The Labor Market Impact of Artificial Intelligence: Local vs. Aggregate Effect[1]

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[1]Disclaimer: The views expressed in this paper are those of the author and should not be attributed to the IMF, its Executive Board, or its management. All errors are my own.

Introduction

Question: How does AI impact the labor market?

- AI (McElheran et al. (2024)): machine learning, image recognition, speech recognition, text mining, automated guided vehicle (AGV).
- Theoretically many forces: displacement (-), productivity (+), new tasks (+).
- Empirical work mostly at the *micro* level, using firm, establishment, or individual data.

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This paper: Study the *macro* level effect of AI on local and aggregate labor market:

1. What is the effect of AI on employment and wage in high vs. low AI exposure commuting zones (CZs)? — relative regional estimates
2. Is the employment effect unequally distributed?
3. What do the relative regional estimates imply for aggregate effects on the US economy? — aggregate estimates

Preview of Results

Local Labor Market: Shift-Share IV Approach

- Relative regional estimates: CZs with higher AI adoption experienced more *negative* changes in the employment-to-population ratio and wage in 2010-2021.
- Distributional impact on employment similar to routine-biased technological change.

  -ve in manufacturing, low-skill services; middle-skill workers; non-STEM occupations

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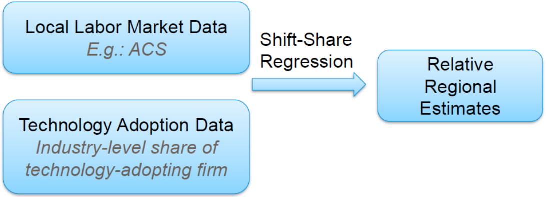
Relative Regional Effect $\neq$ Aggregate Effect

Aggregate Effect: GE Multi-Region Model Calibrated to Match Regional Estimates

- Model delivers structural counterpart of cross-regional empirical regression.
- Aggregate effect can be *positive*: depends on the degree of AI cost savings.

Methodology Overview

Gauge aggregate labor market effects of a technology using publicly available data



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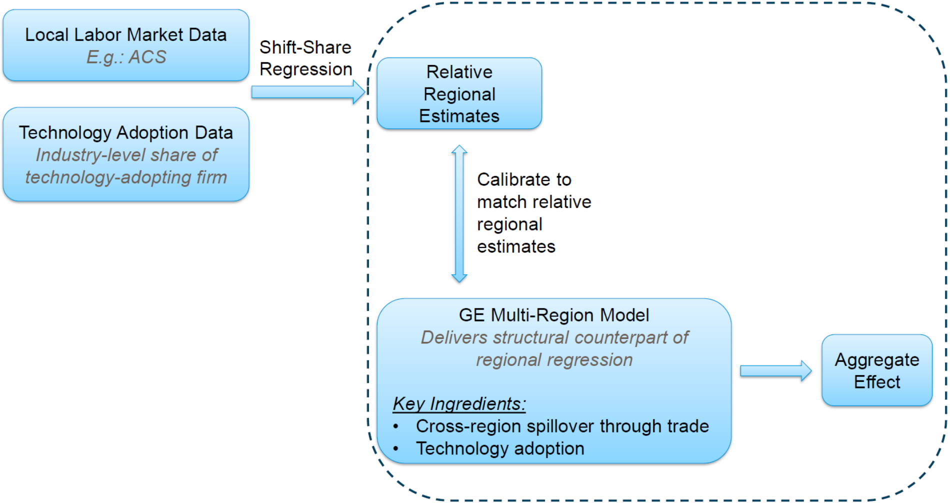

Outline

- Empirics and Local Labor Market Effect
- Model and Calibration
- Aggregate Effect

Empirics and Local Labor Market Effect

Empirical Methodology: Shift-Share Design

Regression Specification:

$$\Delta_{2010}^{2021} Y_i = \alpha_{d(i)} + \beta AIExposure_i + \gamma X_i + \varepsilon_i$$

- i: commuting zone, d: census division.
- Y_i: labor market outcomes. E.g.: employment-to-population ratio, wage.
- X_i: commuting zone characteristics. E.g.: initial demographic composition, industrial structure, exposures to other labor market shocks (robotization, import competition).

