Recent Employment Growth in Cities, Suburbs, and Rural Communities

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Federal Reserve Bank of Boston
Research Department

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Bank of Boston™

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Eric Rosengren, President of Boston Fed

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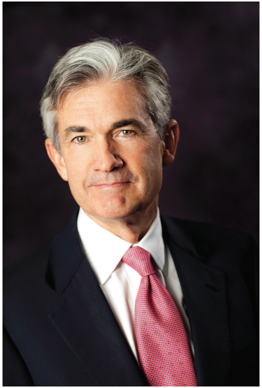

Jerome Powell, Chair of Federal Reserve

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- We will also use some county-level demographic data from Census

Four Population-Density Groups

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Density Percentiles	No. of Counties	Share of Pop.
1–85	2,473	$\approx$ 30%
86–95	291	$\approx$ 25%
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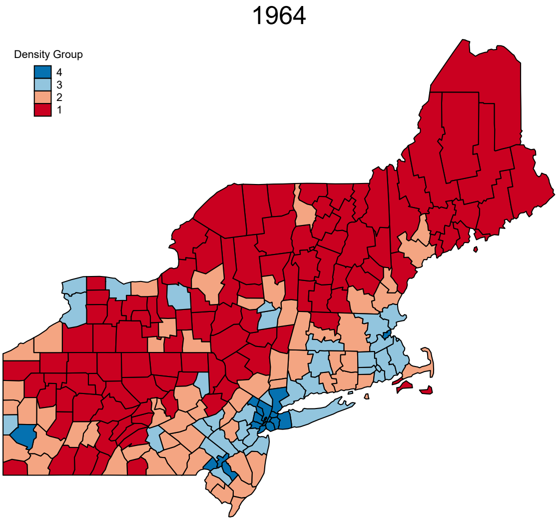

Population and Employment Shares

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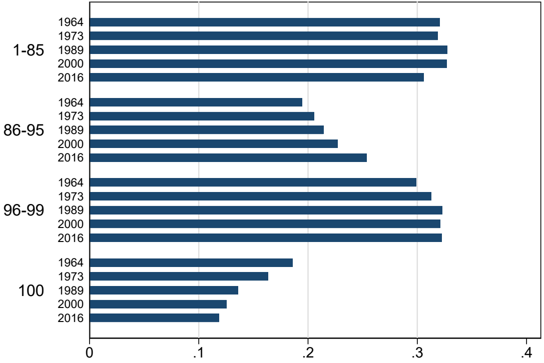
Share of National Population



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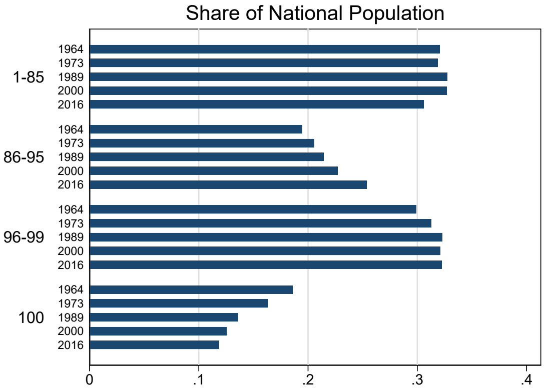

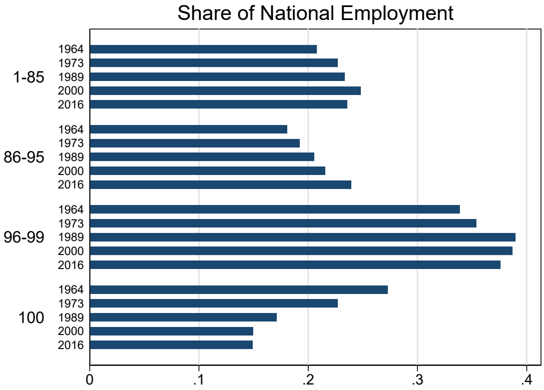

Suburbanization Trends: Empl. & Pop. Shares in Densest County

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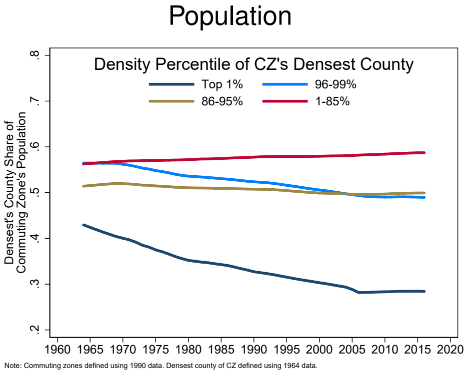

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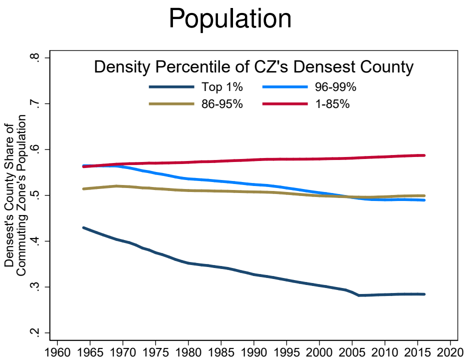
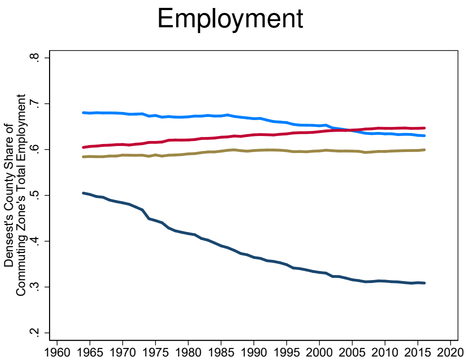


Note: Commuting zones defined using 1990 data. Densest county of CZ defined using 1964 data.



