Social Ties and Residential Choice: Micro Evidence and Equilibrium Implications

Martin Koenen and Drew Johnston

July 25, 2025

Introduction

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- **Today:** Social networks (friends and family) help explain these facts

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    - Migration patterns line up with Census / IRS data Details

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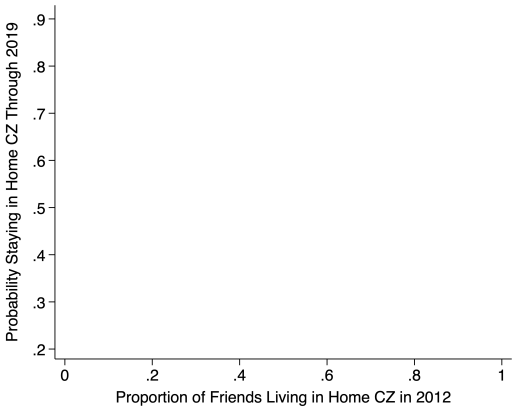
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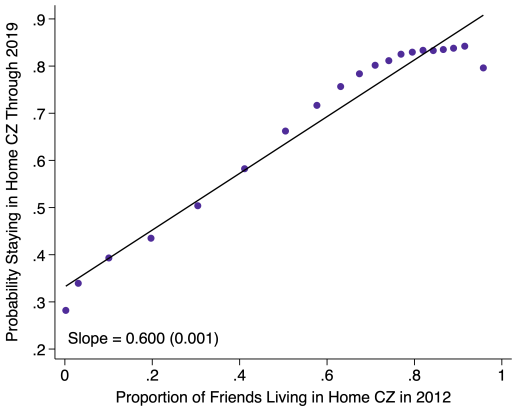
- Focus on active U.S. users, born 1985-1997 ($\approx$ 85% coverage)

Residential Mobility, Social Networks and Wage Growth



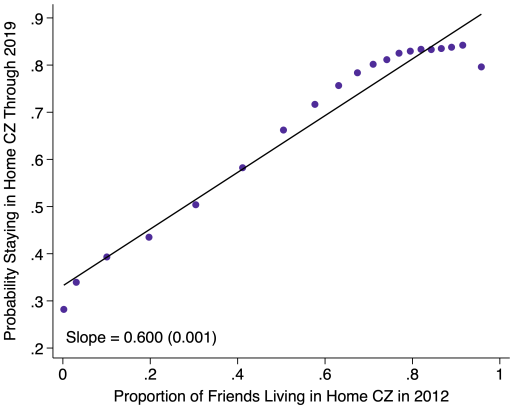
Employment growth | Other CZs | Sprung-Keyser et al.

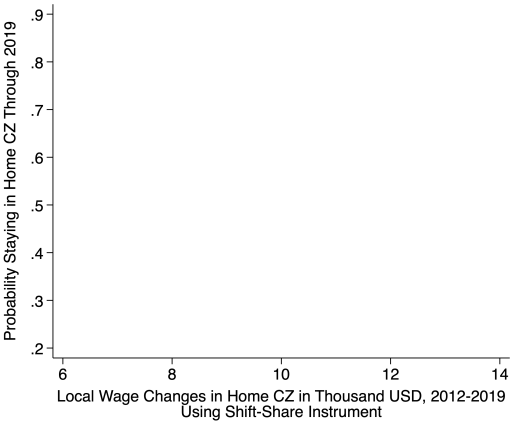
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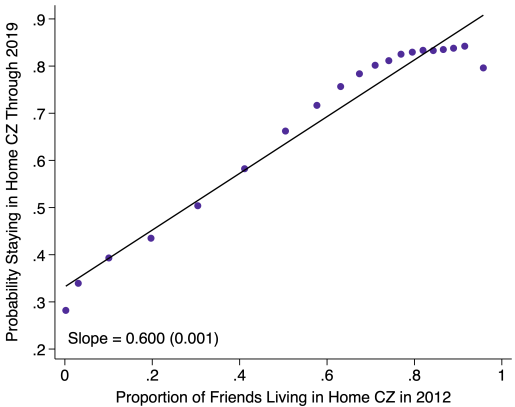
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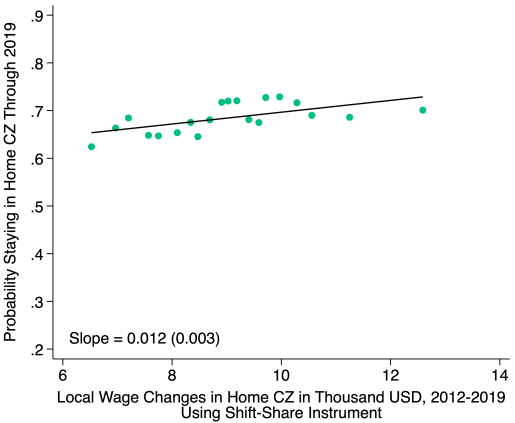




