Tale of Two Labor Markets: Structural Determinants of Cyclical Unemployment Across the Urban-Rural Divide

RA Research Program: Research Proposal

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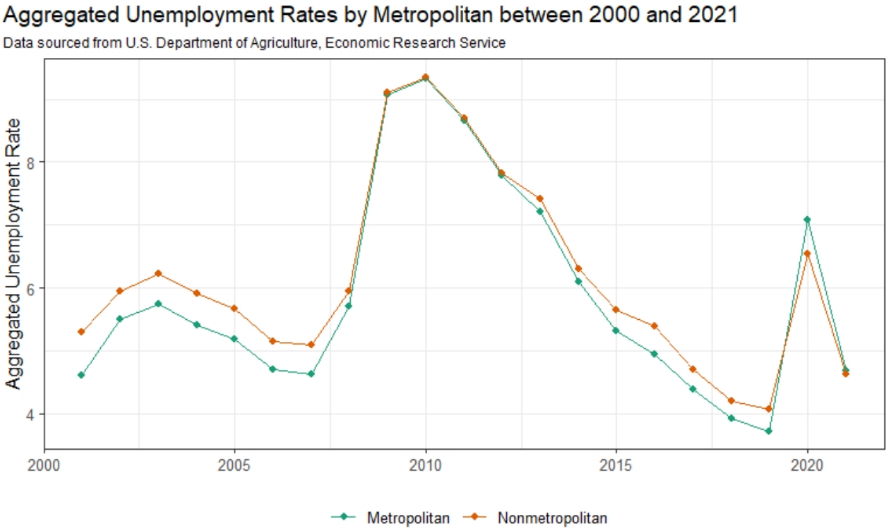
Overview

Outline

Humble Start



Initial Modeling

Table 1: Non-Linear Local Projection OLS Estimates

	Nonmetropolitan ($N = 1970$)			Metropolitan ($N = 1169$)		
Horizon	Shock	log(GDP)	log(Labor Force)	Shock	log(GDP)	log(Labor Force)
2006	1.000			1.000		
2007	1.138***	−0.028	8.298***	1.271***	−1.354***	5.418***
	(0.020)	(0.204)	(0.602)	(0.008)	(0.069)	(0.233)
2008	0.988***	−0.144	18.742***	1.177***	−3.518***	11.277***
	(0.032)	(0.491)	(1.351)	(0.013)	(0.165)	(0.501)
2009	0.805***	−0.377	25.918***	1.001***	−5.567***	14.948***
	(0.037)	(0.750)	(1.897)	(0.015)	(0.253)	(0.679)
2010	0.783***	−1.601*	23.777***	0.982***	−4.831***	13.673***
	(0.036)	(0.633)	(1.765)	(0.014)	(0.231)	(0.627)
2011	0.622***	−1.401*	22.881***	0.811***	−4.236***	13.100***
	(0.034)	(0.596)	(1.751)	(0.014)	(0.218)	(0.619)
2012	0.504***	−0.951	22.992***	0.623***	−4.158***	12.673***
	(0.033)	(0.659)	(1.845)	(0.013)	(0.228)	(0.643)
2013	0.625***	−0.729	21.995***	0.702***	−4.251***	11.835***
	(0.031)	(0.701)	(1.856)	(0.012)	(0.238)	(0.642)
2014	0.463***	−1.185	20.097***	0.560***	−4.896***	11.225***
	(0.027)	(0.723)	(1.917)	(0.011)	(0.240)	(0.681)
2015	0.383***	−2.454***	20.978***	0.424***	−5.529***	11.839***
	(0.023)	(0.756)	(2.104)	(0.010)	(0.257)	(0.756)
2016	0.257***	−2.908***	19.189***	0.285***	−5.377***	7.277***
	(0.019)	(0.848)	(2.818)	(0.008)	(0.289)	(1.107)

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

p-values correspond to the t-test of coefficients. Lagged covariates of the predictors were excluded due to strong dependency and nearly identical results from the statistical tests.

