	43.00	43.00
Critical value 2SLS ($\tau = 10\%$)	21.56	21.56	21.56	21.56
Hansen's J-stat p-value	0.50	0.15	0.18	0.44

Notes: $N = 4599$ local labor market regions-by-year (district-by-year).

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Auto + Non-Auto: Markdowns for Hetero. Workers in the East

	Dependent variable: Annual change in aggregate markdowns					
	Union: Below the median			Union: Above the median		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
ΔPredicted robot exposure	0.058	0.069	0.005	0.007	-0.011	-0.011
(*automobile industry*)	(0.068)	(0.237)	(0.059)	(0.044)	(0.158)	(0.056)
Kleibergen-Paap weak ID test	32.35	32.35	32.35	83.73	83.73	83.73
Hansen's J-stat p-value	0.94	0.86	0.85	0.64	0.58	0.49
N	527	527	527	922	922	922

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Auto + Non-Auto: Markdowns for Hetero. Workers in the West

	Dependent variable: Annual change in aggregate markdowns					
	Union: Below the median			Union: Above the median		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
ΔPredicted robot exposure	0.033	0.077	-0.002	0.006	-0.000	-0.006
(*automobile industry*)	(0.089)	(1.231)	(0.095)	(0.005)	(0.017)	(0.003)
Kleibergen-Paap weak ID test	14.55	14.55	14.55	20.33	20.33	20.33
Hansen's J-stat p-value	0.90	0.79	0.54	0.71	0.33	0.91
N	1660	1660	1660	1490	1490	1490

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Robots in All Industries: Markdowns for Hetero. Workers in the East

	Dependent variable: Annual change in aggregate markdowns		
	Routine (1)	NRM (2)	NRC (3)
ΔPredicted robot exposure	0.007	0.001	0.000
	(0.006)	(0.028)	(0.006)
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	9.85	9.85	9.85
Critical value 2SLS ($\tau = 10\%$)	20.16	20.15	20.15
Critical value 2SLS ($\tau = 20\%$)	12.88	12.87	12.87
Critical value 2SLS ($\tau = 30\%$)	10.17	10.17	10.17
Hansen's J-stat p-value	0.76	0.32	0.43
N	1238	1238	1238

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Robots in All Industries: Markdowns for Hetero. Workers in the West

	Dependent variable: Annual change in aggregate markdowns		
	Routine (1)	NRM (2)	NRC (3)
ΔPredicted robot exposure	-0.001	0.004	0.000
	(0.009)	(0.024)	(0.010)
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	35.04	35.04	35.04
Critical value 2SLS ($\tau = 10\%$)	17.56	17.56	17.56
Hansen's *J*-stat *p*-value	0.39	0.12	0.81
N	2590	2590	2590

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Firm-Level Analysis ⏩ Back

- Employment
  - ⏩ Baseline ⏩ East and West ⏩ East and West w/ diff. union coverage
- Wages
  - ⏩ Baseline ⏩ East and West ⏩ East and West w/ diff. union coverage
- Wage markdowns
  - ⏩ Baseline ⏩ East and West ⏩ East and West w/ diff. union coverage

Plant-Level Effects on Employment

	Dependent variable: Annual % change in plant-level employment			
	All workers	Heterogeneous workers		
		Routine	NRM	NRC
	(1)	(2)	(3)	(4)
ΔPredicted robot exposure	-0.008	-0.020	-0.009	0.012
	(0.005)	(0.007)	(0.013)	(0.008)
N	7623	7623	7623	7623

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Plant-Level Effects on Employment in the East and West

	Dependent variable: Annual % change in plant-level employment		
	Routine (1)	NRM (2)	NRC (3)
	Panel A. East Germany		
ΔPredicted robot exposure	-0.016	-0.013	0.022
	(0.004)	(0.006)	(0.006)
N	3649	3649	3649
	Panel B. West Germany		
ΔPredicted robot exposure	-0.001	-0.017	0.006
	(0.008)	(0.014)	(0.008)
N	3823	3823	3823

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Plant-Level Employment Effects Heterogeneous by Union Coverage

