Recent Employment Growth in Cities, Suburbs, and Rural Communities

Benjamin K. Couillard and Christopher L. Foote

Federal Reserve Bank of Boston
Research Department

October 3, 2019
Disclaimer: We do not speak for:

Eric Rosengren, President of Boston Fed
Disclaimer: We do not speak for:

Eric Rosengren, President of Boston Fed

Jerome Powell, Chair of Federal Reserve
Empirical Approach

- Many potential dimensions for spatial analysis of labor markets

- Rural vs. urban
- Center cities vs. suburbs
- "Superstar" cities vs. less-successful cities

Data: County Business Patterns (yearly, 1964–2016)

- Employment
  - Total (≈ private nonfarm)
  - Manufacturing (sometimes imputed from county's establishment-size distribution)

- Payrolls
  - Avg. earnings per job (total only)

We combine some small counties & Virginia city/counties

Exclude AK and HI

≈ 3,100 US counties

→ 2,909 sample “counties” in our balanced dataset

We will also use some county-level demographic data from Census Couillard & Foote (Boston Fed)
Empirical Approach

- Many potential dimensions for spatial analysis of labor markets
  - Rural vs. urban

Data: County Business Patterns (yearly, 1964–2016)
- Employment
  - Total (≈ private nonfarm)
  - Manufacturing (sometimes imputed from county’s establishment-size distribution)

Payrolls
- Avg. earnings per job (total only)

We combine some small counties & Virginia city/counties
- Exclude AK and HI
- ≈ 3,100 US counties
  - → 2,909 sample “counties” in our balanced dataset

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

Couillard & Foote (Boston Fed)
Empirical Approach

- Many potential dimensions for spatial analysis of labor markets
  - Rural vs. urban
  - Center cities vs. suburbs

- Data: County Business Patterns (yearly, 1964–2016)
  - Employment
    - Total (≈ private nonfarm)
    - Manufacturing (sometimes imputed from county’s establishment-size distribution)
  - Payrolls
    - Avg. earnings per job (total only)

- We combine some small counties & Virginia city/counties
- Exclude AK and HI
- ≈ 3,100 US counties
  - → 2,909 sample “counties” in our balanced dataset

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

Couillard & Foote (Boston Fed)
Empirical Approach

- Many potential dimensions for spatial analysis of labor markets
  - Rural vs. urban
  - Center cities vs. suburbs
  - “Superstar” cities vs. less-successful cities

Data: County Business Patterns (yearly, 1964–2016)

Employment
- Total (≈ private nonfarm)
- Manufacturing (sometimes imputed from county’s establishment-size distribution)

Payrolls
→ Avg. earnings per job (total only)

We combine some small counties & Virginia city/counties
Exclude AK and HI

≈ 3,100 US counties → 2,909 sample “counties” in our balanced dataset

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

Couillard & Foote (Boston Fed)
Empirical Approach

- Many potential dimensions for spatial analysis of labor markets
  - Rural vs. urban
  - Center cities vs. suburbs
  - “Superstar” cities vs. less-successful cities
- Data: County Business Patterns (yearly, 1964–2016)

Data:
- Employment (≈ private nonfarm)
- Payrolls → Avg. earnings per job (total only)
- We combine some small counties & Virginia city/counties
- Exclude AK and HI
- ≈ 3,100 US counties → 2,909 sample “counties” in our balanced dataset
- We will also use some county-level demographic data from Census

Couillard & Foote (Boston Fed)

Recent Employment Growth
Empirical Approach

- Many potential dimensions for spatial analysis of labor markets
  - Rural vs. urban
  - Center cities vs. suburbs
  - “Superstar” cities vs. less-successful cities

- Data: County Business Patterns (yearly, 1964–2016)
  - Employment

- Total (≈ private nonfarm)
  - Manufacturing (sometimes imputed from county’s establishment-size distribution)

- Payrolls
  - Avg. earnings per job (total only)

- We combine some small counties & Virginia city/counties
- Exclude AK and HI
- ≈ 3,100 US counties
  - → 2,909 sample “counties” in our balanced dataset

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

Couillard & Foote (Boston Fed)
Recent Employment Growth
Empirical Approach

- Many potential dimensions for spatial analysis of labor markets
  - Rural vs. urban
  - Center cities vs. suburbs
  - “Superstar” cities vs. less-successful cities
- Data: County Business Patterns (yearly, 1964–2016)
  - Employment
    - Total (≈ private nonfarm)
- We combine some small counties & Virginia city/counties
- Exclude AK and HI
- ≈ 3,100 US counties → 2,909 sample “counties” in our balanced dataset
- We will also use some county-level demographic data from Census
Empirical Approach

- Many potential dimensions for spatial analysis of labor markets
  - Rural vs. urban
  - Center cities vs. suburbs
  - “Superstar” cities vs. less-successful cities
- Data: County Business Patterns (yearly, 1964–2016)
  - Employment
    - Total (∼ private nonfarm)
    - Manufacturing (sometimes imputed from county’s establishment-size distribution)
Empirical Approach

