Examining City-level Progressive Taxation in the Presence of Migration, Congestion, and Heterogeneous Returns to Experience

Tamiraa Sanjaajav | Faculty Sponsor: Dr. Omer Koru
Economics Department | Quantitative Analysis Center | Wesleyan University

Introduction

Large cities generate strong agglomeration benefits by accelerating individual skill growth, but high congestion costs hit all workers equally regardless of experience. Because inexperienced workers earn less, these fixed living costs create an entry barrier that prices young, high-growth talent out of major metropolitan areas. This project develops a structural model showing that city-level progressive taxation solves this spatial distortion. By redistributing income to low-income workers, local progressive taxes reduce the net cost of living for early-career talent, encouraging their migration into large cities. In turn, expanding the pool of young, dynamic workers strengthens local agglomeration forces—boosting aggregate productivity and returns for experienced workers. As a result, city-level progressive taxation can be efficiency-boosting and welfare-enhancing across the entire income distribution.

Research Question

- How should progressive city-level income taxes be designed when migration, agglomeration economies, and congestion jointly determine workers' location choices and productivity?

Methodology

Data

First, we use microdata from the **American Community Survey (ACS)** to analyze city characteristics such as top income inequality and current taxation policies to see how agglomeration benefits are distributed. Second, we study if and how top income inequality and taxation policies affect migration. Third, we will use the data we've gathered in our structural model to characterize optimal local tax rates.

Top Income Inequality

To account for the censoring of high incomes in publicly available household survey data, we use the following maximum likelihood estimator outlined in a working paper by Gottlieb et al. (2023) to estimate the Pareto parameter of the tail of our distribution.

$$\frac{1}{\hat{\alpha}} = \frac{1}{N_{unc}} \left[\sum_{i \in \mathcal{N}_{unc}} w_i \ln\left(\frac{x_i}{x_{min}}\right) + N_{cen} \ln\left(\frac{\bar{x}}{x_{min}}\right) \right]$$

Migration Matrix

- To analyze individual characteristics of migrants, we construct metro-to-metro migration matrices using current and past (one year ago) residence metro from ACS. We validate our results against data published by the Census Bureau.

Taxation Data

- We are constructing a novel dataset compiled from government websites mapping current tax rates at the state, county, and city levels. This is currently a work in progress to be continued in the next steps of the project.

Results

Figure 1.Metro size raises inequality at the top of the distribution

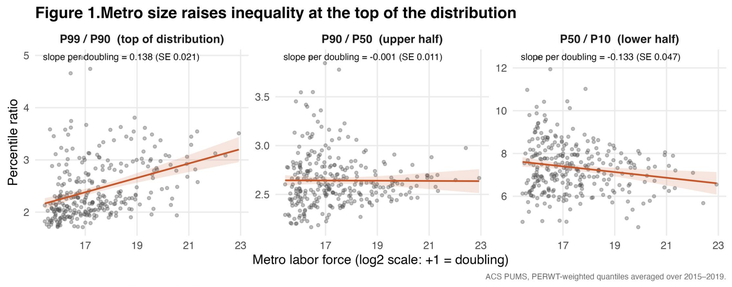
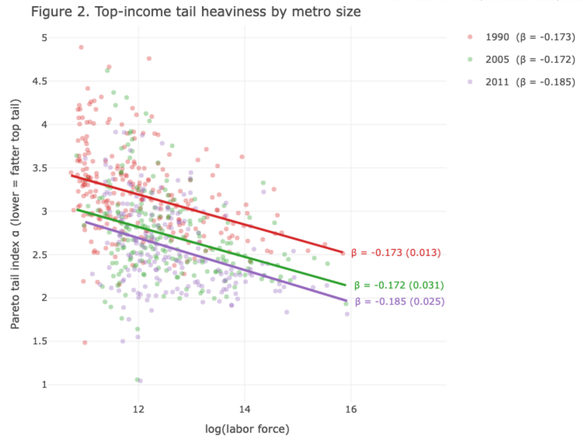


Figure 2. Top-income tail heaviness by metro size



Pareto Parameters

Figure 1 shows that income inequality stems primarily from dispersion at the top of the distribution rather than at the bottom. Figure 2 further illustrates that labor force size correlates with higher top-income inequality, which allows us to use the Pareto tail slope as a measure of agglomeration externality. These wage income estimates have been validated against IRS SOI data.