	Dependent variable: Annual % change in plant-level employment					
	Union: Bottom 8 deciles			Union: Top 2 deciles		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	-0.012	-0.012	0.005	-0.013	-0.023	0.076
	(0.006)	(0.007)	(0.008)	(0.015)	(0.028)	(0.024)
N	3149	3149	3149	224	224	224
	Panel B. West Germany					
ΔPredicted robot exposure	0.008	0.001	-0.015	-0.008	0.000	0.003
	(0.009)	(0.014)	(0.017)	(0.006)	(0.004)	(0.004)
N	3273	3273	3273	182	182	182

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Plant-Level Effects on Wages

	Dependent variable: Annual % change in plant-level average wage			
	All workers	Heterogeneous workers		
		Routine	NRM	NRC
	(1)	(2)	(3)	(4)
ΔPredicted robot exposure	0.002	0.008	-0.006	0.012
	(0.007)	(0.010)	(0.006)	(0.013)
N	7623	7623	7623	7623

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Plant-Level Effects on Wages in the East and West

	Dependent variable: Annual % change in plant-level average wage		
	Routine	NRM	NRC
	(1)	(2)	(3)
	Panel A. East Germany		
ΔPredicted robot exposure	-0.005	-0.001	-0.006
	(0.003)	(0.004)	(0.007)
N	3649	3649	3649
	Panel B. West Germany		
ΔPredicted robot exposure	-0.005	0.013	0.016
	(0.010)	(0.015)	(0.015)
N	3823	3823	3823

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Plant-Level Wage Effects Heterogeneous by Union Coverage

	Dependent variable: Annual % change in plant-level average wage					
	Union: Bottom 8 deciles			Union: Top 2 deciles		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	-0.001	-0.004	0.011	-0.011	0.009	-0.025
	(0.007)	(0.005)	(0.007)	(0.018)	(0.025)	(0.018)
N	3149	3149	3149	224	224	224
	Panel B. West Germany					
ΔPredicted robot exposure	-0.002	-0.005	0.035	0.001	-0.003	0.015
	(0.020)	(0.012)	(0.016)	(0.006)	(0.003)	(0.011)
N	3273	3273	3273	182	182	182

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Plant-Level Effects on Markdowns

	Panel A. All workers		
	Germany (1)	East Germany (2)	West Germany (3)
ΔPredicted robot exposure	0.009	0.009	-0.007
	(0.010)	(0.006)	(0.010)
N	7623	3649	3823
	Panel B. Heterogeneous workers		
	Routine (1)	NRM (2)	NRC (3)
ΔPredicted robot exposure	0.007	0.012	0.001
	(0.007)	(0.008)	(0.009)
N	7623	7623	7623

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Plant-Level Effects on Markdowns in the East and West

	Dependent variable: Annual change in plant-level markdowns		
	Routine (1)	NRM (2)	NRC (3)
	Panel A. East Germany		
ΔPredicted robot exposure	0.012	-0.002	0.002
	(0.005)	(0.009)	(0.008)
N	3649	3649	3649
	Panel B. West Germany		
ΔPredicted robot exposure	-0.002	0.013	-0.005
	(0.004)	(0.014)	(0.006)
N	3823	3823	3823

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Plant-Level Effects on Markdowns Heterogeneous by Union Coverage

	Dependent variable: Annual change in plant-level markdowns					
	Union: Bottom 8 deciles			Union: Top 2 deciles		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	0.018	0.004	-0.004	-0.037	-0.004	0.004
	(0.010)	(0.007)	(0.007)	(0.044)	(0.054)	(0.049)
N	3149	3149	3149	224	224	224
	Panel B. West Germany					
ΔPredicted robot exposure	0.000	0.000	-0.004	-0.001	-0.002	-0.000
	(0.011)	(0.022)	(0.011)	(0.002)	(0.003)	(0.003)
N	3273	3273	3273	182	182	182