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Challenges on $\boldsymbol{AIExposure_i}$:

- No readily available data of AI adoption at commuting zone level.
- AI adoption is unlikely exogenous.

  E.g.: unobserved local demand shocks, anticipation of AI adoption, path dependence of ICT...

Data Sources

AI Adoption Data (2021): — shift

- Annual Business Survey (ABS) Digital Technology Module: US, 47 industries
- ICT Usage in Enterprises: EU, 27 industries
- Main measure: *average* industry share of AI-adopting firms across 5 sub-technologies
  Top (4-6%): data processing and hosting, computer systems design, publishing
  Bottom ($< 1\%$): entertainment, utilities, construction Details

Commuting Zone Level Data:

- American Community Survey (ACS) — Y_i, X_i
- County Business Patterns (CBP) — share

Bartik-Style AI Exposure Measure

US Exposure:

$$USExpsoure_i = \sum_j \underbrace{\frac{L_{ij2010}}{L_{i2010}}}_{\text{share}} \underbrace{\Delta_{2010}^{2021} AIAdoption_j^{US}}_{\text{shift}}$$

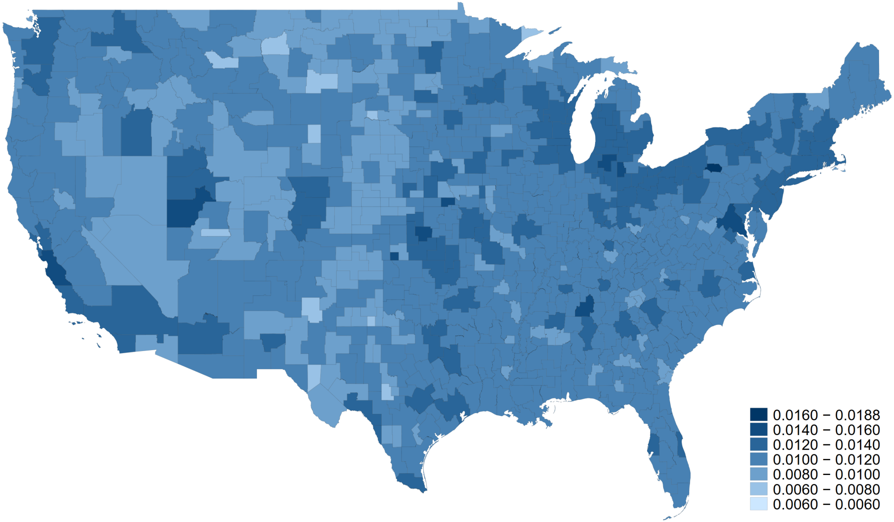
- $AIAdoption_j^{US}$: percentage of firms in industry j that adopt AI in the US.
- Neither the "shift" nor the "share" is likely to be exogenous.

IV: EU Exposure + 1990 Local Share

$$EUExpsoure_i = \sum_j \underbrace{\frac{L_{ij1990}}{L_{i1990}}}_{\text{share}} \underbrace{\Delta_{2010}^{2021} AIAdoption_j^{EU}}_{\text{shift}}$$

- Use EU adoption to capture global technological shocks. ▸ Correlation AI Adoption US vs. EU

$USExposure_i$ by Commuting Zone



Sources: ABS, CBP, and author's calculations.