- Many potential dimensions for spatial analysis of labor markets
  - Rural vs. urban
  - Center cities vs. suburbs
  - “Superstar” cities vs. less-successful cities
- Data: County Business Patterns (yearly, 1964–2016)
  - Employment
    - Total (≈ private nonfarm)
    - Manufacturing (sometimes imputed from county’s establishment-size distribution)
  - Payrolls → Avg. earnings per job (total only)

We combine some small counties & Virginia city/counties
Exclude AK and HI
≈ 3,100 US counties → 2,909 sample “counties” in our balanced dataset

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

Couillard & Foote (Boston Fed)
Empirical Approach

- Many potential dimensions for spatial analysis of labor markets
  - Rural vs. urban
  - Center cities vs. suburbs
  - “Superstar” cities vs. less-successful cities
- Data: County Business Patterns (yearly, 1964–2016)
  - Employment
    - Total (≈ private nonfarm)
    - Manufacturing (sometimes imputed from county’s establishment-size distribution)
  - Payrolls → Avg. earnings per job (total only)
- We combine some small counties & Virginia city/counties
Empirical Approach

- Many potential dimensions for spatial analysis of labor markets
  - Rural vs. urban
  - Center cities vs. suburbs
  - “Superstar” cities vs. less-successful cities
- Data: County Business Patterns (yearly, 1964–2016)
  - Employment
    - Total (≈ private nonfarm)
    - Manufacturing (sometimes imputed from county’s establishment-size distribution)
  - Payrolls → Avg. earnings per job (total only)
- We combine some small counties & Virginia city/counties
- Exclude AK and HI
Empirical Approach

- Many potential dimensions for spatial analysis of labor markets
  - Rural vs. urban
  - Center cities vs. suburbs
  - “Superstar” cities vs. less-successful cities

- Data: County Business Patterns (yearly, 1964–2016)
  - Employment
    - Total (≈ private nonfarm)
    - Manufacturing (sometimes imputed from county’s establishment-size distribution)
  - Payrolls → Avg. earnings per job (total only)

- We combine some small counties & Virginia city/counties

- Exclude AK and HI

- ≈ 3,100 US counties → 2,909 sample “counties” in our balanced dataset
Empirical Approach

- Many potential dimensions for spatial analysis of labor markets
  - Rural vs. urban
  - Center cities vs. suburbs
  - “Superstar” cities vs. less-successful cities

- Data: County Business Patterns (yearly, 1964–2016)
  - Employment
    - Total (≈ private nonfarm)
    - Manufacturing (sometimes imputed from county’s establishment-size distribution)
  - Payrolls → Avg. earnings per job (total only)

- We combine some small counties & Virginia city/counties
- Exclude AK and HI

- ≈ 3,100 US counties → 2,909 sample “counties” in our balanced dataset
- We will also use some county-level demographic data from Census
### Four Population-Density Groups

<table>
<thead>
<tr>
<th>Density Group</th>
<th>No. of Counties</th>
<th>Share Percentiles</th>
</tr>
</thead>
<tbody>
<tr>
<td>1–85</td>
<td>2,473</td>
<td>≈ 30%</td>
</tr>
<tr>
<td>86–95</td>
<td>291</td>
<td>≈ 25%</td>
</tr>
<tr>
<td>96–99</td>
<td>116</td>
<td>≈ 30%</td>
</tr>
<tr>
<td>100</td>
<td>29</td>
<td>≈ 15%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>2,909</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>
## Four Population-Density Groups

<table>
<thead>
<tr>
<th>Density Percentiles</th>
<th>No. of Counties</th>
<th>Share of Pop.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1–85</td>
<td>2,473</td>
<td>≈ 30%</td>
</tr>
<tr>
<td>86–95</td>
<td>291</td>
<td>≈ 25%</td>
</tr>
<tr>
<td>96–99</td>
<td>116</td>
<td>≈ 30%</td>
</tr>
<tr>
<td>100</td>
<td>29</td>
<td>≈ 15%</td>
</tr>
</tbody>
</table>

| Total               | 2,909          | 100%          |
### Four Population-Density Groups

<table>
<thead>
<tr>
<th>Density Percentiles</th>
<th>No. of Counties</th>
<th>Share of Pop.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1–85</td>
<td>2,473</td>
<td>≈ 30%</td>
</tr>
<tr>
<td>86–95</td>
<td>291</td>
<td>≈ 25%</td>
</tr>
<tr>
<td>96–99</td>
<td>116</td>
<td>≈ 30%</td>
</tr>
<tr>
<td>100</td>
<td>29</td>
<td>≈ 15%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>2,909</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>
Population and Employment Shares