Outline

Urban/Rural Economic Divides: Key Findings

- **Proximity effects**: Proximity to urban counties benefit rural counties (Patridge and Rickman, 2008)
- **Economic development**: Spatial boundaries increasingly blurry, while growing more distinct (investment, migration, technology, transportation) (Lichter and Brown, 2011)
- **Recovery patterns**: Rural areas experienced less severe job loss but weaker recovery after GFC (Hertz et al., 2014)
- **Industry-variant**: Industrial composition of counties saw variable severity of unemployment shocks after GFC (Thiede and Monnat, 2016)
- **Differential development factors**: Economic development is driven by different factors in urban/rural counties like human capital and natural resources (Wu and Gopinath, 2008)

Decomposition Methods

- **Time-varying parameter models**: Median-unbiased estimator with Kalman filtering (Stock and Watson, 1998). Unobserved components model with stochastic volatility (UC-SV0) (Stock and Watson, 2016). Comparing Beveridge-Nelson Estimation to Unobserved-Component Estimates for GDP (Morley et al. 2003).
- **Blinder-Oaxaca Decomposition**: Decomposes differences of group means into "explained" and "unexplained" components. Traditionally been used in labor economic studies. (Blinder, 1973; Oaxaca, 1973)
- **Alternative methods**: Techniques beyond mean decomposition, including quantile regression and Recentered Influence Function (RIF) approaches, analyze differences across the entire unemployment distribution and other statistics like variance, revealing how urban-rural gaps may vary with economic conditions (Fortin et al., 2011)

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Research Question, Hypothesis, and Objectives

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To what extent do urban and rural labor market economies exhibit structurally distinct distributional patterns in cyclical unemployment? How much of the patterns are explainable by observable characteristics?

Hypothesis

Based on previous intuition, we expect urban unemployment cycles to be more volatile and persistent than those in rural counties.

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Based on previous intuition, we expect urban unemployment cycles to be more volatile and persistent than those in rural counties.

To test the hypothesis, we have two main research objectives:

- **Trend-Cycle Decomposition**: Decompose unemployment rates into trend and cyclical components.
- **Model Urban/Rural Differences**: Use the Blinder-Oaxaca decomposition to compare cyclical unemployment rates.

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Data Description: Unemployment

To perform the decompositions, we require data across multiple sources at the county-level: unemployment rates, urban/rural classifications, and county-level explanatory variables.

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Unemployment and Labor Force Data

Monthly county-level unemployment rates from 1990 to 2025 for approximately 3100 counties are assembled from the Bureau of Labor Statistics' Local Area Unemployment Statistics (LAUS) program.

This dataset reports unemployment, employment, and labor force estimates. These data are compiled using a combination of survey-derived (Current Population Survey for large counties and metropolitan areas) and administrative sources (e.g., unemployment insurance claims, QCEW for smaller counties). Not seasonally adjusted.

Data Description: Explanatory Variables

As for many econometric models, the results of the Blinder-Oaxaca Decomposition have been found to be sensitive to the researcher's choice of covariates (Jann, 2008).

Most explanatory variables are reported at a quarterly frequency for each county spanning from 1990 to 2024, rather than a monthly frequency.

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Unemployment and Labor Force Data

- Economic structure: employment by sector/industry (e.g., from QCEW).
- Demographics: age, race, educational attainment (from Census/ERS datasets).
- Public assistance: transfer payments, unemployment insurance (from FRED, ERS).

Most of these are available at the county level via the Economic Research Service's county data files, BLS data by the Quarterly Census of Employment and Wages (QCEW) and Business Employment Dynamics (BED), and the U.S. Census Bureau Current Population Survey (CPS).

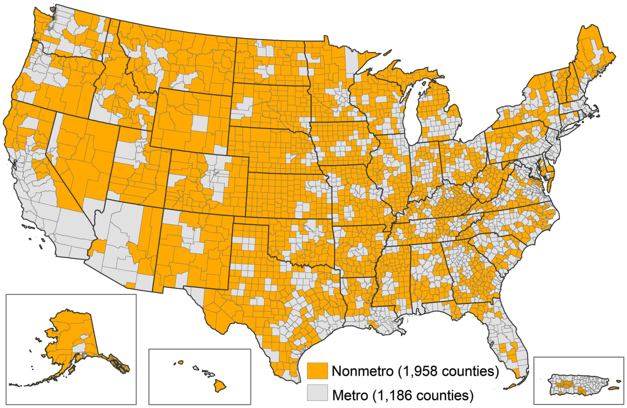
Data Description: Classifications

Counties are classified according to the USDA's Rural-Urban Continuum Codes (RUCC), with classifications for 1989, 2004, 2015, and 2023 (Economic Research Service, 2023).