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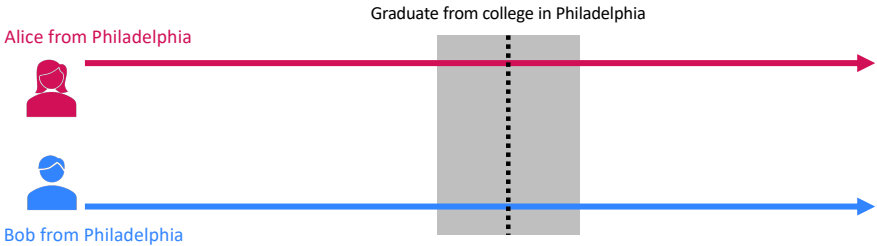
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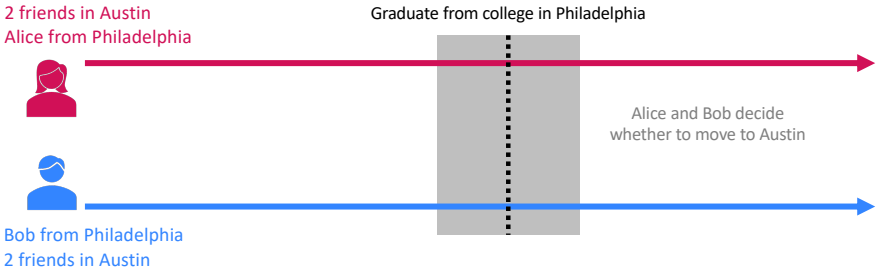


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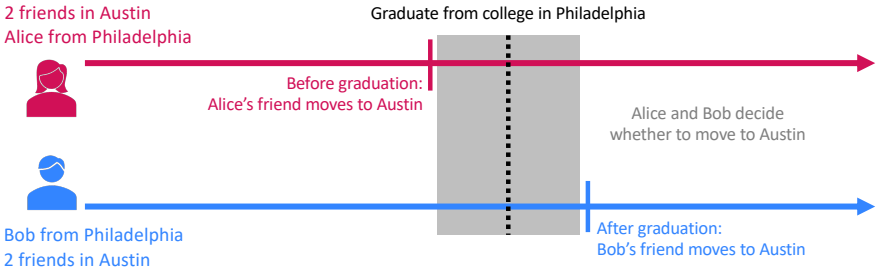
Research Design



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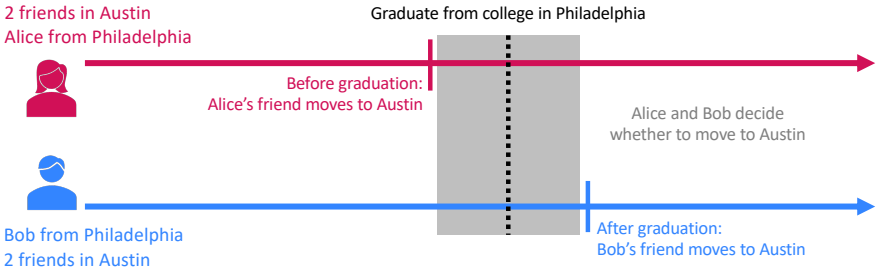