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Relative to population-weighted mean across all counties

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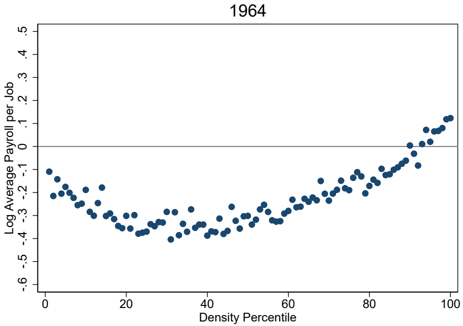

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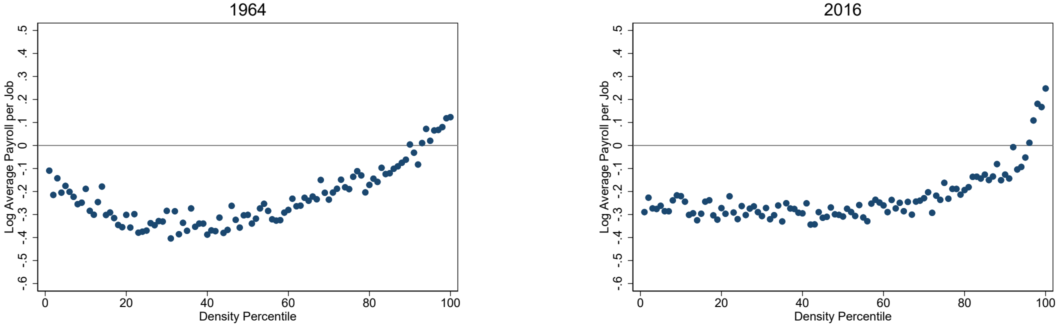

Earnings per Job Dispersion: Inter-Quartile Range

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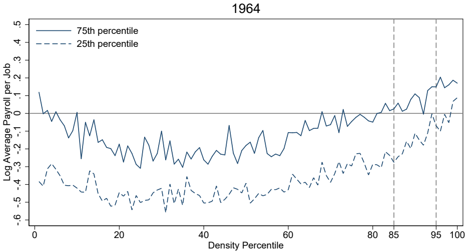

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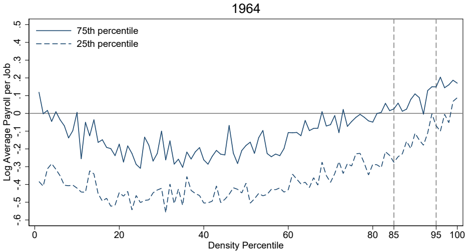

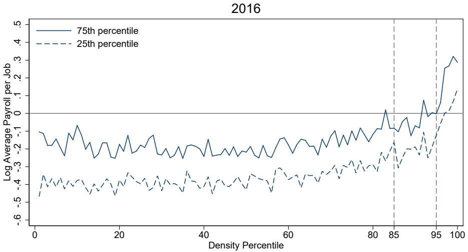

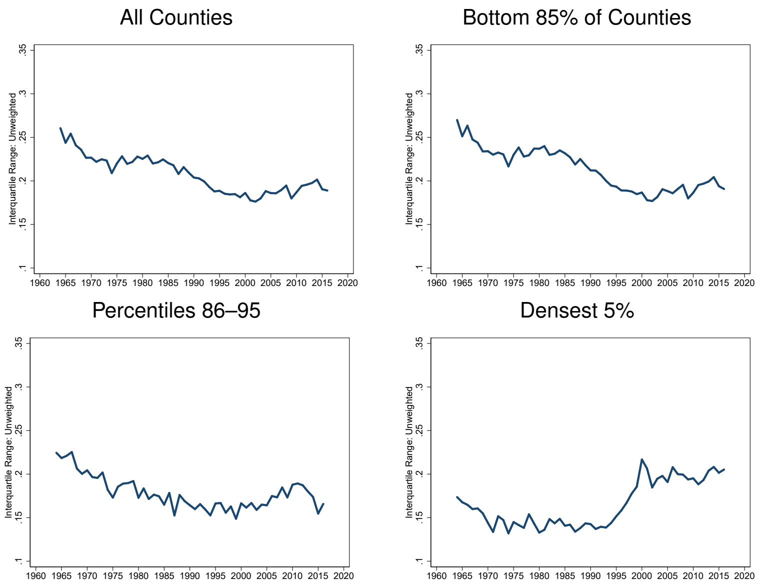
All Counties
Bottom 85% of Counties
Percentiles 86–95
Densest 5%
Interquartile Range: Unweighted
.1
.15
.2
.25
.3
.35
1960
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020

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  - Log share of persons with bachelor's degrees (interpolated from Census and ACS)

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$$Y_t = X_t\beta_t + WX_t\gamma_t + \varepsilon_t$$