Overall Employment-to-Population

	1990 Share 2010-2021 (1)	1990-1995 Average 2010-2021 (2)	1990 Share 1980-2010 (3)	1990-1995 Average 1980-2010 (4)
USExposure	-7.511**	-8.375***	2.217	0.716
	(3.067)	(3.129)	(4.739)	(5.075)
Observations	722	722	722	722
R-squared	0.28	0.26	0.56	0.55
First-stage coefficient	0.075***	0.086***	0.075***	0.086***
	(0.010)	(0.011)	(0.010)	(0.011)
First-stage F-statistic	58.2	57.3	58.2	57.3

Notes: All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

- 1980-2010 ("falsification test"): no effect.
- 2010-2021: negative effect, 1 std (-0.976 ppts), 75th-25th percentile (-1.25 ppts).

Robustness: 1995 Share

Robustness

- Use 1995 share as the initial share for exposure measure. Results
- Exclude Top 1% AI exposure CZs. Results
- Use log of employment level as dependent variable. Results
- Use alternative measure (maximum instead of average) for US AI adoption. Results
- Use 2019 as the end year of the long-difference. Results
- Use 2005 as the initial year of the long-difference. Results

Wage

	2010-2018 Annual Wage (1)	2010-2018 Hourly Wage (2)	1980-2010 Annual Wage (3)	1980-2010 Hourly Wage (4)
Exposure to AI	-18.053*	-12.782	3.719	5.051
	(9.297)	(9.034)	(18.550)	(17.953)
Observations	722	722	722	722
R-squared	0.53	0.53	0.64	0.59
First-stage coefficient	0.075***	0.075***	0.075***	0.075***
First-stage F-statistic	58.2	58.2	58.2	58.2

Notes: All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Distributional Impact

Similar to routine-biased technological change. Negative overall impact driven by:

- Broad sector: manufacturing, low-skill services ▸ Results
- Occupation: non-STEM, middle-skill ▸ Results
- Education: mid-level (high school, some college) ▸ Results
- Age: two ends of the age distribution (very young: 16-25, very old: 46-65) ▸ Results
- Gender: male ▸ Results

Model and Calibration

Model: Household

Household's problem:

$$u(C_i, S_i, L_i) = \frac{(C_i^{\chi} S_i^{1-\chi})^{1-\psi} - 1}{1-\psi} - \frac{B}{1+\varepsilon} L_i^{1+\varepsilon}$$

$$\text{s.t. } C_i + P_i^S S_i \leq w_i L_i + \chi_i^{\Pi} \Pi$$

- i: commuting zone (region).
- C_i: tradable good consumption, S_i: non-tradable good (service) consumption.
- $\chi \in (0,1)$: expenditure share on tradable good, ψ: degree of risk aversion, ε: inverse Frisch elasticity of labor supply.
- Π: non-labor income, χ^{Π}: share of non-labor income to region i (so $\sum_i \chi_i^{\Pi} = 1$).
- Tradable good is the numeraire, so $P_i^C = 1$.

Model: Production

Tradable final good:

$$Y_i = \left(\sum_j \nu_j^{\frac{1}{\sigma}} Y_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \sigma > 0 \text{ and } \sum_j \nu_j = 1$$

- j: industry.

Tradable industry good:

$$Y_{ij} = \left(\sum_k \nu_{kj}^{\frac{1}{\lambda}} X_{kij}^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}}, \lambda > 0 \text{ and } \sum_k \nu_{kj} = 1$$

- k: source region. t_{ki}: trade cost from k to i.
- Assume free trade ($t_{ki} = 1, \forall k, i$), so $P_i^C = 1, \forall i$.

Model: Task-Based Framework for Industry Production

$$X_{ij} = \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)} A_{ij} \Bigg(\underbrace{\left(\int_0^1 x_{ij}(\omega)^{\frac{\eta_j - 1}{\eta_j}} d\omega \right)^{\frac{\eta_j}{\eta_j - 1}}}_{\omega\text{: heterogeneous variety producer}} \Bigg)^{\alpha} \underbrace{K_{ij}^{1-\alpha}}_{\text{non-AI capital}}$$

where

$$x_{ij}(\omega) = \underbrace{z_{ij}(\omega)}_{\text{variety producer productivity}} \min_{s \in [0,1]} \{x_{ij}(\omega, s)\}$$

AI can replace human labor in the set of tasks $s \in [0, \theta_j]$, subject to upfront fixed cost f_M:

$$x_{ij}(\omega, s) = \begin{cases} \gamma_M M_{ij}(s) + \gamma_L L_{ij}(s), & \text{if } s \leq \theta_j \\ \gamma_L L_{ij}(s), & \text{if } s > \theta_j \end{cases}$$

Model: Closing the Model

Labor and AI capital are immobile across regions, while non-AI capital is freely mobile.