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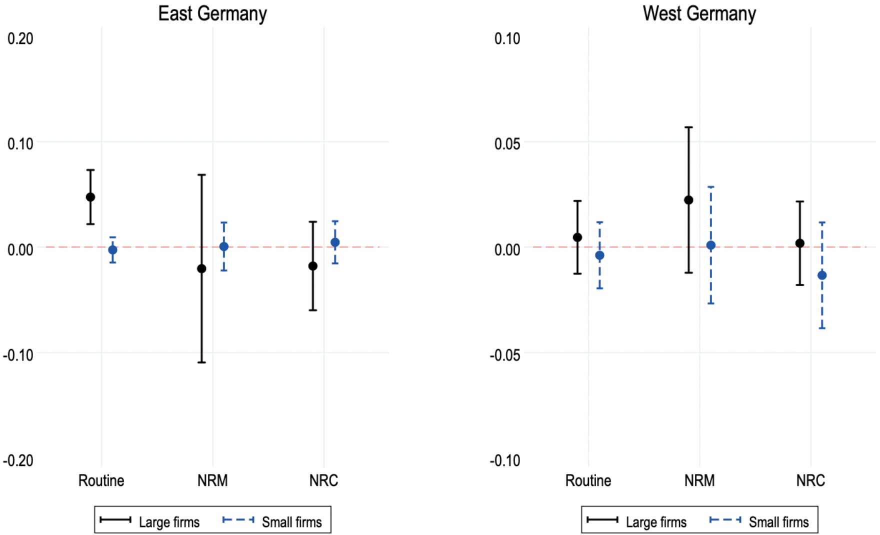
Plant-Level Effects on Markdowns Heterogeneous by Firm Size



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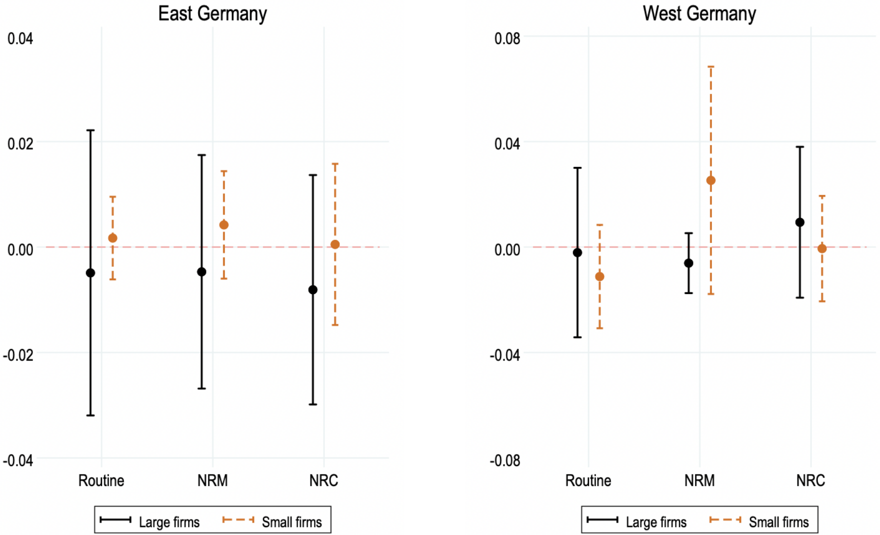
Plant-Level Effects on Wages Heterogeneous by Firm Size



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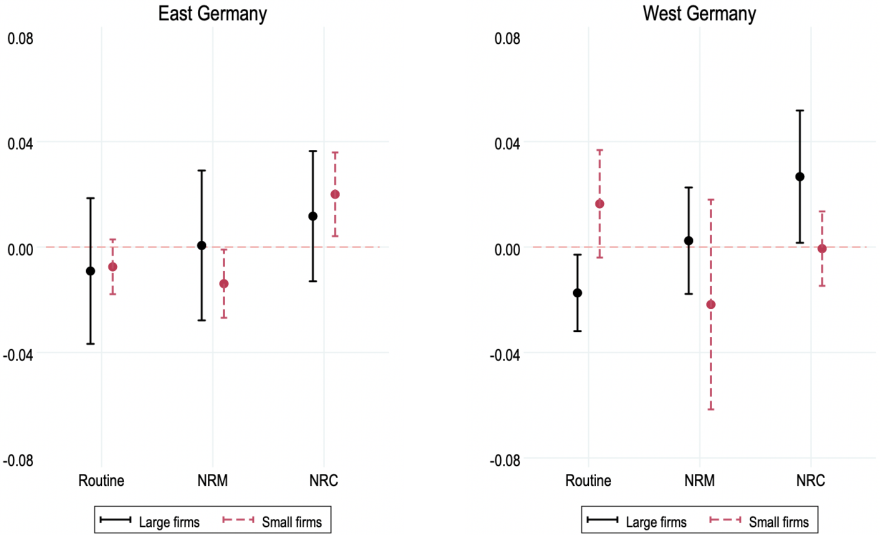
Plant-Level Effects on Employment Heterogeneous by Firm Size