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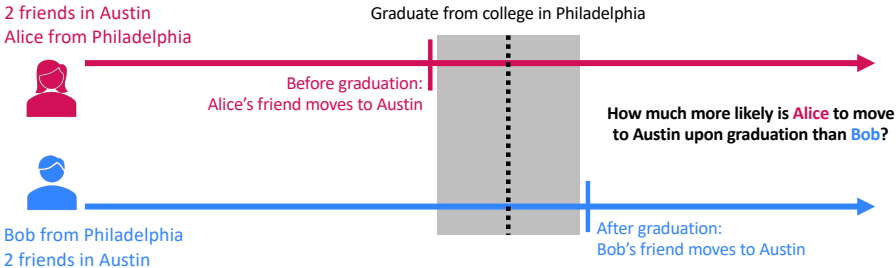
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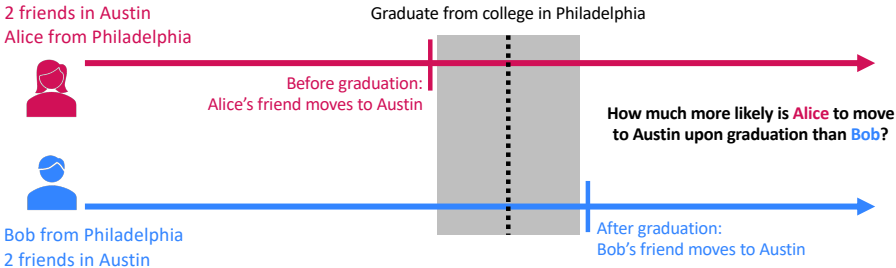
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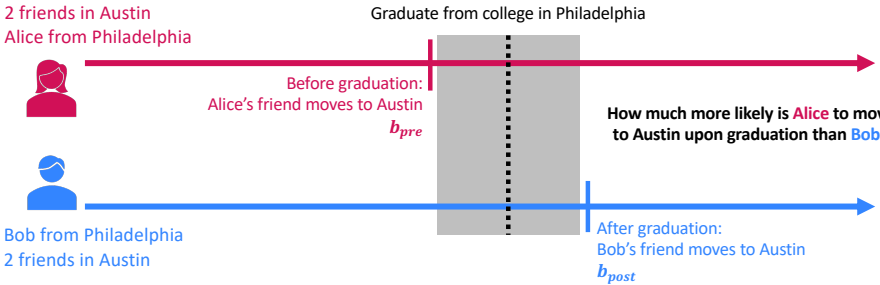
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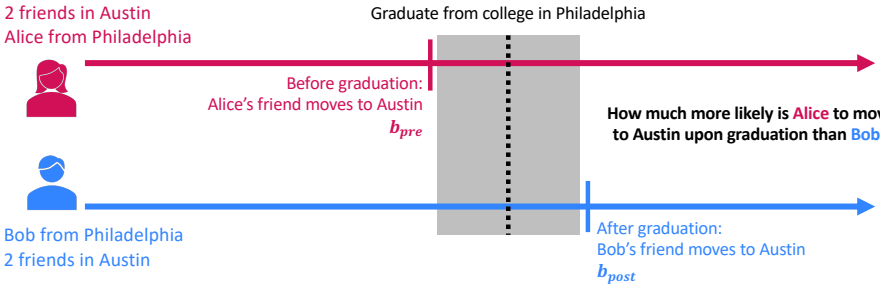
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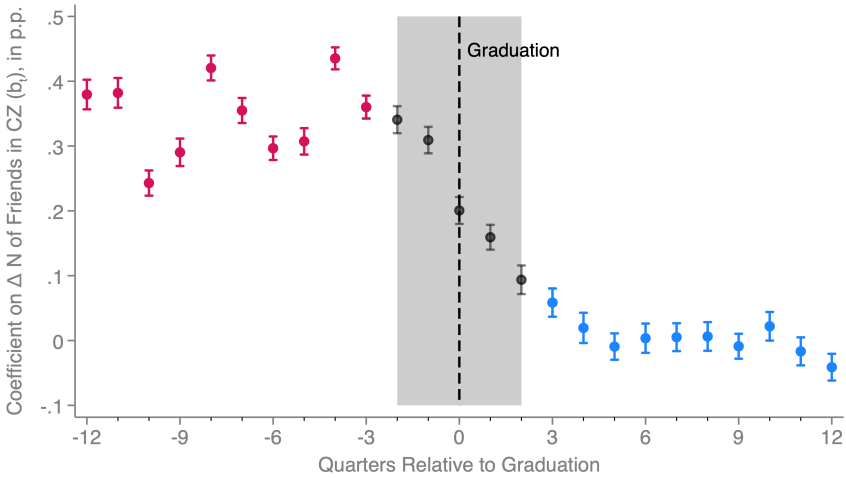
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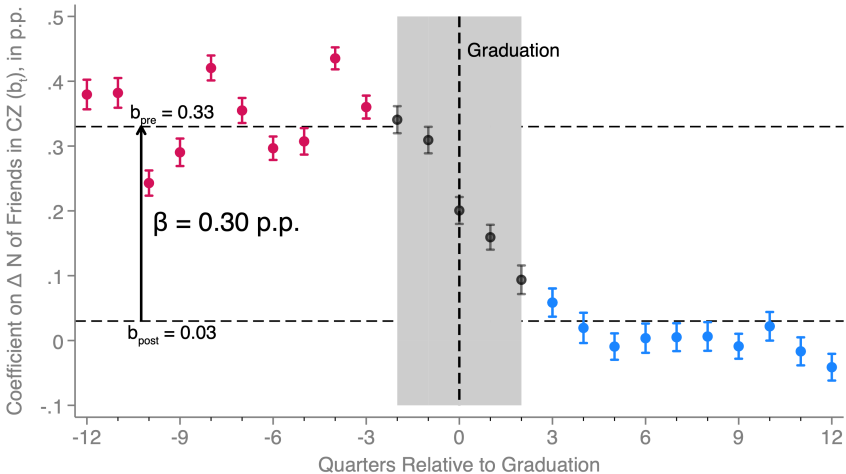
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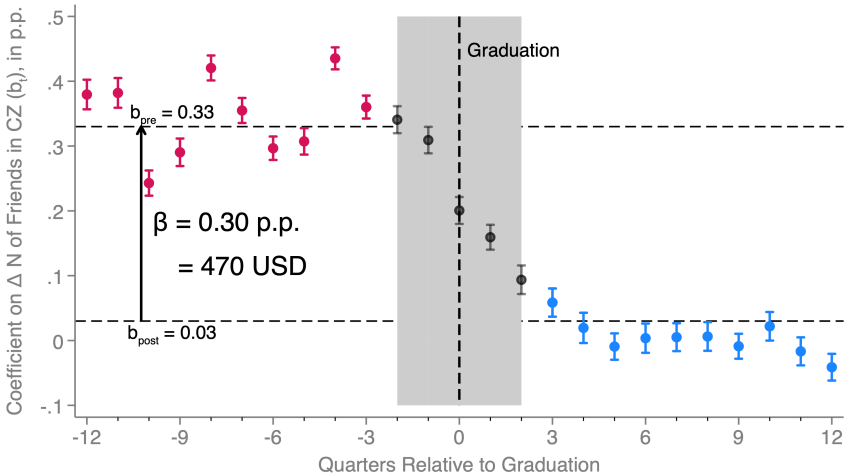
Effect of Friends' Moves on Residential Choice