Share of National Population

- **1964**: 0.3
- **1973**: 0.3
- **1989**: 0.3
- **2000**: 0.3
- **2016**: 0.3

**1-85**

- **1964**: 0.3
- **1973**: 0.3
- **1989**: 0.3
- **2000**: 0.3
- **2016**: 0.3

**86-95**

- **1964**: 0.3
- **1973**: 0.3
- **1989**: 0.3
- **2000**: 0.3
- **2016**: 0.3

**96-99**

- **1964**: 0.3
- **1973**: 0.3
- **1989**: 0.3
- **2000**: 0.3
- **2016**: 0.3

**100**

- **1964**: 0.3
- **1973**: 0.3
- **1989**: 0.3
- **2000**: 0.3
- **2016**: 0.3

Couillard & Foote (Boston Fed) Recent Employment Growth October 3, 2019 5 / 22
# Suburbanization Trends: Empl. & Pop. Shares in Densest County

1964 Classifications

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Top 1%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>96-99%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>86-95%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-85%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Top 1%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>96-99%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>86-95%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-85%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Commuting zones defined using 1990 data. Densest county of CZ defined using 2016 data.
Suburbanization Trends: Empl. & Pop. Shares in Densest County

1964 Classifications

Population

Density Percentile of CZ's Densest County

- Top 1%
- 96-99%
- 86-95%
- 1-85%

Note: Commuting zones defined using 1990 data. Densest county of CZ defined using 1964 data.
Suburbanization Trends: Empl. & Pop. Shares in Densest County

1964 Classifications

Population

Density Percentile of CZ's Densest County

- Top 1%
- 96-99%
- 86-95%
- 1-85%

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

Employment

Densest's County Share of Commuting Zone's Total Employment

Note: Commuting zones defined using 1990 data. Densest county of CZ defined using 2016 data.

Couillard & Foote (Boston Fed)
Earnings per Job Averages by Density Percentile
Relative to population-weighted mean across all counties
Earnings per Job Averages by Density Percentile
Relative to population-weighted mean across all counties

Couillard & Foote (Boston Fed)
Earnings per Job Averages by Density Percentile
Relative to population-weighted mean across all counties

-6 -5 -4 -3 -2 -1 0 1 2 3 4 5
Log Average Payroll per Job
0 20 40 60 80 100
Density Percentile

1964

2016

Couillard & Foote (Boston Fed)
Recent Employment Growth
October 3, 2019
Earnings per Job Dispersion: Inter-Quartile Range

Recent Employment Growth
October 3, 2019 8 / 22
Earnings per Job Dispersion: Inter-Quartile Range

1964

Density Percentile

75th percentile

25th percentile

Log Average Payroll per Job

-0.6 -0.5 -0.4 -0.3 -0.2 -0.1 0 0.1 0.2 0.3 0.4 0.5

0 20 40 60 80 85 95 100

Couillard & Foote (Boston Fed)
Earnings per Job Dispersion: Inter-Quartile Range

1964

2016

Couillard & Foote (Boston Fed)
Recent Employment Growth
October 3, 2019
County-Level Regression Model

- **Timing:**

  - Regressions run separately year-by-year (not panel)
  - Dependent Variable: Average earnings per job
  - Regressors: Average January temperature, Log population density and indicator for densest 5% of counties, Manufacturing share of employment, Log share of persons with bachelor's degrees (interpolated from Census and ACS)

  - Couillard & Foote (Boston Fed) Recent Employment Growth
County-Level Regression Model

- **Timing:**
  - Regressions run separately year-by-year (not panel)
County-Level Regression Model

- **Timing:**
  - Regressions run separately year-by-year (not panel)

- **Dependent Variable:**
County-Level Regression Model

**Timing:**
- Regressions run separately year-by-year (not panel)

**Dependent Variable:**
- Average earnings per job
County-Level Regression Model

- **Timing:**
  - Regressions run separately year-by-year (not panel)

- **Dependent Variable:**
  - Average earnings per job

- **Regressors:**
  - Average January temperature
  - Log population density and indicator for densest 5% of counties
  - Manufacturing share of employment
  - Log share of persons with bachelor's degrees (interpolated from Census and ACS)
County-Level Regression Model

- **Timing:**
  - Regressions run separately year-by-year (not panel)

- **Dependent Variable:**
  - Average earnings per job

- **Regressors:**
  - Average January temperature

Couillard & Foote (Boston Fed)
Recent Employment Growth
October 3, 2019
County-Level Regression Model

- **Timing:**
  - Regressions run separately year-by-year (not panel)

- **Dependent Variable:**
  - Average earnings per job

- **Regressors:**
  - Average January temperature
  - Log population density and indicator for densest 5% of counties
County-Level Regression Model

- **Timing:**
  - Regressions run separately year-by-year (not panel)

- **Dependent Variable:**
  - Average earnings per job

- **Regressors:**
  - Average January temperature
  - Log population density and indicator for densest 5% of counties
  - Manufacturing share of employment
County-Level Regression Model

- **Timing:**
  - Regressions run separately year-by-year (not panel)

- **Dependent Variable:**
  - Average earnings per job

- **Regressors:**
  - Average January temperature
  - Log population density and indicator for densest 5% of counties
  - Manufacturing share of employment
  - Log share of persons with bachelor’s degrees (interpolated from Census and ACS)
Spatial Specification

\[ Y_t = X_t \beta_t + WX_t \gamma_t + \varepsilon_t \]
\[ Y_t = X_t \beta_t + WX_t \gamma_t + (\lambda_t W \varepsilon_t + \nu_t) \]