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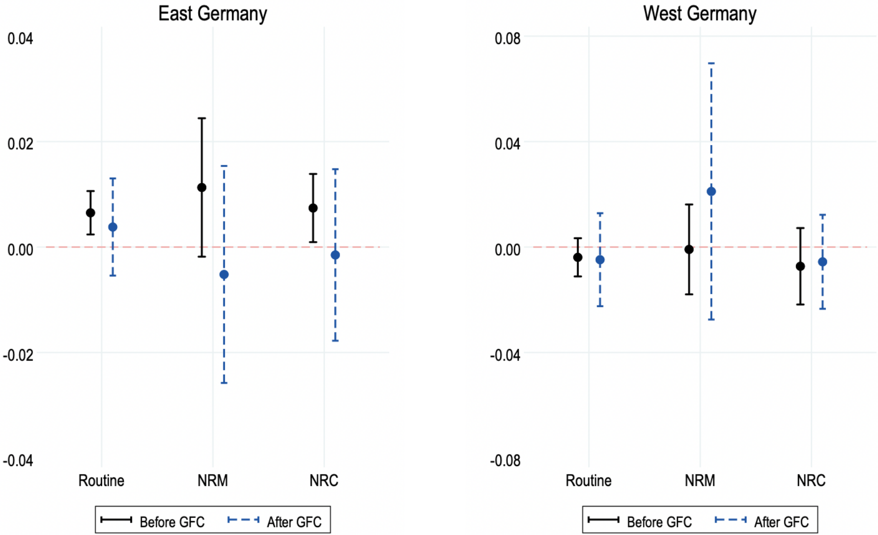
Plant-Level Effects on Markdowns Heterogeneous around GFC



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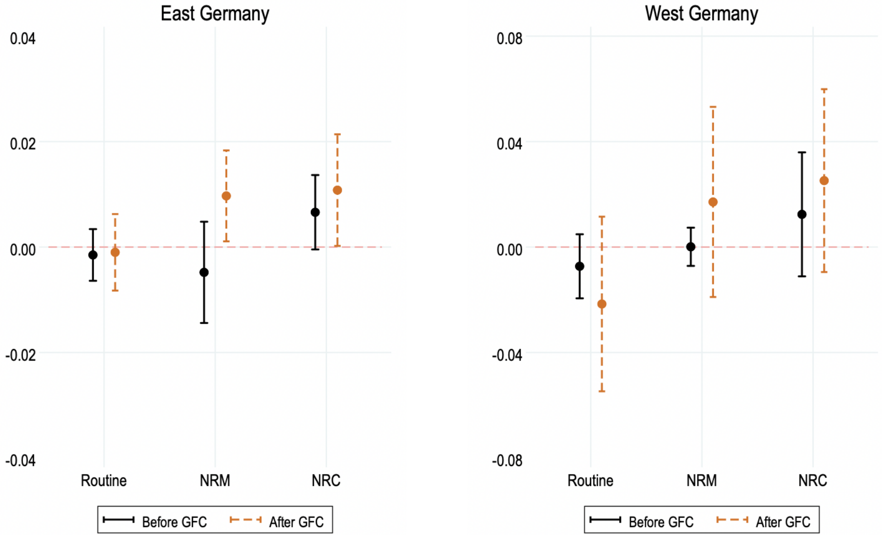
Plant-Level Effects on Wages Heterogeneous around GFC