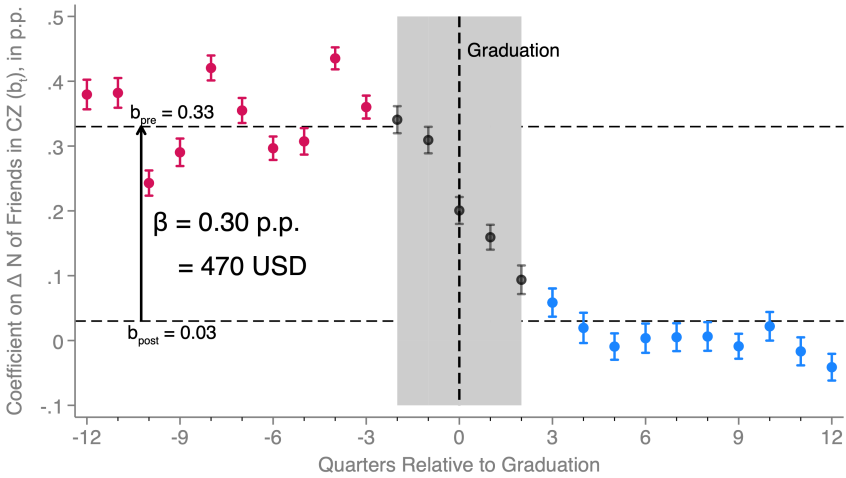
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  1. Social networks drive residential choices [Partial Equilibrium]
     - Reduced form evidence on effects of social networks on residential choice

  2. **Networks explain patterns of migration [General Equilibrium]**
     - Incorporate results from (1) into spatial equilibrium model
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Spatial Equilibrium Model with Social Ties

- Generalize Rosen-Roback style spatial equilibrium model to incorporate social ties
- Model comprises local production Details, local housing market Details, and workers

Spatial Equilibrium Model with Social Ties – Workers

Basic Model

$$U_{ij} = \alpha_w \ln(w_j) - \alpha_h \ln(r_j) + A_j + \epsilon_{ij}$$

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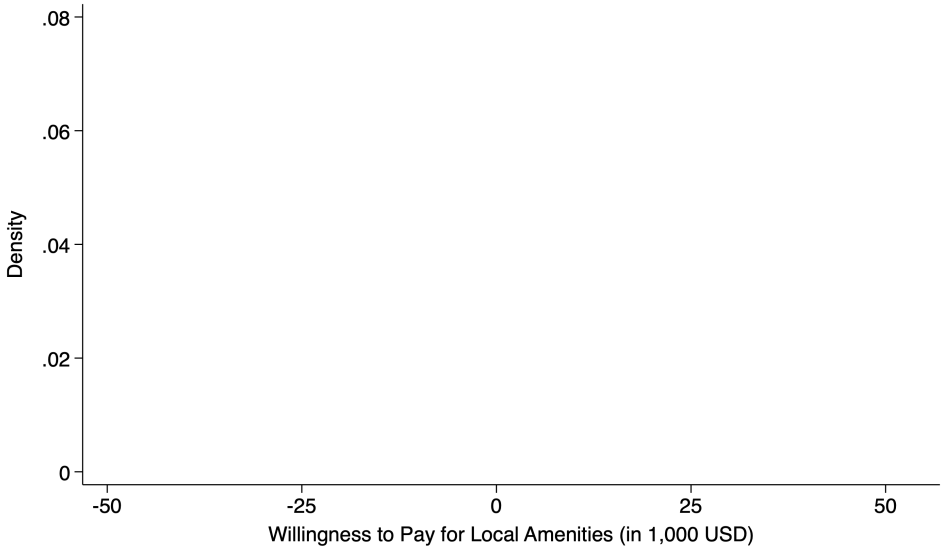
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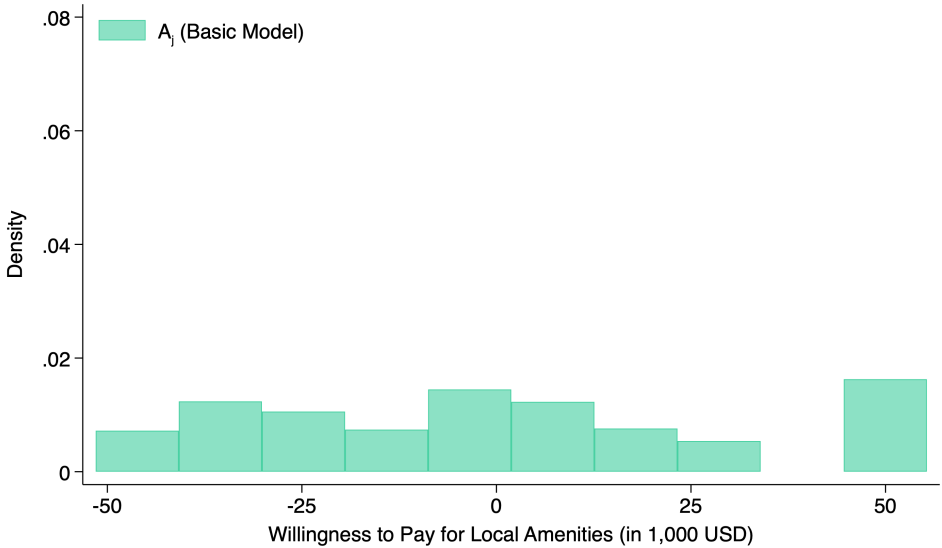
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  - A_j and $\tilde{A}_j$: residuals so that model implied pop. match observed pop.