Nonmetro counties are classified as some combination of:

- open countryside,
- rural towns (places with fewer than 5,000 people and 2,000 housing units), and
- urban areas with populations ranging up to 50,000 people that are not part of larger labor market areas.

Metropolitan (metro) and nonmetropolitan (nonmetro) counties, 2023



Note: Alaska, Hawaii, and Puerto Rico are not drawn to scale. Metro/nonmetro delineations are not available for other U.S. island territories.
Source: USDA, Economic Research Service using data from the U.S. Office of Management and Budget and U.S. Department of Commerce, Bureau of the Census.

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Trend-Cycle Decomposition: Stock & Watson (2016)

The Stock-Watson time-varying parameter approach provides a sophisticated framework for decomposing unemployment into trend and cyclical components:

$$y_{i,t} = \tau_{i,t} + c_{i,t} + \varepsilon_{i,t}, \text{ where} \tag{1}$$

- $y_{i,t}$: Level of the (seasonally adjusted) unemployment rate for county i at time t
- $\tau_{i,t}$: Time-varying natural rate of unemployment (NAIRU)
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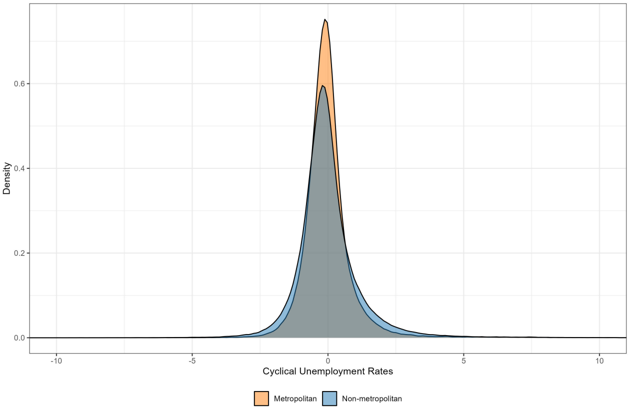
Following Stock & Watson (2016), we model the trend component as a random walk with time-varying drift, allowing for structural changes in labor markets:

$$\tau_{i,t} = \tau_{i,t-1} + \beta_{i,t} + \eta_{i,t}; \;\; \eta_{i,t} \sim N(0, \sigma_\tau^2); \;\; \beta_{i,t} = \beta_{i,t-1} + \nu_{i,t}; \;\; \nu_{i,t} \sim N(0, \sigma_\beta^2) \tag{2}$$

The cyclical component follows a stationary AR(2) process with potentially time-varying coefficients to capture changes in persistence:

$$c_{it} = \phi_{1,i,t} \cdot c_{i,t-1} + \phi_{2,i,t} \cdot c_{i,t-2} \tag{3}$$

Cyclical Unemployment Comparison



Cyclical unemployment decomposed using Hodrick-Prescott filter ($\lambda = 14400$). Performing the Asymptotic two-sample Kolmogorov-Smirnov test, we have a test statistic of $D = 0.0607$ and p-value less than 2.2e-16. Maximum difference of 6.07% in their cumulative probability.

Blinder–Oaxaca Decomposition: Concept and Origins

- The Blinder–Oaxaca decomposition separates group differences in an outcome variable into an **“explained”** part (due to differences in characteristics) and an **“unexplained”** part (due to differences in returns to characteristics).

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- **Example intuition**: Suppose average wages are \$25/hour in City A and \$20/hour in City B. If workers in City A have, on average, 2 more years of education, and each year of education is worth about \$1/hour, then \$2 of the gap is *explained* by education. The remaining \$3/hour is *unexplained* — potentially due to differences in how the labor market rewards the same characteristics, or to unobserved factors.

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- **Origins**: Introduced independently by Oaxaca and Blinder (1973) to study gender and racial wage gaps.

Blinder-Oaxaca Decomposition: Technical Formulation

Let $C_g = \alpha_g + X_g^\top \beta_g + \varepsilon_g$, with $E(\varepsilon_g) = 0$ and $g \in \{U, R\}$.