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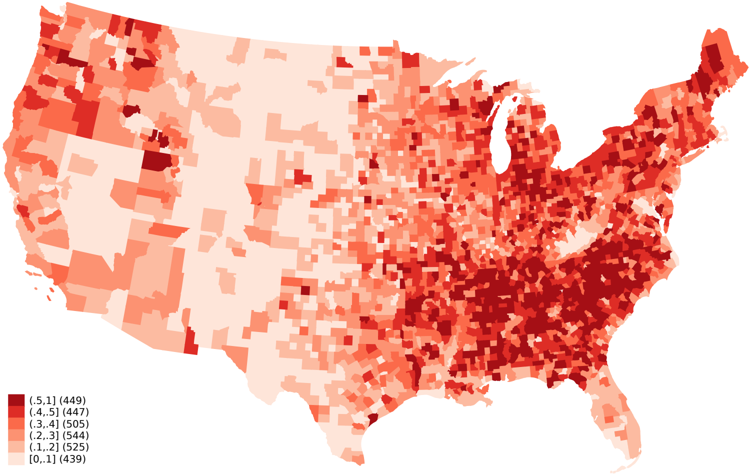
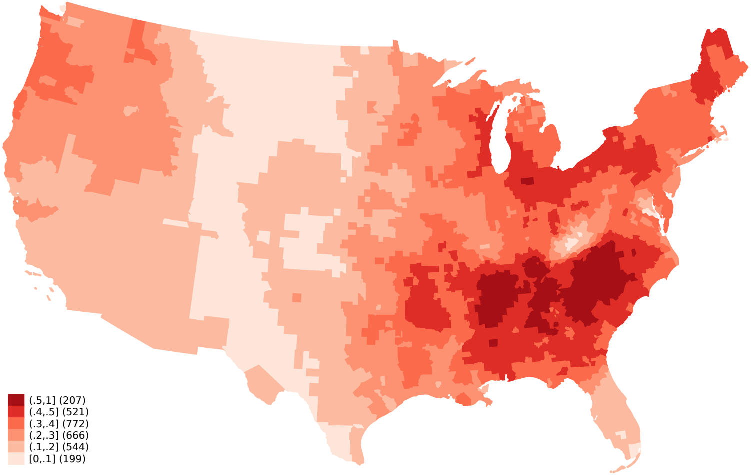
- Estimate via GMM

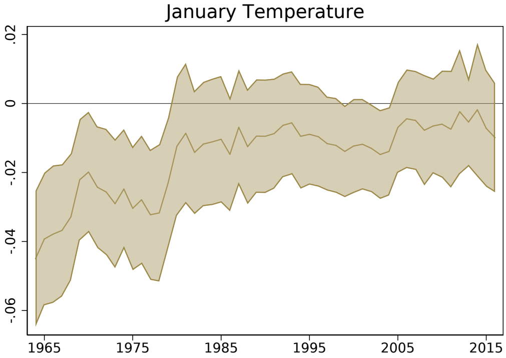
Manufacturing Shares in 1980



Neighboring Manufacturing Shares in 1980



Log Earnings Per Job: Average January Temperature



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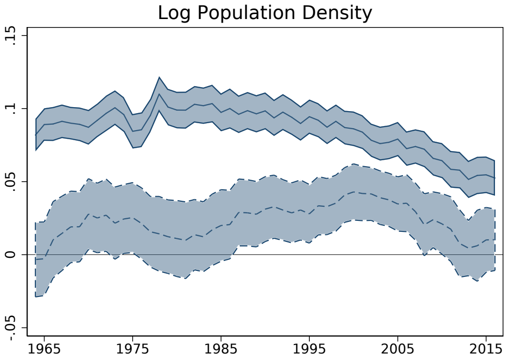

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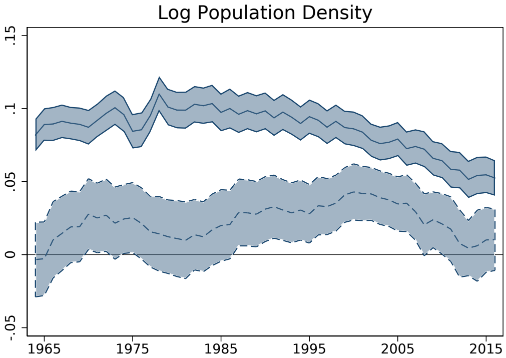

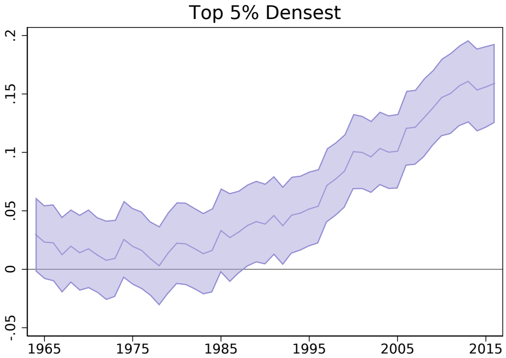

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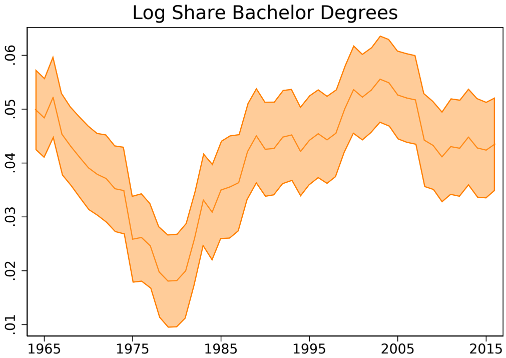

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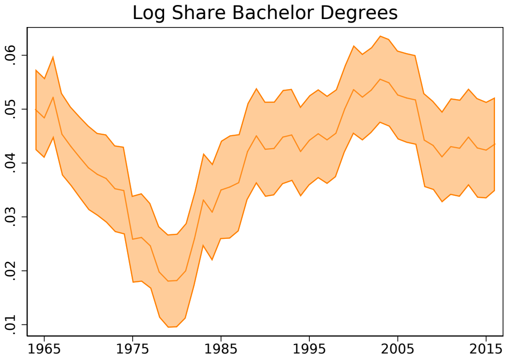

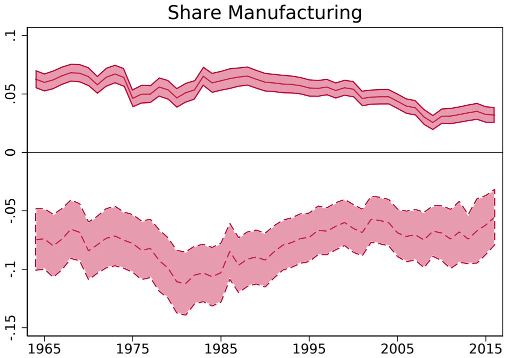

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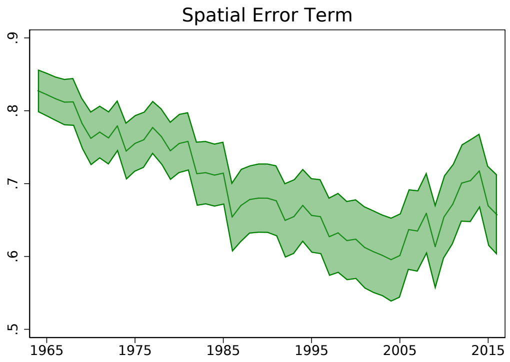