Non-tradable good supply:

$$S_i = L_i^S$$

AI capital supply:

$$M_i = D(1+\kappa)I_i^{\frac{1}{1+\kappa}}$$

- I_i: investment (in units of final tradable good), $\kappa > 0$: inverse of AI capital supply elasticity, implying an upward-sloping AI capital supply curve.

Non-AI capital: freely mobile at cost $R_i^K = R^K, \forall i$.

Structural Counterpart of Empirical Regression

Empirical regression: $d \ln L_i = \hat{\beta}_L^{IV} \sum_j l_{ij} d\pi_j^f$ and $d \ln w_i = \hat{\beta}_w^{IV} \sum_j l_{ij} d\pi_j^f$, where π_j^f is the percentage of AI-adopting firms in industry j.

Under reasonable parametric assumptions,

$$(\chi + (1-\chi)\psi - \psi\omega^L)\hat{\beta}_w^{IV} = (\psi\omega^L + \varepsilon)\hat{\beta}_L^{IV}$$

and

$$d \ln L_i = \underbrace{-\frac{\left(\tau^z + (1-\lambda)\alpha\mu^z + \frac{\tau^{P^Y} + (1-\lambda)\alpha\mu^{P^Y} + (\lambda-\sigma)}{1-\alpha\mu^{P^Y}}\alpha\mu^z\right)\frac{z^{*\phi}}{\phi}}{(1-(1-\rho)\omega^L) - \frac{(\psi\omega^L+\varepsilon)(\rho(1-\lambda)\alpha - 1 + (1-\rho)\omega^L)}{(\chi+(1-\chi)\psi-\psi\omega^L)}}}_{=\hat{\beta}_L^{IV}\text{, relative regional effect}} \sum_j l_{ij} d\pi_j^f$$

Calibration

Parameter	Description	Value	Source/Target
Production:			
σ	Elasticity of substitution (industries)	1	Cobb-Douglas production
λ	Elasticity of substitution (traded varieties)	5	Standard
η	Elasticity of substitution (firms)	6	Markup = 1.2 (Basu (2019))
ϕ	Pareto distribution, shape parameter	10.13	$\frac{\text{Average firm sales}}{\text{Standard Deviation of firm sales}} = 0.212$
α	Labor and AI capital share	0.72	Labor share = 0.6
Preference:			
χ	Tradable sector share	0.23	$\frac{\text{Manufacturing Employment}}{\text{Total employment}} = 0.18$
ψ	Degree of risk aversion	0.05	Marginal propensity of leisure = $\frac{\psi}{\varepsilon}\omega^L = 0.1$ (Imbens et al. (2001))
ε	Inverse of Frisch elasticity of labor supply	0.49	$\hat{\beta}_w^{IV} = -18.053$
AI:			
κ	Inverse of supply elasticity of AI	0.79	Acemoglu and Restrepo (2020)
Δ	cost savings of AI	0.27	Acemoglu (2024)
Initial conditions:			
π_0^f	Initial fraction of AI-adoption firms	10^{-5}	Assumption
θ_0	Initial set of AI-automable tasks	0.065	$\hat{\beta}_L^{IV} = -7.511$

Aggregate Effect

Aggregate Effect

Define $d\ln L = \sum_i \chi_i^w d\ln L_i$ and $d\ln w = \sum_i \chi_i^w d\ln w_i$, where χ_i^w is the share of national wage bill for commuting zone i.