- Weighting matrix \( W \) is “second-order contiguity matrix”
Spatial Specification

\[ Y_t = X_t \beta_t + WX_t \gamma_t + \varepsilon_t \]
\[ Y_t = X_t \beta_t + WX_t \gamma_t + \left( \lambda_t W \varepsilon_t + \nu_t \right) \]

- Weighting matrix \( W \) is “second-order contiguity matrix”
- Neighboring variables will be weighted averages of \( X \)’s in surrounding counties
Spatial Specification

\[ Y_t = X_t \beta_t + WX_t \gamma_t + \varepsilon_t \]

\[ Y_t = X_t \beta_t + WX_t \gamma_t + \left( \lambda_t W \varepsilon_t + \nu_t \right) \]

- Weighting matrix \( W \) is “second-order contiguity matrix”
- Neighboring variables will be weighted averages of \( X \)’s in surrounding counties
- Errors can also be spatially correlated
Spatial Specification

\[ Y_t = X_t \beta_t + WX_t \gamma_t + \varepsilon_t \]

\[ Y_t = X_t \beta_t + WX_t \gamma_t + (\lambda_t W \varepsilon_t + \nu_t) \]

- Weighting matrix \( W \) is “second-order contiguity matrix”
- Neighboring variables will be weighted averages of \( X \)’s in surrounding counties
- Errors can also be spatially correlated
- \( \lambda_t \) measures strength of error correlation (“clumpiness” of residuals)
Spatial Specification

\[ Y_t = X_t \beta_t + WX_t \gamma_t + \varepsilon_t \]
\[ Y_t = X_t \beta_t + WX_t \gamma_t + (\lambda_t W \varepsilon_t + \nu_t) \]

- Weighting matrix \( W \) is “second-order contiguity matrix”
- Neighboring variables will be weighted averages of \( X \)'s in surrounding counties
- Errors can also be spatially correlated
- \( \lambda_t \) measures strength of error correlation (“clumpiness” of residuals)
- Estimate via GMM
Neighboring Manufacturing Shares in 1980

[Map showing neighboring manufacturing shares in 1980 with color coding for different share intervals.]
Log Earnings Per Job: Average January Temperature
Log Earnings Per Job: Density Regressors

Log Population Density


Top 5% Densest

Recent Employment Growth

Couillard & Foote (Boston Fed)
Log Earnings Per Job: Density Regressors

-0.05
0
0.05
0.1
0.15
Log Population Density

-0.05 0 0.05 0.1 0.15 1965 1975 1985 1995 2005 2015
Top 5% Densest

Couillard & Foote (Boston Fed)
Recent Employment Growth
October 3, 2019 15 / 22
Log Earnings Per Job: Education and Manufacturing Shares

Couillard & Foote (Boston Fed) Recent Employment Growth October 3, 2019 16 / 22
Log Earnings Per Job: Education and Manufacturing Shares

Log Share Bachelor Degrees

Share Manufacturing

Couillard & Foote (Boston Fed)
Hypothesis: Starting in mid-1990s, superstar cities pull away from other cities. IQR of earnings rises at top end of density distribution (seen earlier). Similar movements in superstar cities' constituent counties increase "clumpiness" of regression residuals ($\lambda_t$).
Hypothesis: Starting in mid-1990s, superstar cities pull away from other cities. IQR of earnings rises at top end of density distribution (seen earlier). Similar movements in superstar cities' constituent counties increase “clumpiness” of regression residuals ($\lambda_t$).

Couillard & Foote (Boston Fed)
Hypothesis: Starting in mid-1990s, superstar cities pull away from other cities. The interquartile range of earnings rises at the top end of the density distribution (seen earlier). Similar movements in superstar cities to constituent counties increase "clumpiness" of regression residuals ($\lambda_t$).
Hypothesis: Starting in mid-1990s, superstar cities pull away from other cities.
Log Earnings Per Job: Spatial Error Term

- Hypothesis: Starting in mid-1990s, superstar cities pull away from other cities
- IQR of earnings rises at top end of density distribution (seen earlier)
Hypothesis: Starting in mid-1990s, superstar cities pull away from other cities

IQR of earnings rises at top end of density distribution (seen earlier)

Similar movements in superstar cities constituent counties increase “clumpiness” of regression residuals ($\lambda_t$)
Review of Main Results

- Rural vs. urban

Relative earnings-per-job in densest 5% counties picks up in 1980s, even controlling for county’s college share and its manufacturing-employment share.

Low employment and population growth in 2000s.

“Superstar” cities vs. less-successful cities.

Conditional on county-level density, earnings-per-job dispersion generally declines for most of the sample period. But dispersion starts rising in 1990s, probably because of superstar cities.

Center cities vs. suburbs.

Evidence that employment suburbanization stalled for ≈20 commuting zones with densest core counties starting in 2000s.

Less evidence for ≈50 cities with less-dense cores.