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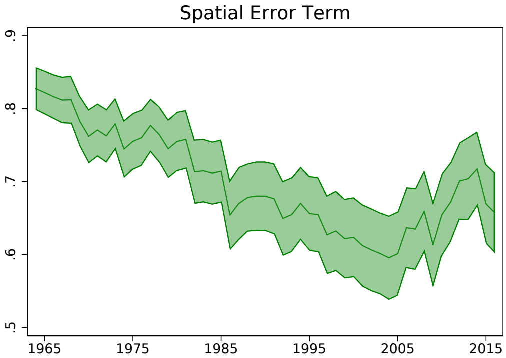

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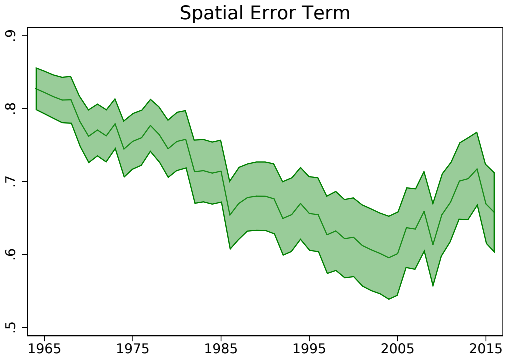

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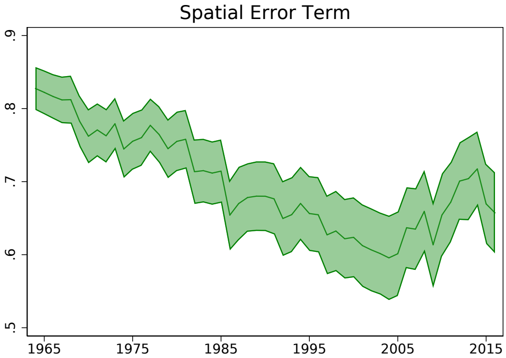

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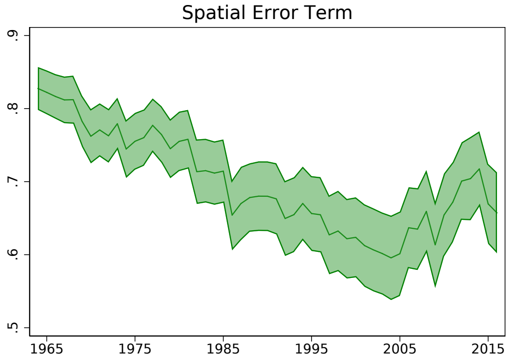

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- Similar movements in superstar cities constituent counties increase "clumpiness" of regression residuals (λ_t)

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  - <u>Population</u> suburbanization slows in 2000s for both groups

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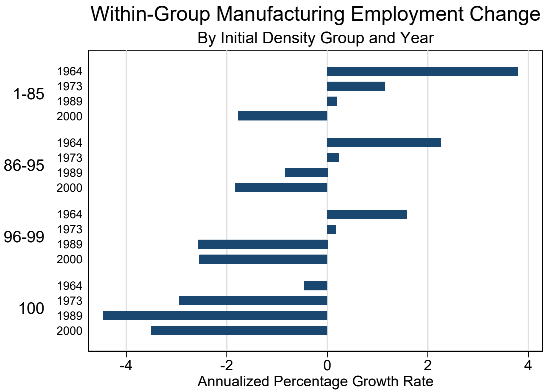

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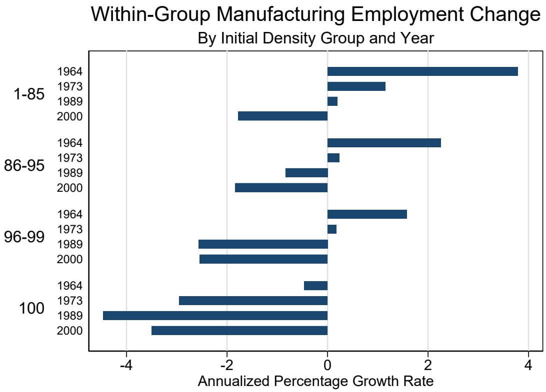

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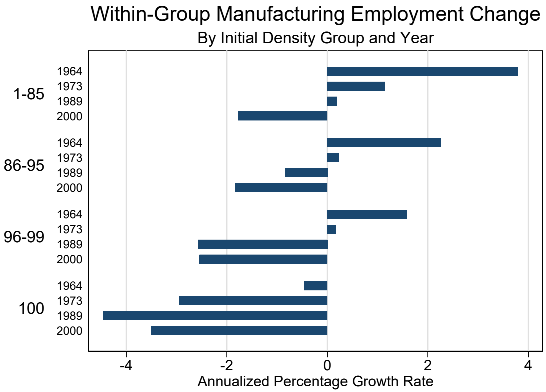

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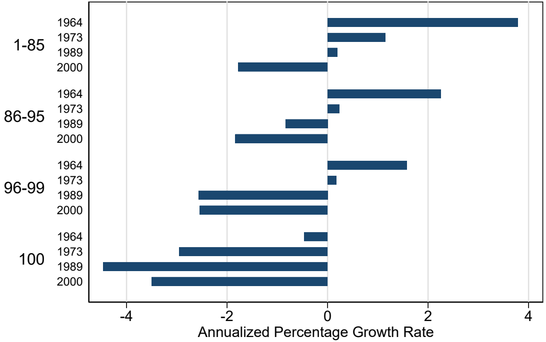
Within-Group Manufacturing Employment Change
By Initial Density Group and Year