- **Parameters and model**:
  - C_U and C_R: Cyclical unemployment for urban and rural counties
  - X_U and X_R: Vectors of covariates (county characteristics)
  - β_U and β_R: Vectors of coefficients
  - α_U and α_R: Intercepts for urban and rural models

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- **Threefold decomposition**:

$$\begin{aligned} D &= E[C_U] - E[C_R] \\ &= \beta_U E(X_U) - \beta_R E(X_R) + (\alpha_U - \alpha_R) \\ &= \underbrace{(X_U - X_R)\beta_R}_{\text{Endowments}} + \underbrace{X_R(\beta_U - \beta_R)}_{\text{Coefficients}} + \underbrace{(\alpha_U - \alpha_R)}_{\text{Intercept}} \end{aligned}$$

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$$

- **Statistical inference**:
  - **Coefficients**: Bootstrap.
  - **Decomposition**: Delta Method. If $D = g(\hat{\theta})$ where $\hat{\theta} = (\hat{\alpha}_U, \hat{\alpha}_R, \hat{\beta}_U, \hat{\beta}_R, \bar{X}_U, \bar{X}_R)$, then

$$\text{Var}(D) \approx \nabla g(\hat{\theta})^T \text{Var}(\hat{\theta}) \nabla g(\hat{\theta}), \text{where } \nabla g(\hat{\theta}) \text{ is gradient of } g \text{ at } \hat{\theta}.$$

BO-Decomposition of Cyclical Metro/Non-Metro Means

For county i, quarter t, and group g, we have $C_{i,t,g} = \alpha_i + \gamma_t + \vec{X}_{i,t,g}^{\top}\vec{\beta} + \varepsilon_{i,t,g}$. Let $\vec{X}_{i,t,g}$ include average quarterly employment, number of firms, and total wages.

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Component	Estimate	Std. Error	95% CI
Metro Mean	-0.0043	0.0027	[-0.0097, 0.0010]
Non-Metro Mean	-0.0035	0.0023	[-0.0080, 0.0010]
Mean Difference	-0.0008	0.0035	[-0.0078, 0.0061]
Explained	-0.0006	0.0023	[-0.0050, 0.0039]
Unexplained	-0.0003	0.0040	[-0.0081, 0.0075]
Total	-0.0009	0.0046	[-0.0098, 0.0081]

RIF Decomposition: Extending Blinder-Oaxaca Beyond the Mean

- The Recentered Influence Function (RIF) approach extends decomposition methods to analyze differences across entire distributions, not just means
- **Key advantages**:
  - Decomposes differences in any distributional statistic (quantiles, variance, Gini coefficient)
  - Maintains the simple regression-based framework of Blinder-Oaxaca
  - Allows for detailed decomposition of individual covariate contributions
  - Reveals heterogeneous effects across the distribution (e.g., different urban-rural gaps at different unemployment quantiles)
- **Applications**: Developed by Firpo, Fortin, and Lemieux (2009) to analyze wage inequality
  - For cyclical unemployment: Can reveal if rural areas face larger gaps during severe downturns (upper quantiles) than during normal periods
  - Uncovers if the variance of cyclical unemployment differs systematically between urban and rural areas

RIF Decomposition: Intuition and Interpretation

- **Goal**: Compare a distributional statistic (e.g., a quantile) between two groups and split the gap into:
  - **Explained**: due to differences in characteristics (composition)
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- **How it works**:
  - The Recentered Influence Function (RIF) transforms each observation y so that its *average* equals the statistic of interest (e.g., the τ-quantile).
  - This lets us run a standard regression on the transformed y and interpret coefficients as contributions to that statistic.

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- **Example**: Suppose the 90th percentile of cyclical unemployment is 5% in rural areas and 7% in urban areas.
  - The RIF transformation tells us how each county's unemployment affects that 90th percentile.
  - The decomposition might show that 1 percentage point of the 2-point gap is due to different industry mixes (*explained*), and 1 point is due to structural differences in how industries translate into unemployment (*unexplained*).