Population suburbanization slows in 2000s for both groups.
Review of Main Results

- **Rural vs. urban**
  - Relative earnings-per-job in densest 5% counties picks up in 1980s, even controlling for county’s college share and its manufacturing-employment share
Review of Main Results

- Rural vs. urban
  - Relative earnings-per-job in densest 5% counties picks up in 1980s, even controlling for county’s college share and its manufacturing-employment share
  - Low employment and population growth in 2000s

- Superstar cities vs. less-successful cities
  - Conditional on county-level density, earnings-per-job dispersion generally declines for most of the sample period.
  - But dispersion starts rising in 1990s, probably because of superstar cities

- Center cities vs. suburbs
  - Evidence that employment suburbanization stalled for ≈ 20 commuting zones with densest core counties starting in 2000s
  - Less evidence for ≈ 50 cities with less-dense cores

- Population suburbanization slows in 2000s for both groups

Couillard & Foote (Boston Fed)
Review of Main Results

- **Rural vs. urban**
  - Relative earnings-per-job in densest 5% counties picks up in 1980s, even controlling for county’s college share and its manufacturing-employment share
  - Low employment and population growth in 2000s

- **“Superstar” cities vs. less-successful cities**
Review of Main Results

- **Rural vs. urban**
  - Relative earnings-per-job in densest 5% counties picks up in 1980s, even controlling for county’s college share and its manufacturing-employment share
  - Low employment and population growth in 2000s

- **“Superstar” cities vs. less-successful cities**
  - Conditional on county-level density, earnings-per-job dispersion generally declines for most of the sample period.
Review of Main Results

- **Rural vs. urban**
  - Relative earnings-per-job in densest 5% counties picks up in 1980s, even controlling for county’s college share and its manufacturing-employment share.
  - Low employment and population growth in 2000s.

- **“Superstar” cities vs. less-successful cities**
  - Conditional on county-level density, earnings-per-job dispersion generally declines for most of the sample period.
  - But dispersion starts rising in 1990s, probably b/c of superstar cities.
Review of Main Results

- **Rural vs. urban**
  - Relative earnings-per-job in densest 5% counties picks up in 1980s, even controlling for county’s college share and its manufacturing-employment share
  - Low employment and population growth in 2000s

- **“Superstar” cities vs. less-successful cities**
  - Conditional on county-level density, earnings-per-job dispersion generally declines for most of the sample period.
  - But dispersion starts rising in 1990s, probably b/c of superstar cities

- **Center cities vs. suburbs**
Review of Main Results

- **Rural vs. urban**
  - Relative earnings-per-job in densest 5% counties picks up in 1980s, even controlling for county’s college share and its manufacturing-employment share
  - Low employment and population growth in 2000s

- **“Superstar” cities vs. less-successful cities**
  - Conditional on county-level density, earnings-per-job dispersion generally declines for most of the sample period.
  - But dispersion starts rising in 1990s, probably b/c of superstar cities

- **Center cities vs. suburbs**
  - Evidence that employment suburbanization stalled for \( \approx \) 20 commuting zones with densest core counties starting in 2000s
Review of Main Results

- **Rural vs. urban**
  - Relative earnings-per-job in densest 5% counties picks up in 1980s, even controlling for county’s college share and its manufacturing-employment share
  - Low employment and population growth in 2000s

- **“Superstar” cities vs. less-successful cities**
  - Conditional on county-level density, earnings-per-job dispersion generally declines for most of the sample period.
  - But dispersion starts rising in 1990s, probably b/c of superstar cities

- **Center cities vs. suburbs**
  - Evidence that employment suburbanization stalled for ≈ 20 commuting zones with densest core counties starting in 2000s
  - Less evidence for ≈ 50 cities with less-dense cores
Review of Main Results

- **Rural vs. urban**
  - Relative earnings-per-job in densest 5% counties picks up in 1980s, even controlling for county’s college share and its manufacturing-employment share
  - Low employment and population growth in 2000s

- **“Superstar” cities vs. less-successful cities**
  - Conditional on county-level density, earnings-per-job dispersion generally declines for most of the sample period.
  - But dispersion starts rising in 1990s, probably b/c of superstar cities

- **Center cities vs. suburbs**
  - Evidence that employment suburbanization stalled for ≈ 20 commuting zones with densest core counties starting in 2000s
  - Less evidence for ≈ 50 cities with less-dense cores
  - Population suburbanization slows in 2000s for both groups
Manufacturing Employment Growth by Density Group

Growth in factory jobs in less-dense areas early in the sample period
Big losses everywhere post-2000
For manufacturers, 21st century has been an equal opportunity disemployer

Couillard & Foote (Boston Fed)
Manufacturing Employment Growth by Density Group

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

-4 -2 0 2 4
Annualized Percentage Growth Rate

1-85
86-95
96-99
100


Growth in factory jobs in less-dense areas early in the sample period
Big losses everywhere post-2000
For manufacturers, 21st century has been an equal opportunity disemployer

Couillard & Foote (Boston Fed)
Recent Employment Growth
October 3, 2019 19 / 22
Manufacturing Employment Growth by Density Group

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

-4-2024 Annualized Percentage Growth Rate

1-85
86-95
96-99
100

Growth in factory jobs in less-dense areas early in the sample period. Big losses everywhere post-2000. For manufacturers, 21st century has been an equal opportunity disemployer.