Figure 3. Net metro migration by income group, ACS 2023
Triangles point in the direction of net flow; size ~ magnitude; 75 largest metros

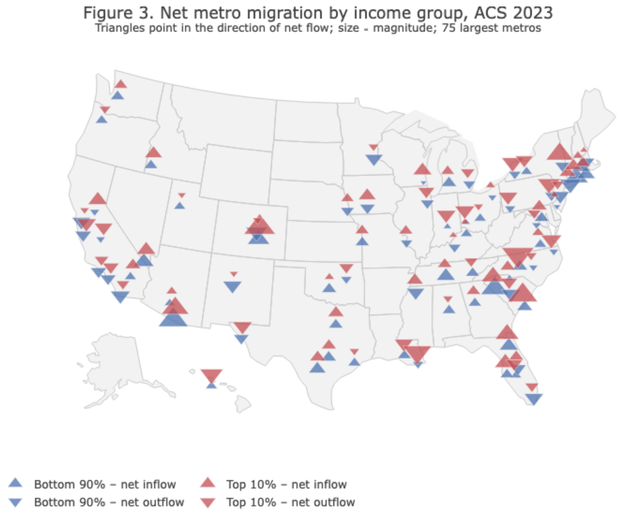


Figure 4. Migration of Individuals in the Top 10% of the Income Distribution (2023)

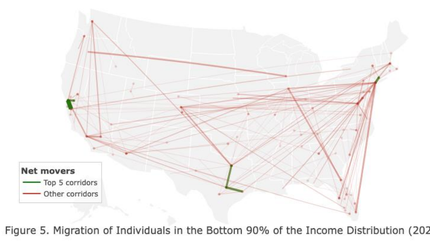
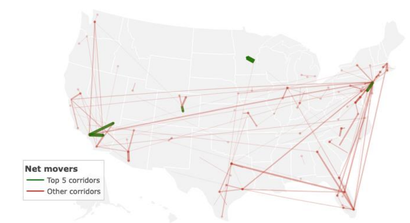


Figure 5. Migration of Individuals in the Bottom 90% of the Income Distribution (2023)



Migration Data

Figure 3 shows that top 10% and bottom 90% overall have mirrored net inflow/outflow patterns with switches happening in select cities on the two coasts. Figures 4 and 5 compare the pattern of migration between the top 10% and bottom 90%.

Next Steps

While our wage-based inequality estimates are largely in place and consistent with existing literature, the migration side can be more developed. We have begun examining how income influences migration decisions, but have not yet disaggregated by age group and other demographics. Further analysis is needed to model how taxation and income inequality jointly shape migration flows. Remaining work also includes mapping tax rates across metros, accounting for differences across tax instruments such as consumption and income taxes, and completing the model used to calibrate the optimal local tax rate.

Scan the QR code for an interactive dashboard created using our research data and a more detailed write up of the project.

References:
Gottlieb, J. D., Hémous, D., Hicks, J., & Olsen, M. (2023). Spillover effects of top income inequality (NBER Working Paper No. 31366). *National Bureau of Economic Research*. https://www.nber.org/papers/w31366
Heathcote, J., Perri, F., Violante, G. L., & Zhang, L. (2023). More unequal we stand? Inequality dynamics in the United States, 1967–2021. *Review of Economic Dynamics*, 50, 235–266. https://doi.org/10.1016/j.red.2023.07.014

Acknowledgements: I would like to thank Professor Koru for their guidance and expertise, everyone at the Quantitative Analysis Center for their help in my professional development, and my family for their endless support.