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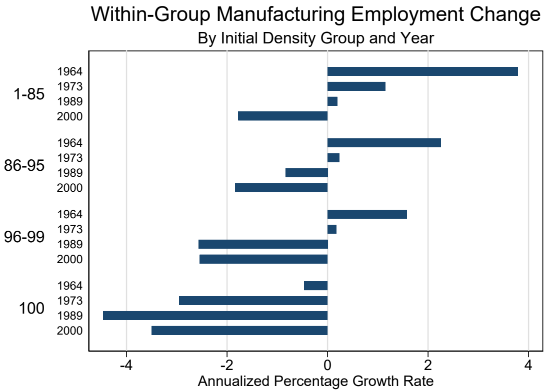

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- For manufacturers, 21st century has been an equal opportunity disemployer

Additional Questions Related to Manufacturing Share

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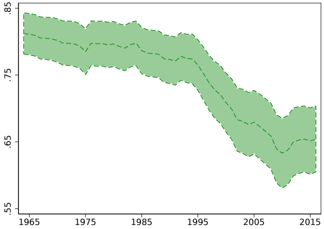

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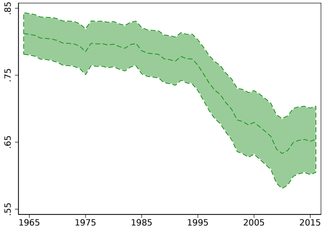

     - Implication: Current job-losers less able to diversify than earlier job losers

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   - A technological reallocation of traditional office tasks away from non-college workers would have large implications for urban/housing policy

The End

Commuting Zones: Population Shares

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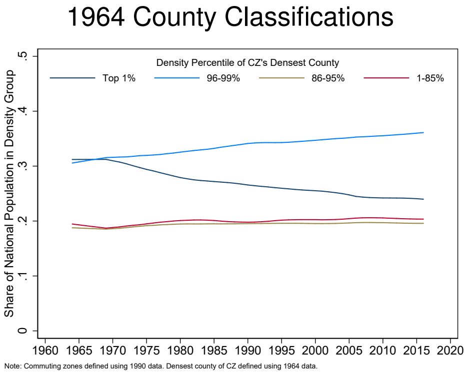

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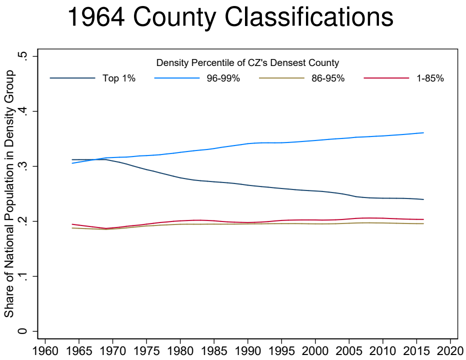
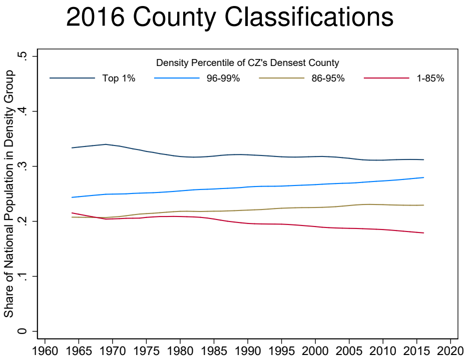


Note: Commuting zones defined using 1990 data. Densest county of CZ defined using 1964 data.



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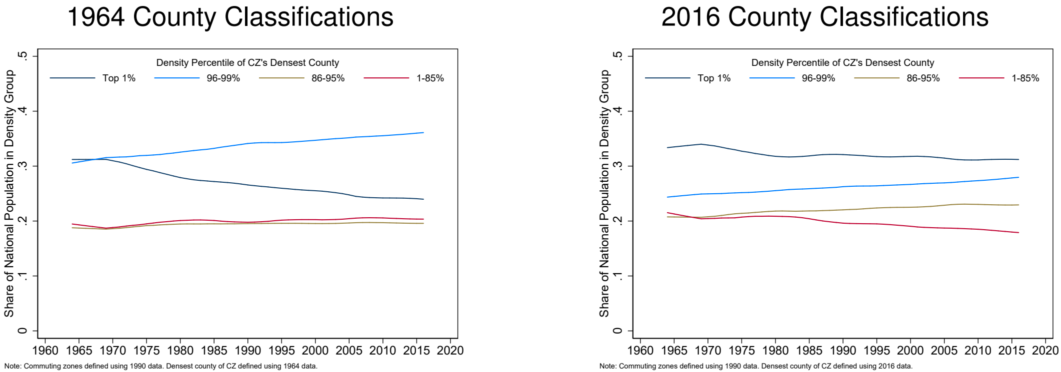

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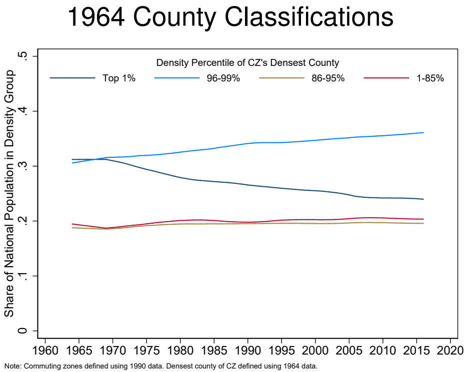