Aggregate effect is given by a system of 6 linear equations for 6 unknowns: $d\ln L$, $d\ln w$, $d\ln R^K$, $d\ln R^M$, $d\ln M$, $d\ln Y$, where:

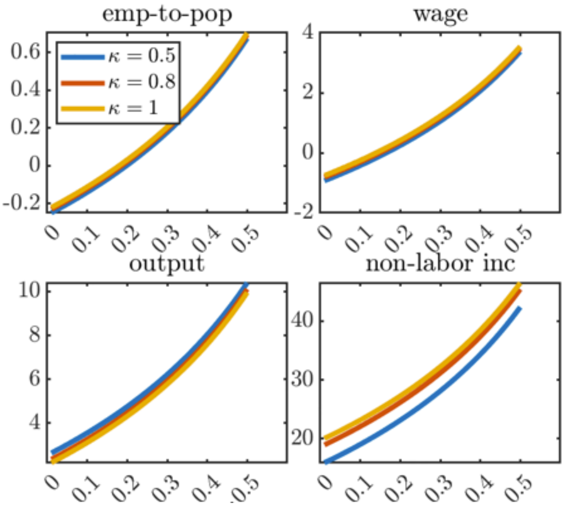
$$d\ln L = \underbrace{\frac{\left(\frac{(1-\rho)\chi}{\psi} - \chi - \rho + \chi\rho - \frac{\rho(1+\tau^Y)\alpha}{\alpha\mu^Y+1-\alpha}\right)\zeta^\pi + \frac{(1+\tau^Y)\alpha\mu^z}{\phi(\alpha\mu^Y+1-\alpha)} - \frac{\tau^z}{\phi}}{1 + \frac{(1-\rho)(\varepsilon-\chi\zeta^L)}{\psi} + \left(\chi + \rho - \chi\rho + \frac{\rho(1+\tau^Y)\alpha}{\alpha\mu^Y+1-\alpha}\right)\zeta^L} z^{*\phi}}_{\text{aggregate effect}} \sum_i \chi_i^w \sum_j l_{ij} d\pi_j^f$$

Baseline Results and Sensitivity to π_0^f

	$\pi_0^f = 10^{-7}$ (1)	$\pi_0^f = 10^{-6}$ (2)	$\pi_0^f = 10^{-5}$ (3)	$\pi_0^f = 10^{-4}$ (4)
Change in aggregate outcomes (%):				
Employment-to-population ratio (ppts)	0.17	0.16	0.14	0.10
Wage	1.03	1.00	0.99	0.72
Output	5.68	5.62	5.45	5.11
Non-labor income	30.34	30.13	29.57	28.46

Notes: $\pi_0^f = 10^{-5}$ (Column (3)) is the baseline.

Importance of AI Cost Savings



Notes: x-axis is AI cost savings Δ. y-axis is percent or percentage points change (%).

Conclusion

1. **Local labor market:** Exploit variation of AI adoption across US commuting zones using shift-share approach:
   - CZs with higher AI adoption experienced more *negative* changes in the employment-to-population ratio and wage in 2010-2021.
   - Distributional impact on employment similar to routine-biased technological change, with negative impact mainly on the lower skill.

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2. **Aggregate effect:** Calibrate GE multi-region model with technology adoption to match local labor market evidence:
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   - Aggregate effect can be *positive*: depends on the degree of AI cost savings.
3. **Framework** to gauge aggregate labor market effects of a technology using publicly available data.