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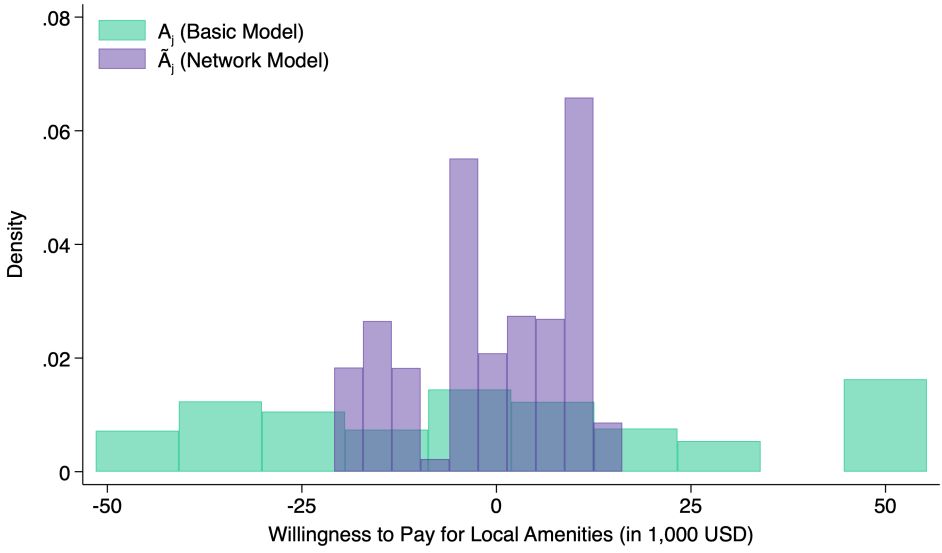
Distribution of WTP for A_j, $\tilde{A}_j$



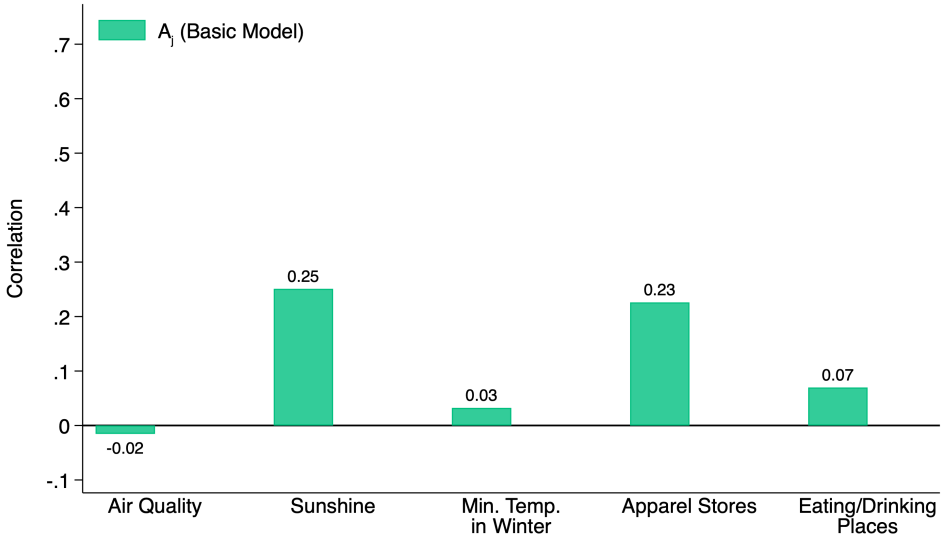
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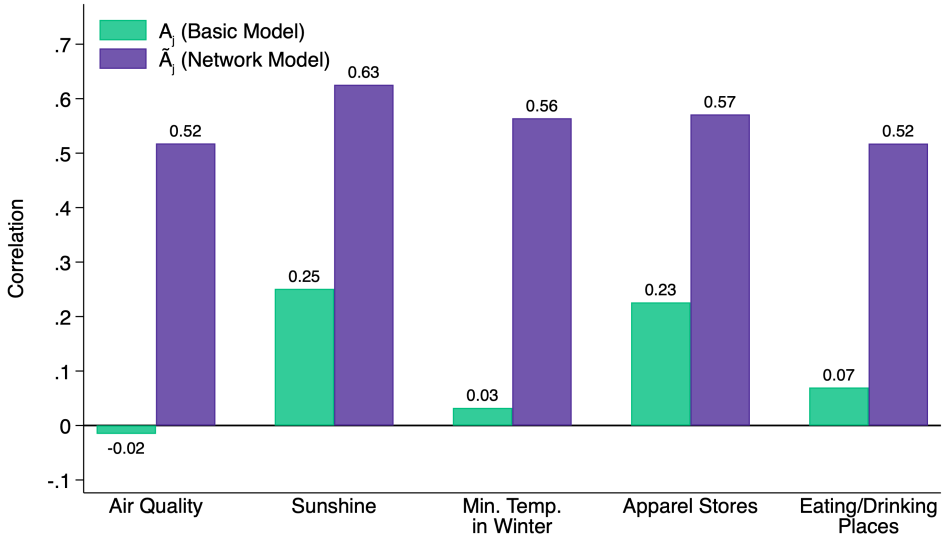
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Correlations Between CZ-Covariates and A_j, $\tilde{A}_j$