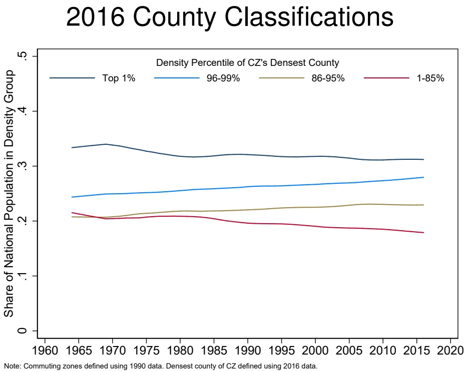

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- Rappaport (2018): Faster growth of "larger, less-crowded locations"

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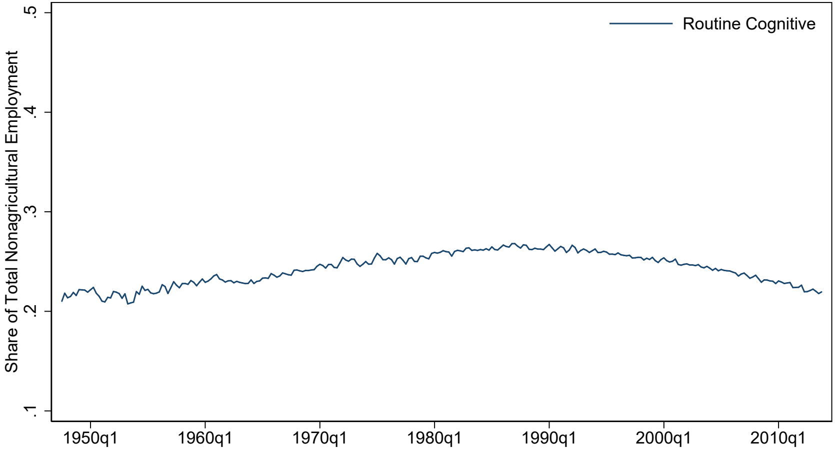
    - Executives making their own travel arrangements using Orbitz/Travelocity/Priceline
    - Researchers typing their own papers using LaTeX or Scientific Word

National Employment by Occupational Group

Source: CPS



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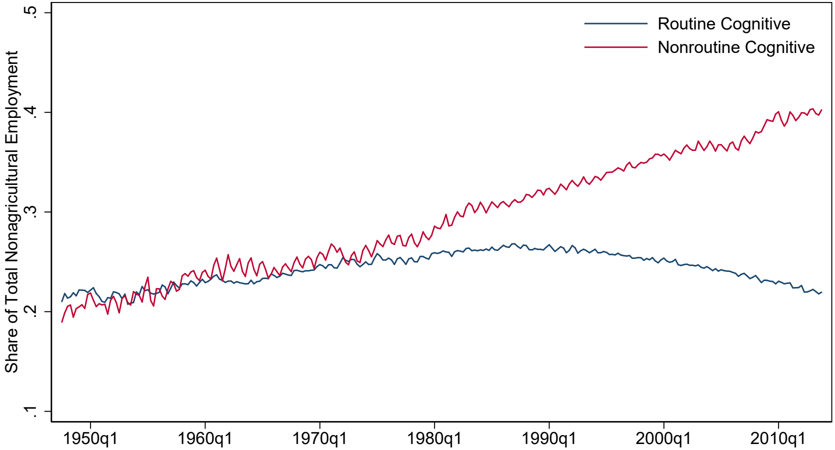

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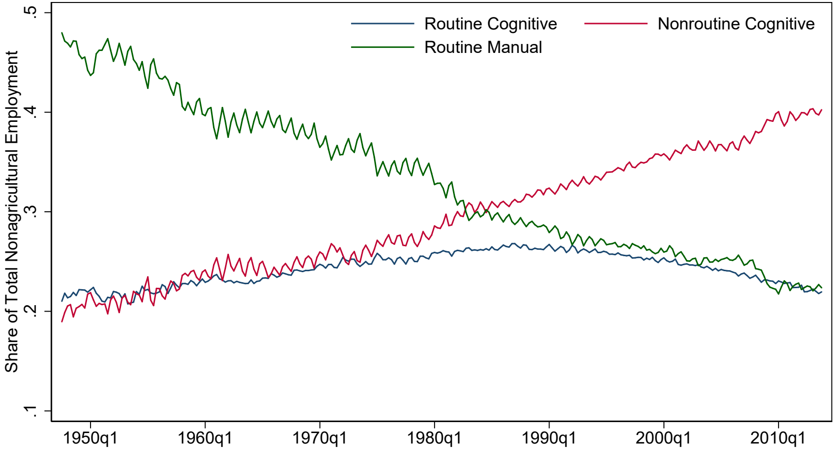

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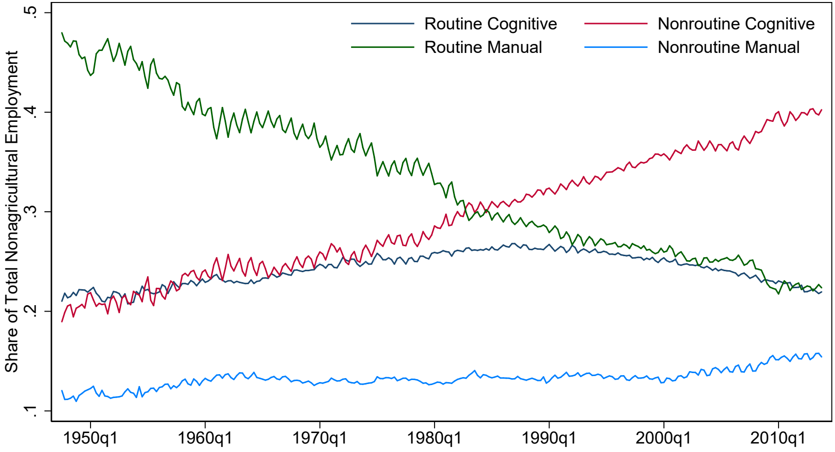