Couillard & Foote (Boston Fed)
Manufacturing Employment Growth by Density Group

- Growth in factory jobs in less-dense areas early in the sample period

Recent Employment Growth

Couillard & Foote (Boston Fed)
Manufacturing Employment Growth by Density Group

- Growth in factory jobs in less-dense areas early in the sample period
- Big losses everywhere post-2000

By Initial Density Group and Year

Growth in factory jobs in less-dense areas early in the sample period
Big losses everywhere post-2000
- Growth in factory jobs in less-dense areas early in the sample period
- Big losses everywhere post-2000
- For manufacturers, 21st century has been an equal opportunity disemployer
Additional Questions Related to Manufacturing Share

1. Why have recent declines in the US manufacturing share had such large effects on local communities? (Charles, Hurst and Schwartz 2018)
Additional Questions Related to Manufacturing Share

1. Why have recent declines in the US manufacturing share had such large effects on local communities? (Charles, Hurst and Schwartz 2018)
   - Human capital differences are likely important (Russ and Shambaugh 2019)
Additional Questions Related to Manufacturing Share

1. Why have recent declines in the US manufacturing share had such large effects on local communities? (Charles, Hurst and Schwartz 2018)
   - Human capital differences are likely important (Russ and Shambaugh 2019)
   - Paper develops a potential spatial angle:

   ![Graph showing the percentage of manufacturing employment from 1965 to 2015 with percentages from 0.55 to 0.85 marked at different years: 1965, 1975, 1985, 1995, 2005, 2015. The graph implies that current job losers are less able to diversify than earlier job losers.]

   Implication: Current job losers are less able to diversify than earlier job losers.
Additional Questions Related to Manufacturing Share

1. Why have recent declines in the US manufacturing share had such large effects on local communities? (Charles, Hurst and Schwartz 2018)
   - Human capital differences are likely important (Russ and Shambaugh 2019)
   - Paper develops a potential spatial angle:
     - Being surrounded by other manufacturing counties partially “insulated” a county from factory-job losses—until 1995
Why have recent declines in the US manufacturing share had such large effects on local communities? (Charles, Hurst and Schwartz 2018)

- Human capital differences are likely important (Russ and Shambaugh 2019)
- Paper develops a potential spatial angle:
  - Being surrounded by other manufacturing counties partially “insulated” a county from factory-job losses—until 1995
  - Spatial error term from manufacturing-share regression:
Additional Questions Related to Manufacturing Share

1. Why have recent declines in the US manufacturing share had such large effects on local communities? (Charles, Hurst and Schwartz 2018)
   - Human capital differences are likely important (Russ and Shambaugh 2019)
   - Paper develops a potential spatial angle:
     - Being surrounded by other manufacturing counties partially “insulated” a county from factory-job losses—until 1995
     - Spatial error term from manufacturing-share regression:

   ![Graph showing changes in manufacturing share over time]

   - Implication: Current job-losers less able to diversify than earlier job losers
Additional Questions Related to Manufacturing Share

2. How does the timing of manufacturing declines in various counties relate to rising within-city earnings inequality (Baum-Snow et al. 2018, Autor 2019)?
How does the timing of manufacturing declines in various counties relate to rising within-city earnings inequality (Baum-Snow et al. 2018, Autor 2019)?

  1. Machine operators (“routine manual”)
  2. Secretaries, stenographers, and typists (“routine cognitive”)

Foote and Ryan (2014): Routine-cognitive share of employment rises until 1990s—then declines.


A technological reallocation of traditional office tasks away from non-college workers would have large implications for urban/housing policy.
How does the timing of manufacturing declines in various counties relate to rising within-city earnings inequality (Baum-Snow et al. 2018, Autor 2019)?

  1. Machine operators ("routine manual")
Additional Questions Related to Manufacturing Share

2. How does the timing of manufacturing declines in various counties relate to rising within-city earnings inequality (Baum-Snow et al. 2018, Autor 2019)?

     1. Machine operators (“routine manual”)
     2. Secretaries, stenographers, and typists (“routine cognitive”)

   - Foote and Ryan (2014): Routine-cognitive share of employment rises until 1990s—then declines.

   - Autor (2019): Decline in urban premium for non-college workers comes mostly after 2000 suggests that technological obsolescence of routine-cognitive workers is to blame.

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

Couillard & Foote (Boston Fed)
Additional Questions Related to Manufacturing Share

2. How does the timing of manufacturing declines in various counties relate to rising within-city earnings inequality (Baum-Snow et al. 2018, Autor 2019)?

  1. Machine operators ("routine manual")
  2. Secretaries, stenographers, and typists ("routine cognitive")

- Foote and Ryan (2014): Routine-cognitive share of employment rises until 1990s—then declines
Additional Questions Related to Manufacturing Share

2 How does the timing of manufacturing declines in various counties relate to rising within-city earnings inequality (Baum-Snow et al. 2018, Autor 2019)?