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Conclusion

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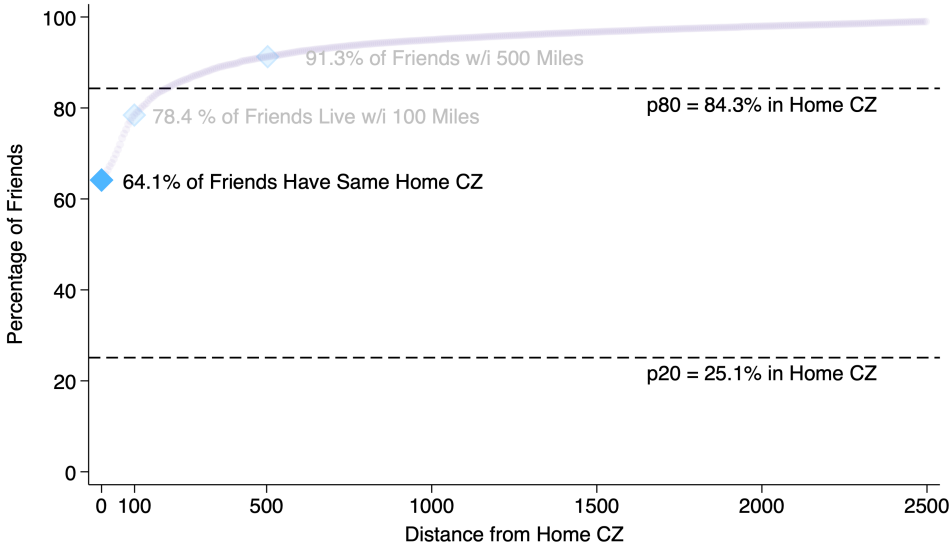
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  - High "social cost" of leaving places with strong social network

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- One reason: Social networks drive residential choices + networks concentrated locally
  - High "social cost" of leaving places with strong social network
- Social cost higher for less-educated individuals because networks more concentrated
  - $\rightarrow$ Less responsive to local economic shocks

Appendix

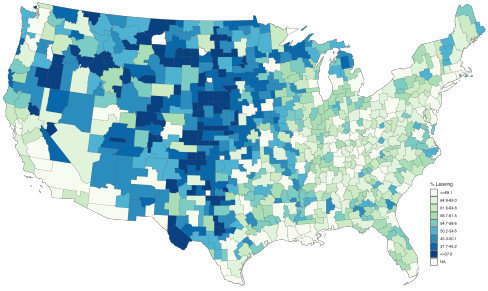
Spatial Concentration of Social Networks



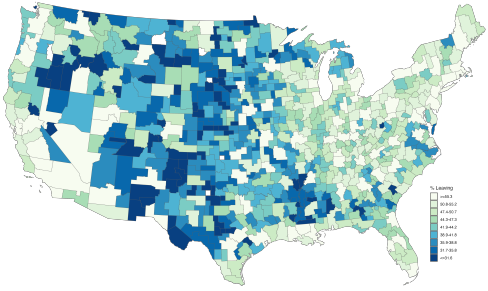
Migration Patterns Line Up With Admin Data - Extensive Margin