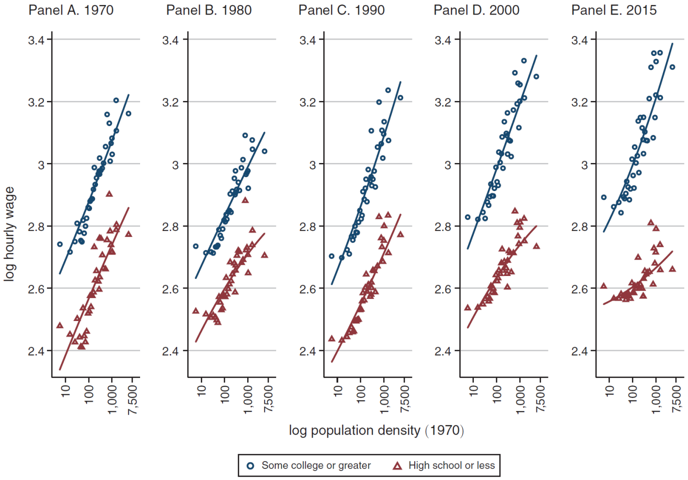
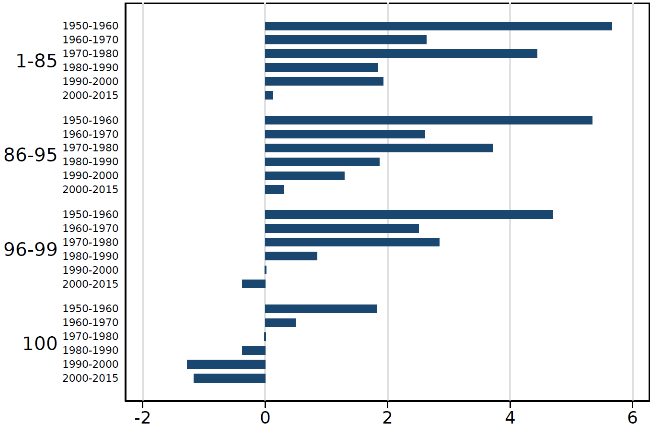


FIGURE 13. REAL LOG HOURLY WAGES OF COLLEGE AND NON-COLLEGE ADULTS, 1970–2015: WORKING-AGE ADULTS

Growth of Clerical/Office-Support Empl, by Density Group

Sources: Decennial Censuses and American Community Survey



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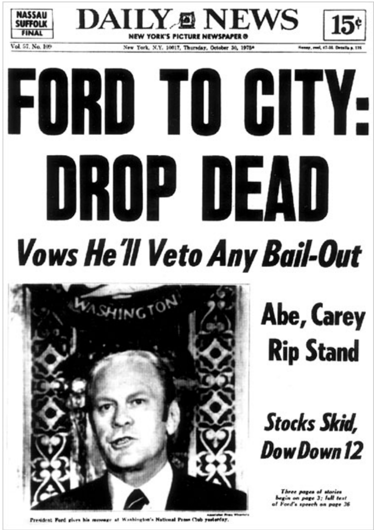

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Abe, Carey Rip Stand

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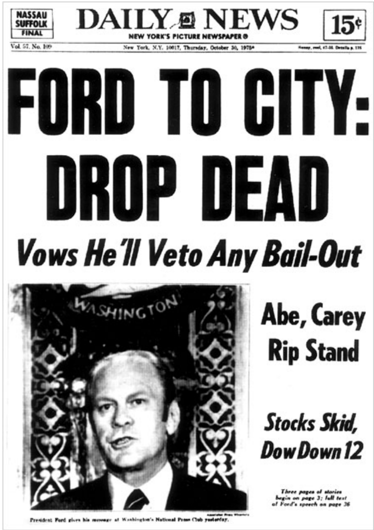
New York City in the 1970s



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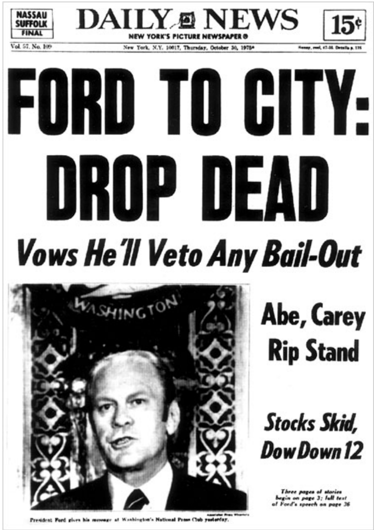
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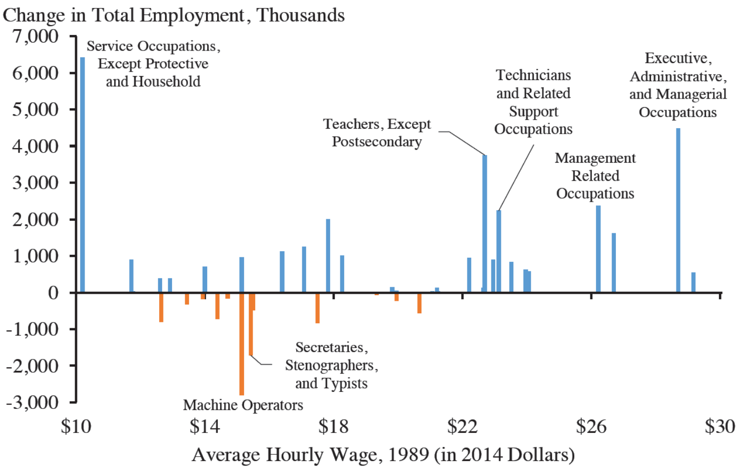
As recently as the 1970s, pretty much every older industrial city seemed simultaneously doomed. Both New York and Detroit were reeling from the decline of their core industries, and if anything, New York seemed worse off because the car industry seemed more tightly tied to Motown than the garment sector did to Gotham. In 1977, workers in Wayne County, Michigan, which includes Detroit, were paid more than workers in Manhattan.