Related Literature

Labor market impact of AI:

- AI exposure: Frey and Osborne (2017), Webb (2020), Felten et al. (2021), Eloundou et al. (2023), Eisfeldt et al. (2023), Cazzaniga et al. (2024), Hampole et al. (2025)
- Firm/establishment/individual: Acemoglu et al. (2022b), Copestake et al. (2023), Babina et al. (2024))
- Local labor market: Bonfiglioni et al. (2025), Aum and Shin (2025)

Macroeconomic impact of technological change:

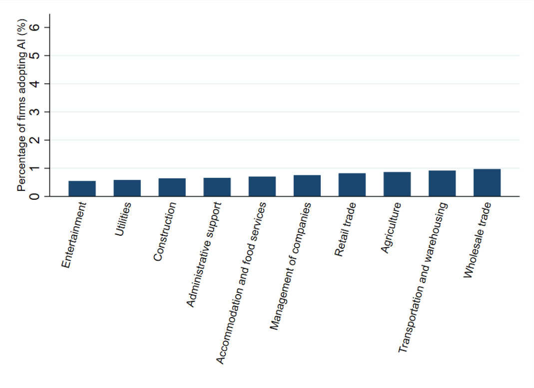
- Average effect: Acemoglu and Restrepo (2019), Acemoglu (2025)
- Distributional effect: Acemoglu and Restrepo (2019), Acemoglu and Autor (2011), Autor et al. (2006), Goos et al. (2014), Traiberman (2019)

Regional data and macro models: Nakamura and Steinsson (2018), Acemoglu and Restrepo (2020)

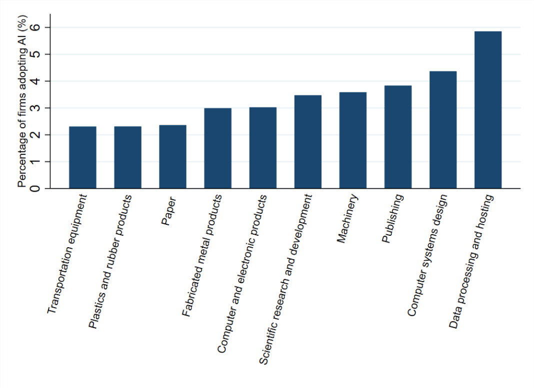
This paper: different AI exposure measure focusing on adoption, study aggregate effect