  1. Machine operators (“routine manual”)
  2. Secretaries, stenographers, and typists (“routine cognitive”)

- Foote and Ryan (2014): Routine-cognitive share of employment rises until 1990s—then declines

Additional Questions Related to Manufacturing Share

2 How does the timing of manufacturing declines in various counties relate to rising within-city earnings inequality (Baum-Snow et al. 2018, Autor 2019)?

  1. Machine operators (“routine manual”)
  2. Secretaries, stenographers, and typists (“routine cognitive”)

- Foote and Ryan (2014): Routine-cognitive share of employment rises until 1990s—then declines


- Suggests that technological obsolescence of routine-cognitive workers is to blame
2 How does the timing of manufacturing declines in various counties relate to rising within-city earnings inequality (Baum-Snow et al. 2018, Autor 2019)?

  1. Machine operators ("routine manual")
  2. Secretaries, stenographers, and typists ("routine cognitive")

- Foote and Ryan (2014): Routine-cognitive share of employment rises until 1990s—then declines


- Suggests that technological obsolescence of routine-cognitive workers is to blame

- 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

**1964 County Classifications**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Top 1%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>96-99%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>86-95%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-85%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Density Percentile of CZ’s Densest County**

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

---

### 2016 County Classifications

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Top 1%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>96-99%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>86-95%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-85%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Note:** Commuting zones defined using 1990 data. Densest county of CZ defined using 2016 data.

---

**Evidence for population growth in middle two tiers in both panels (lt. blue and tan)**

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

Couillard & Foote (Boston Fed)

**Recent Employment Growth**

October 3, 2019
Commuting Zones: Population Shares

1964 County Classifications

Note: Commuting zones defined using 1990 data. Densest county of CZ defined using 1964 data.
Evidence for population growth in middle two tiers in both panels (lt. blue and tan)

Rappaport (2018): Faster growth of “larger, less-crowded locations”
Evidence for population growth in middle two tiers in both panels (lt. blue and tan)
Evidence for population growth in middle two tiers in both panels (lt. blue and tan)

Rappaport (2018): Faster growth of “larger, less-crowded locations”
Theories of Earnings Inequality

- Canonical Model

- Technical progress has been biased toward skilled workers throughout the 20th/21st centuries.
- Changes in the relative supply and demand for skill determine the college premium.

Alternative Models

- Technical change and/or capital can reduce the demand for certain types of labor.
- Summers' 2013 Feldstein Lecture at NBER.
- Robots/foreign workers perform tasks previously done by factory workers.
- New technologies allow high-skill workers to perform tasks previously performed by office workers.
  - Executives making their own travel arrangements using Orbitz/Travelocity/Priceline.
  - Researchers typing their own papers using LATEX or Scientific Word.
Theories of Earnings Inequality

- **Canonical Model**
  - Technical progress has been biased toward skilled workers throughout the 20th/21st centuries
Theories of Earnings Inequality

- **Canonical Model**
  - Technical progress has been biased toward skilled workers throughout the 20th/21st centuries
  - Changes in the relative supply and demand for skill determine the college premium
Theories of Earnings Inequality

- **Canonical Model**
  - Technical progress has been biased toward skilled workers throughout the 20th/21st centuries
  - Changes in the relative supply and demand for skill determine the college premium

- **Alternative Models**
  - Technical change and/or capital can reduce the demand for certain types of labor
  - Acemoglu/Autor’s Ricardian model (2011): Skills → Tasks → Output
  - Robots/foreign workers perform tasks previously done by factory workers
  - New technologies allow high-skill workers to perform tasks previously performed by office workers
  - Executives making their own travel arrangements using Orbitz/Travelocity/Priceline
  - Researchers typing their own papers using LaTeX or Scientific Word
Theories of Earnings Inequality

- **Canonical Model**
  - Technical progress has been biased toward skilled workers throughout the 20th/21st centuries
  - Changes in the relative supply and demand for skill determine the college premium

- **Alternative Models**
Theories of Earnings Inequality

- **Canonical Model**
  - Technical progress has been biased toward skilled workers throughout the 20th/21st centuries
  - Changes in the relative supply and demand for skill determine the college premium

- **Alternative Models**
  - Technical change and/or capital can reduce the demand for certain types of labor

- **Resources**

Theories of Earnings Inequality

■ **Canonical Model**
  ■ Technical progress has been biased toward skilled workers throughout the 20th/21st centuries
  ■ Changes in the relative supply and demand for skill determine the college premium

■ **Alternative Models**
  ■ Technical change and/or capital can reduce the demand for certain types of labor
    ■ Summers’ 2013 Feldstein Lecture at NBER
Theories of Earnings Inequality

- **Canonical Model**
  - Technical progress has been biased toward skilled workers throughout the 20th/21st centuries
  - Changes in the relative supply and demand for skill determine the college premium