Edward L. Glaeser
Triumph of the City
p. 56

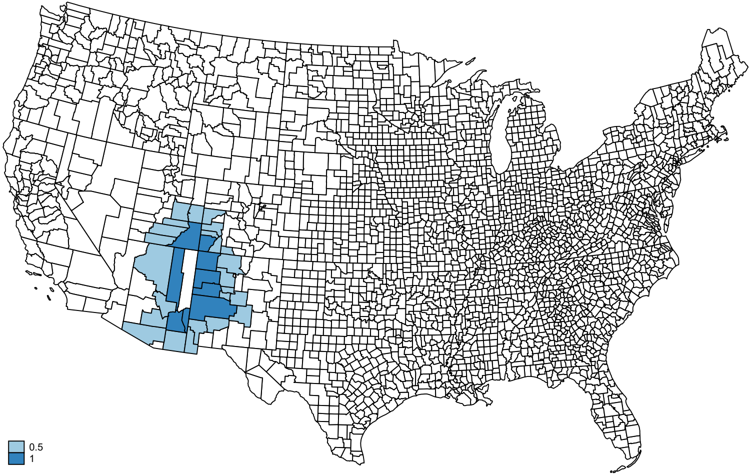
Change in Employment by Detailed Occupation: 1989–2014

Source: Council of Economic Advisers (2015 *Economic Report of the President*)



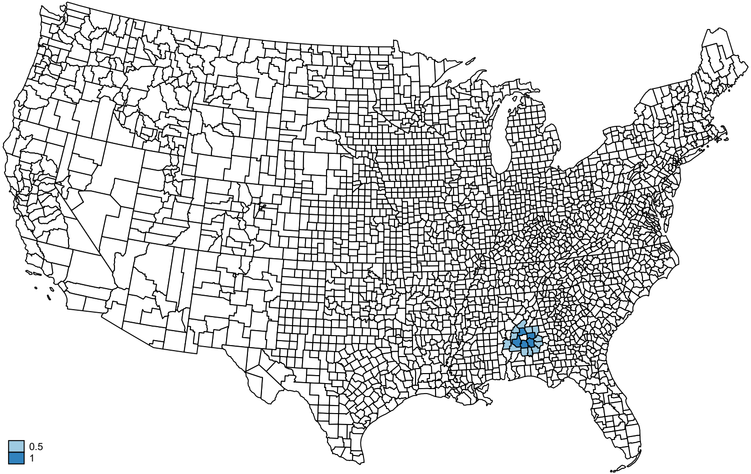
Second-Order Contiguity Matrix

Apache County, AZ



Second-Order Contiguity Matrix

Autauga County, AL



Manufacturing Employment Share by Density Group

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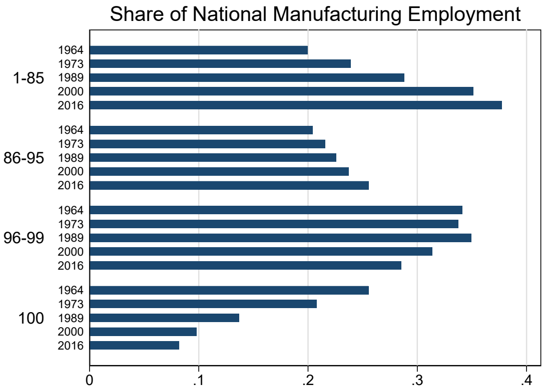

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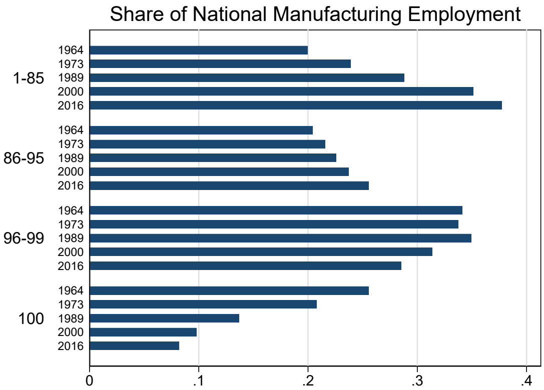

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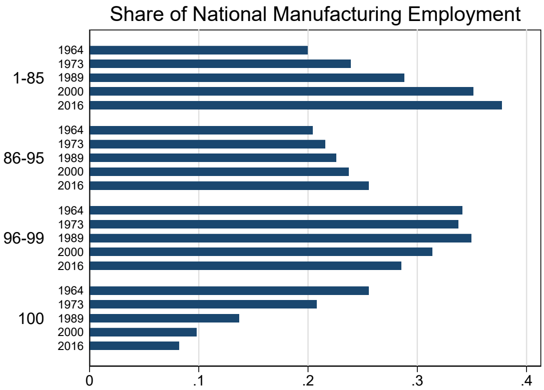

- Striking fact: In 1964, more factory jobs in densest 1% of counties than in the least-dense 85%

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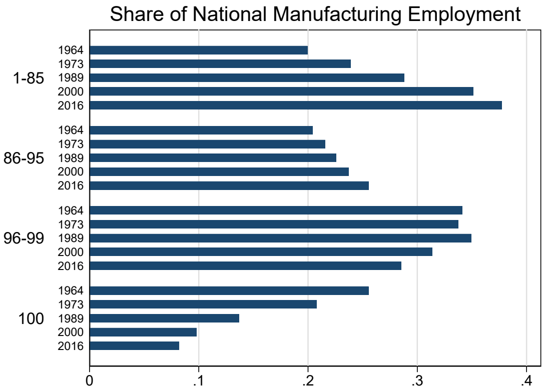

- Striking fact: In 1964, more factory jobs in densest 1% of counties than in the least-dense 85%
- Dramatic reversal in importance of dense vs. rural counties during sample period