Appendix

Industry-Level AI Adoption, US



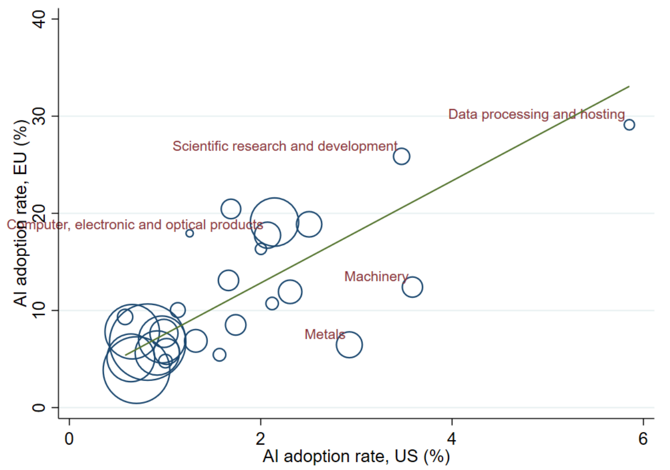
(a) bottom 10 industries



(b) top 10 industries

Sources: ABS (2021) and author's calculations. Back

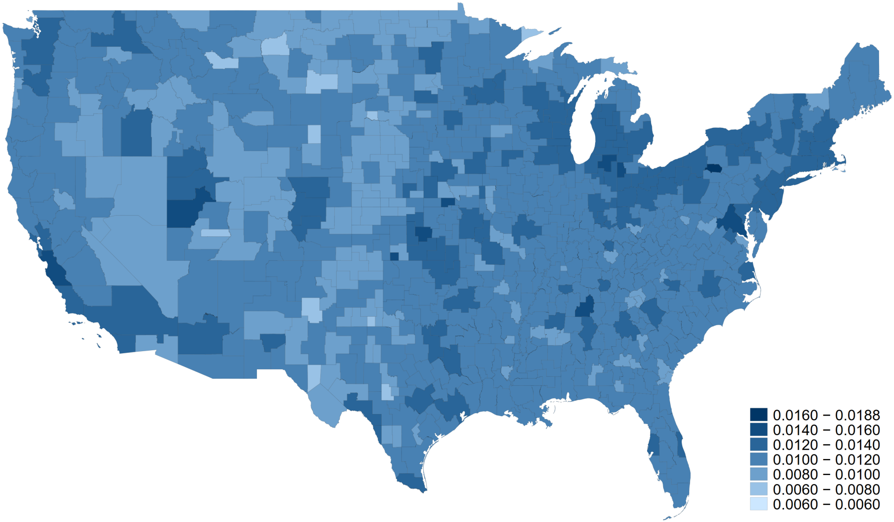
Industry-Level AI Adoption in US vs. EU



Sources: ABS, Eurostat, OEWS, and author's calculations.

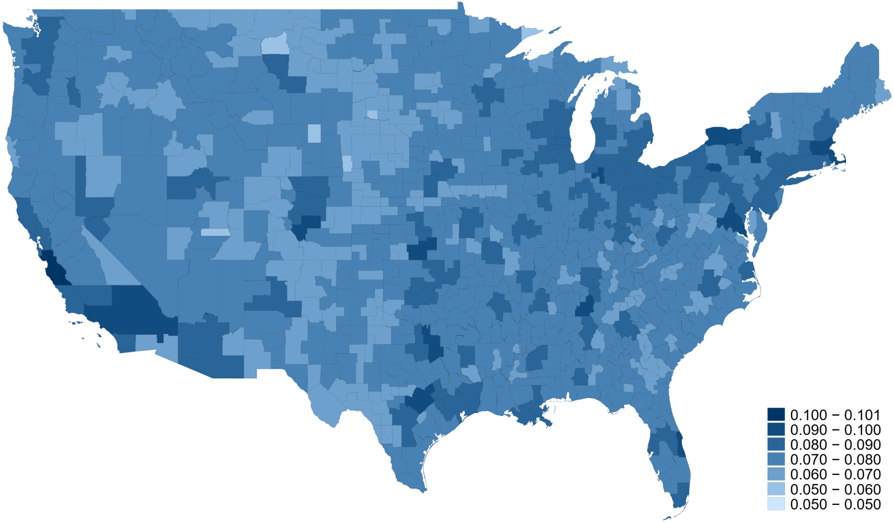
Notes: The green line is the linear regression fit, with coefficient of 5.255 and standard error of 0.874. The size of the blue circle represents the US industry share in 2010. Back

$USExposure_i$ by Commuting Zone



Sources: ABS, CBP, and author's calculations. Back

$EUExposure_i$ by Commuting Zone



Sources: Eurostat, CBP, and author's calculations. Back

Robustness: 1995 Share

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990 Share 1980-2010 (3)	1995 Share 1980-2010 (4)
USExposure	-7.511**	-5.699*	2.217	-1.199
	(3.067)	(2.979)	(4.739)	(5.402)
Observations	722	722	722	722
R-squared	0.28	0.30	0.56	0.55
First-stage coefficient	0.075***	0.084***	0.075***	0.084***
	(0.010)	(0.011)	(0.010)	(0.011)
First-stage F-statistic	58.2	52.8	58.2	52.8

Notes: All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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Robustness: Exclude Top 1% AI Exposure CZs

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
USExposure	-8.968**	-6.345	-10.054***	2.409	-2.533	-0.024
	(4.156)	(3.912)	(4.225)	(6.220)	(7.361)	(6.900)
Observations	714	714	714	714	714	714
R-squared	0.24	0.29	0.22	0.55	0.55	0.55
First-stage coefficient	0.060***	0.066***	0.067***	0.060***	0.066***	0.067***
	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
First-stage F-statistic	41.5	43.1	43.0	41.5	43.1	43.0

Notes: All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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Robustness: Log of Employment Level as Dependent Variable