- **Alternative Models**
  - Technical change and/or capital can reduce the demand for certain types of labor
    - Summers’ 2013 Feldstein Lecture at NBER
    - Acemoglu/Autor’s Ricardian model (2011): Skills → Tasks → Output
Theories of Earnings Inequality

- **Canonical Model**
  - Technical progress has been biased toward skilled workers throughout the 20th/21st centuries
  - Changes in the relative supply and demand for skill determine the college premium

- **Alternative Models**
  - Technical change and/or capital can reduce the demand for certain types of labor
    - Summers’ 2013 Feldstein Lecture at NBER
    - Acemoglu/Autor’s Ricardian model (2011): Skills → Tasks → Output
  - Robots/foreign workers perform tasks previously done by factory workers
Theories of Earnings Inequality

**Canonical Model**
- Technical progress has been biased toward skilled workers throughout the 20th/21st centuries
- Changes in the relative supply and demand for skill determine the college premium

**Alternative Models**
- Technical change and/or capital can reduce the demand for certain types of labor
  - Summers’ 2013 Feldstein Lecture at NBER
  - Acemoglu/Autor’s Ricardian model (2011): Skills → Tasks → Output
- Robots/foreign workers perform tasks previously done by factory workers
- New technologies allow high-skill workers to perform tasks previously performed by office workers
Theories of Earnings Inequality

■ **Canonical Model**
  ■ Technical progress has been biased toward skilled workers throughout the 20th/21st centuries
  ■ Changes in the relative supply and demand for skill determine the college premium

■ **Alternative Models**
  ■ Technical change and/or capital can reduce the demand for certain types of labor
    ■ Summers’ 2013 Feldstein Lecture at NBER
    ■ Acemoglu/Autor’s Ricardian model (2011): Skills → Tasks → Output
  ■ Robots/foreign workers perform tasks previously done by factory workers
  ■ New technologies allow high-skill workers to perform tasks previously performed by office workers
    ■ Executives making their own travel arrangements using Orbitz/Travelocity/Priceline
  ■ Researchers typing their own papers using LaTeX or Scientific Word
Theories of Earnings Inequality

■ **Canonical Model**
  ■ Technical progress has been biased toward skilled workers throughout the 20th/21st centuries
  ■ Changes in the relative supply and demand for skill determine the college premium

■ **Alternative Models**
  ■ Technical change and/or capital can reduce the demand for certain types of labor
    ■ Summers’ 2013 Feldstein Lecture at NBER
    ■ Acemoglu/Autor’s Ricardian model (2011): Skills $\rightarrow$ Tasks $\rightarrow$ Output
  ■ Robots/foreign workers perform tasks previously done by factory workers
  ■ New technologies allow high-skill workers to perform tasks previously performed by office workers
    ■ 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

<table>
<thead>
<tr>
<th>Year</th>
<th>Share of Total Nonagricultural Employment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950q1</td>
<td></td>
</tr>
<tr>
<td>1960q1</td>
<td></td>
</tr>
<tr>
<td>1970q1</td>
<td></td>
</tr>
<tr>
<td>1980q1</td>
<td></td>
</tr>
<tr>
<td>1990q1</td>
<td></td>
</tr>
<tr>
<td>2000q1</td>
<td></td>
</tr>
<tr>
<td>2010q1</td>
<td></td>
</tr>
</tbody>
</table>

Routine Cognitive

Recent Employment Growth

October 3, 2019 22 / 22
National Employment by Occupational Group

Source: CPS

Share of Total Nonagricultural Employment

- Routine Cognitive
- Nonroutine Cognitive
- Routine Manual

Couillard & Foote (Boston Fed)

Recent Employment Growth

October 3, 2019
### National Employment by Occupational Group

**Source:** CPS

<table>
<thead>
<tr>
<th></th>
<th>1950q1</th>
<th>1960q1</th>
<th>1970q1</th>
<th>1980q1</th>
<th>1990q1</th>
<th>2000q1</th>
<th>2010q1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Routine Cognitive</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonroutine Cognitive</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Routine Manual</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonroutine Manual</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---

**Graph:**
- **Routine Cognitive**
- **Nonroutine Cognitive**
- **Routine Manual**
- **Nonroutine Manual**

X-axis: 1950q1 to 2010q1
Y-axis: Share of Total Nonagricultural Employment (0.1 to 0.5)

**Legend:**
- Routine Cognitive (Graph Style: Black, Line Style: Solid)
- Nonroutine Cognitive (Graph Style: Red, Line Style: Solid)
- Routine Manual (Graph Style: Green, Line Style: Solid)
- Nonroutine Manual (Graph Style: Blue, Line Style: Solid)

**Couillard & Foote (Boston Fed)**

**Recent Employment Growth**

October 3, 2019
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

Recent Employment Growth
New York City in the 1970s

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
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
New York City in the 1970s

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
New York City in the 1970s

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
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

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

Couillard & Foote (Boston Fed)
Striking fact: In 1964, more factory jobs in the densest 1% of counties than in the least-dense 85%.

Dramatic reversal in importance of dense vs. rural counties during sample period.

Couillard & Foote (Boston Fed)
Manufacturing Employment Share by Density Group

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