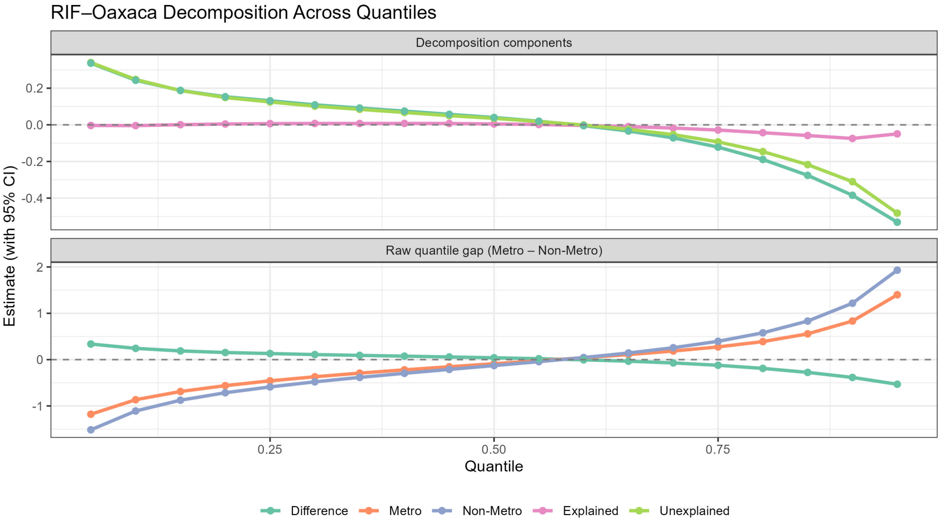
RIF Decomposition: Technical Formulation

- **The Influence Function (IF) and RIF**:
  - For distributional statistic $\nu(F_Y)$, the influence function $IF(y;\nu)$ measures the effect of adding an observation y on ν
  - $RIF(y;\nu) = \nu(F_Y) + IF(y;\nu)$ is centered at the statistic value
  - For quantile q_τ: $RIF(y;q_\tau) = q_\tau + \frac{\tau - \mathbf{1}\{y \leq q_\tau\}}{f_Y(q_\tau)}$ where $f_Y(q_\tau)$ is the density at q_τ
- **RIF-regression decomposition**:
  - Run regressions: $E[RIF(Y_g;\nu)|X] = X_g\beta_g$ for $g \in \{U, R\}$ (urban/rural)
  - Decompose differences in statistic ν:

$$\Delta^\nu_{UR} = \underbrace{(\bar{X}_U - \bar{X}_R)\beta^\nu_R}_{\text{Explained}} + \underbrace{\bar{X}_R(\beta^\nu_U - \beta^\nu_R) + (\alpha^\nu_U - \alpha^\nu_R)}_{\text{Unexplained}} \tag{4}$$

- **Statistical inference**:
  - Standard errors via bootstrap or analytical methods accounting for two estimation steps: (1) estimation of the RIF itself, (2) estimation of the coefficients
  - Special considerations needed for quantile estimation due to density estimation
  - Validity relies on assumptions of linearity in the conditional expectation of the RIF

RIF Decomposition Preliminary Results



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Conclusion

Preliminary results indicate that metro and non-metro counties exhibit structurally different cyclical unemployment distributions.

- At lower quantiles, non-metro counties have more negative cyclical unemployment
- At upper quantiles, non-metro counties have higher cyclical unemployment
- Unexplained differences dominate explained differences

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Research Proposal

This research proposal aims to examine whether urban and rural labor markets exhibit structurally different behaviors in the distribution of cyclical unemployment. Using trend-cycle decomposition to isolate cyclical components and a Recentered Influence Function-based Blinder-Oaxaca decomposition across quantiles, we are able to identify behaviors that indicate different cyclical component distributions.

Policy implications: Rural counties may require stronger counter-cyclical stabilizers.

Discussion

1. How should I address the issue of the BO-Decomposition being dependent upon the results of the trend-cycle decomposition?
2. How should I verify that we have a “good” trend-cycle decomposition?
3. Would spatial dependence between the counties be a concern?
4. Feel free to jump pitch in!

Thank You!

My door is open to hear your thoughts this afternoon!

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Outline

Hodrick-Prescott Filter: Time Series Decomposition

The Hodrick-Prescott filter is a common technique in macroeconomics for extracting trend and cyclical components from time series data.

Mathematical formulation: For a time series $\{y_t\}_{t=1}^{T}$, HP filter minimizes:

$$\sum_{t=1}^{T}(y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1}[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \quad (5)$$

where τ_t is the trend component and λ is a smoothing parameter.

Key aspects:

- λ controls the smoothness of the trend: larger values produce smoother trends
- Conventional values: $\lambda = 1600$ for quarterly data, $\lambda = 14400$ for monthly data
- Provides a simple, tractable approach to decomposing unemployment into trend and cycle
- Limitations include sensitivity to endpoints, arbitrary choice of λ, and potential spurious cyclicality

While more sophisticated approaches like unobserved components models offer advantages, the HP filter provides a transparent benchmark for comparison.