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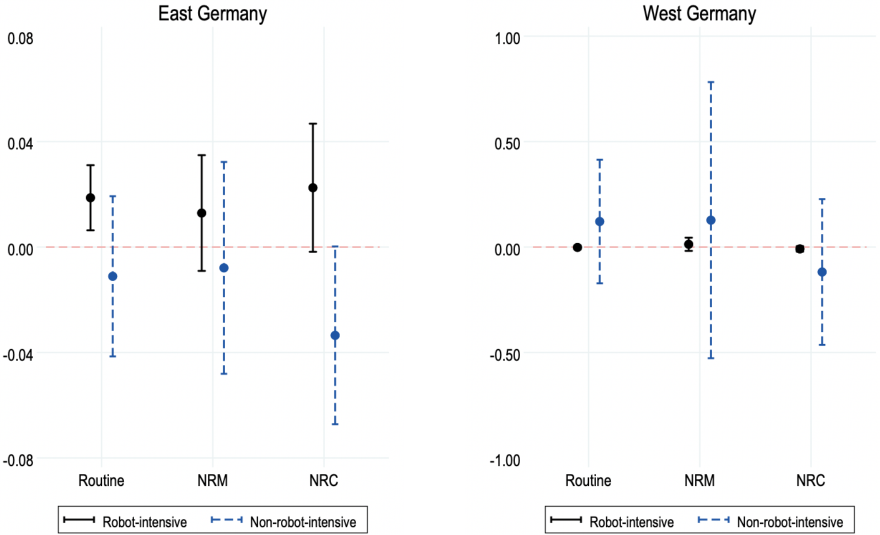
Plant-Level Effects on Markdowns Heterogeneous across Industries



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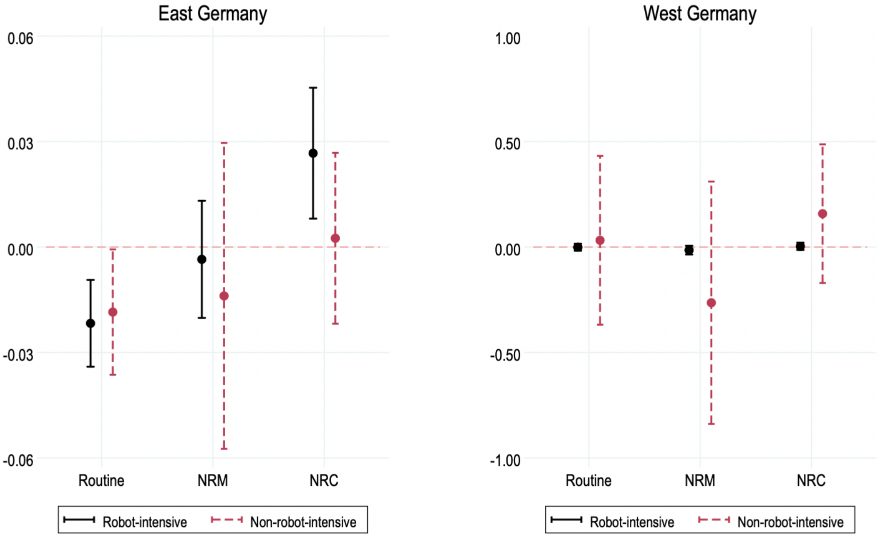
Plant-Level Effects on Employment Heterogeneous across Industries



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Results: Separate Bargaining ⏩ Back

Proposition 1. Suppose that the firm separately bargains with the union(s) representing routine and nonroutine workers.

1. w_L and Y_L decrease when $\bar{\pi}_L$ or automation threat increases.
2. w_H and Y_H increase when $\bar{\pi}_L$ or automation threat increases.
3. An increase in wage and bargaining outcome for nonroutine workers equals $1 - \beta$ times a decline in wage and bargaining outcomes for routine workers, where $0 \leq \beta \leq 1$. It indicates an overall decrease in workers' wages and bargaining outcomes.
4. The firm profit, $Q - Y_L - Y_H$, increases when $\bar{\pi}_L$ or automation threat increases.

Proposition 2. Wage markdowns over routine (nonroutine) workers increase (decrease) when $\bar{\pi}_L$ or automation threat increases.

Results: Joint Bargaining ⏩ Back

Proposition 3. Suppose that the firm jointly bargains with the union representing routine and nonroutine workers.

1. w_L and Y_L decrease when $\bar{\pi}_{LH}$ or automation threat increases.
2. w_H and Y_H decrease when $\bar{\pi}_{LH}$ or automation threat increases.
3. The firm profit, $Q - Y_L - Y_H$, increases when $\bar{\pi}_{LH}$ or automation threat increases.

Proposition 4. Wage markdowns over routine and nonroutine workers increase when $\bar{\pi}_{LH}$ or automation threat increases.