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
USExposure	-10.970**	-8.759*	-12.351***	2.162	-3.237	-0.269
	(4.856)	(4.701)	(4.951)	(7.190)	(8.245)	(7.605)
Observations	722	722	722	722	722	722
R-squared	0.95	0.95	0.95	0.99	0.98	0.99
First-stage coefficient	0.075	0.084	0.086	0.075	0.084	0.086
First-stage F-statistic	59.5	53.2	58.0	59.4	54.2	59.5

Notes: All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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Robustness: Alternative Measure for US Industry-Level AI Adoption

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
USExposure	-3.785**	-2.897*	-4.325***	1.117	-0.610	0.370
	(1.628)	(1.584)	(1.740)	(2.403)	(2.746)	(2.622)
Observations	722	722	722	722	722	722
R-squared	0.20	0.25	0.16	0.55	0.55	0.55
First-stage coefficient	0.149	0.165	0.166	0.149	0.165	0.166
First-stage F-statistic	33.2	29.2	30.7	33.2	29.2	30.7

Notes: All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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Robustness: 2019 as End Year

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
USExposure	-7.060**	-6.450**	-8.240***	2.217	-1.199	0.716
	(3.088)	(2.918)	(3.129)	(4.739)	(5.402)	(5.075)
Observations	722	722	722	722	722	722
R-squared	0.37	0.38	0.35	0.56	0.55	0.55
First-stage coefficient	0.075	0.084	0.086	0.075	0.084	0.086
First-stage F-statistic	58.2	52.8	57.3	58.2	52.8	57.3

Notes: All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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Robustness: 2005 as Initial Year

	1990 Share 2010-2021 (1)	1995 Share 2010-2021 (2)	1990-1995 Average 2010-2021 (3)	1990 Share 1980-2010 (4)	1995 Share 1980-2010 (5)	1990-1995 Average 1980-2010 (6)
USExposure	-7.109**	-5.160*	-7.840***	2.098	-1.086	0.671
	(2.899)	(2.712)	(2.946)	(4.479)	(4.892)	(4.751)
Observations	722	722	722	722	722	722
R-squared	0.27	0.30	0.25	0.55	0.55	0.55
First-stage coefficient	0.080	0.092	0.092	0.080	0.092	0.092
First-stage F-statistic	57.5	69.4	56.6	57.5	69.4	56.6

Notes: All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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Distribution Impact: Broad Sector

	Agriculture (1)	Manufacturing (2)	Construction (3)	Low-Skill Services (4)	High-Skill Services (5)
USExposure	0.914**	-5.118*	1.047	-5.292***	0.939
	(0.460)	(2.782)	(1.091)	(2.039)	(1.635)
Observations	722	722	722	722	722

Notes: All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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Distribution Impact: Occupation

	Non-STEM	STEM	Low-Skill	Middle-Skill	High-Skill
	(1)	(2)	(3)	(4)	(5)
USExposure	-6.997***	-0.514	-0.230	-4.936*	-2.345
	(2.881)	(1.049)	(0.980)	(2.559)	(1.701)
Observations	722	722	722	722	722

Notes: All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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Distribution Impact: Education

	Below High School (1)	High School (2)	Some College (3)	College and Above (4)
USExposure	-2.598	-9.723***	-6.216*	-0.550
	(5.850)	(3.935)	(3.729)	(2.401)
Observations	722	722	722	722

Notes: All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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Distribution Impact: Age and Gender

	16-25 (1)	26-35 (2)	36-45 (3)	46-55 (4)	56-65 (5)	Male (6)	Female (7)
USExposure	-11.519**	-2.962	-5.576	-7.746**	-7.969*	-9.191**	-5.581*
	(5.606)	(3.423)	(4.007)	(3.750)	(4.108)	(4.214)	(3.089)
Observations	722	722	722	722	722	722	722

Notes: All regressions are weighted by 2010 commuting zone population. Robust standard errors are in parentheses and clustered at the state level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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