- Percentage of Individuals Having Left Childhood CZ by Age 26

(a) Sprung-Keyser, Hendren 2022



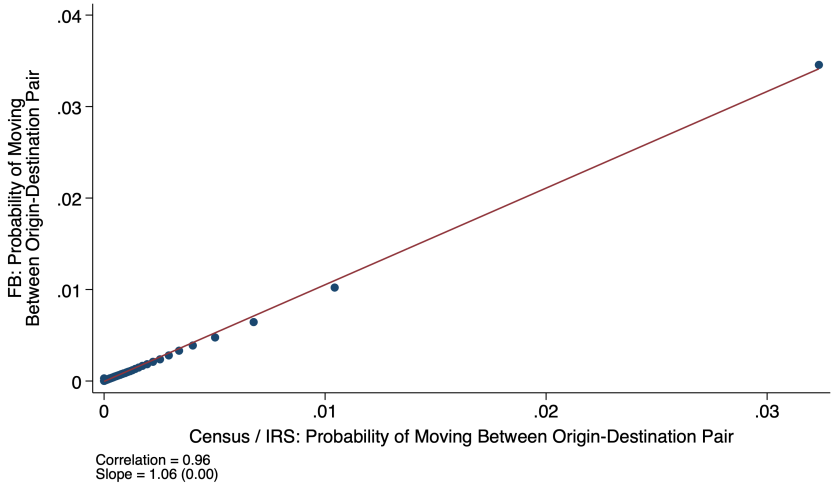
(b) Facebook



- Correlation = 0.91

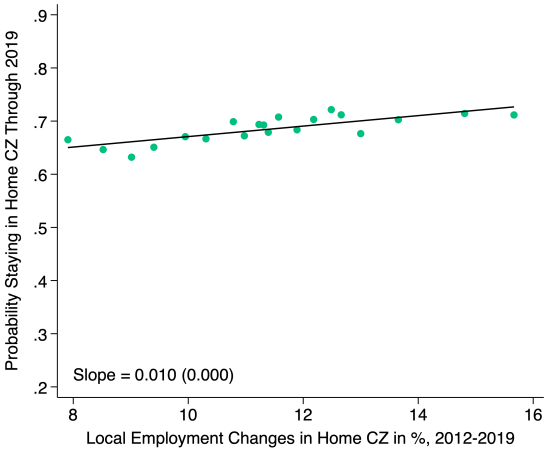
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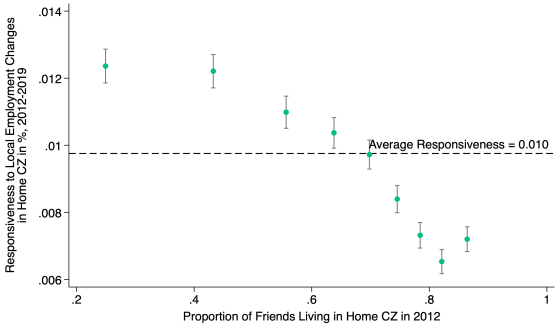
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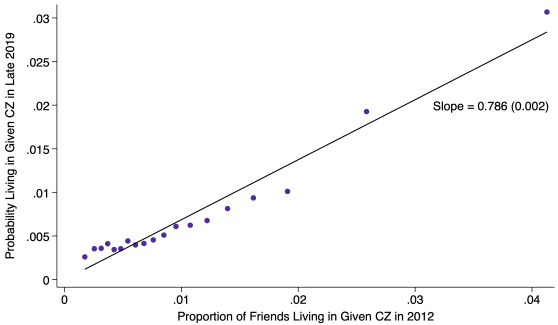
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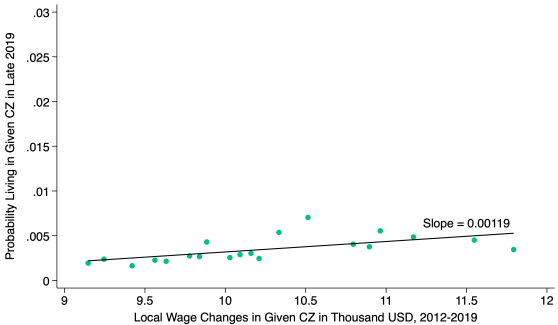




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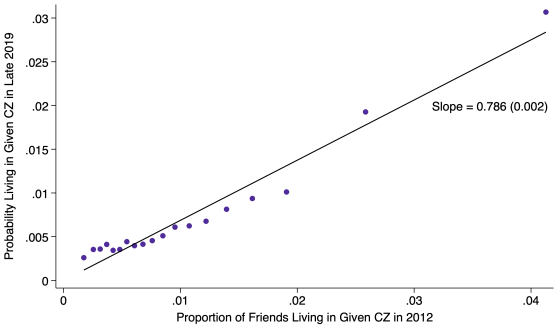
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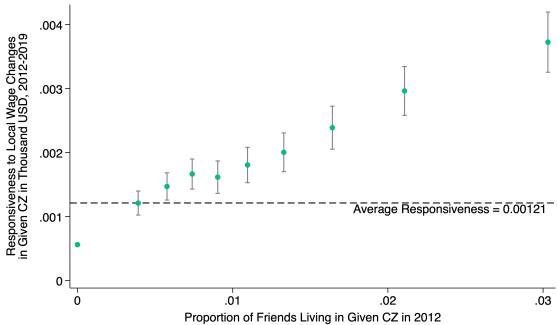




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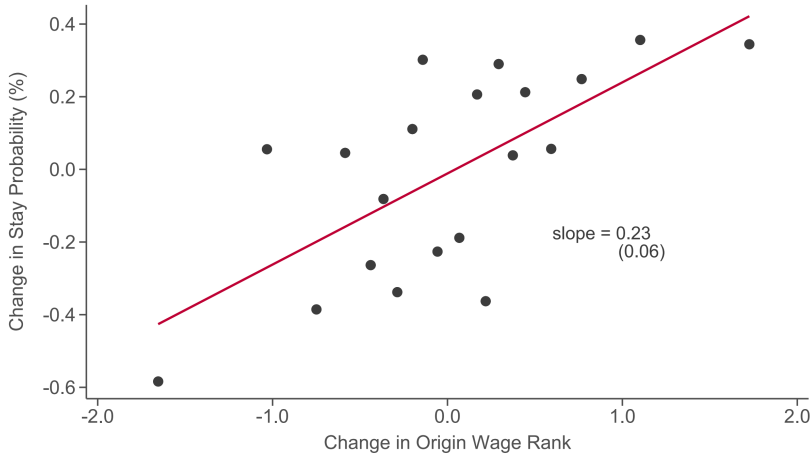
Residential Mobility, Social Networks and Wage Growth





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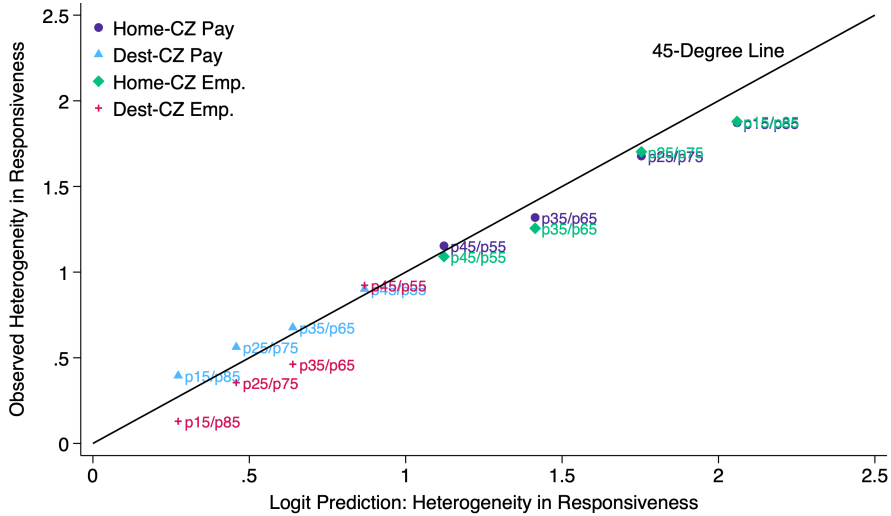
Staying in Childhood CZ vs. Local Wage Growth



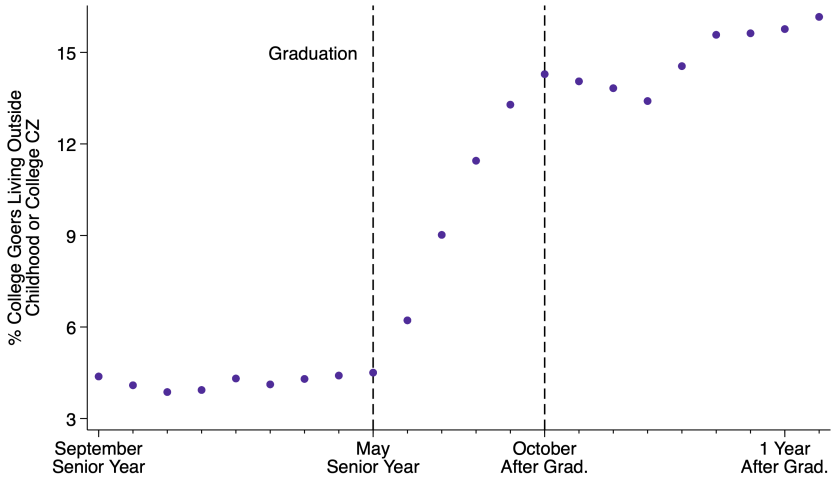
- *Source: Sprung-Keyser et al. (2022)*

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Observed and Predicted Responsiveness to Wage Changes

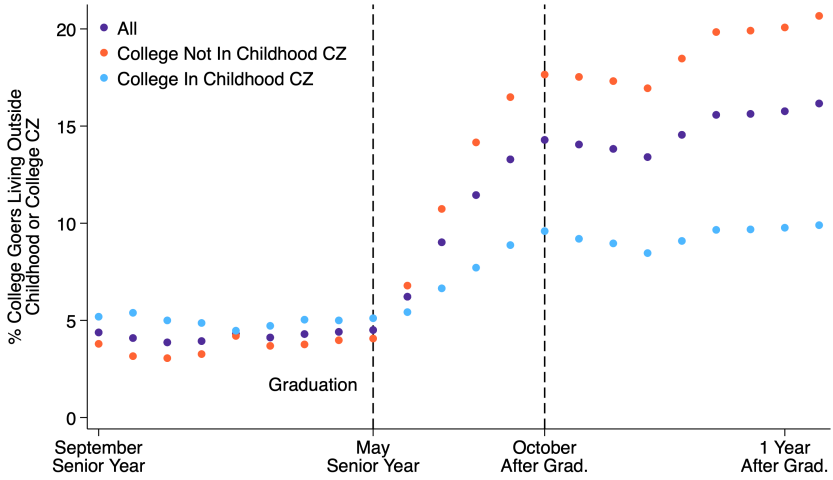


Mobility Around College Graduation



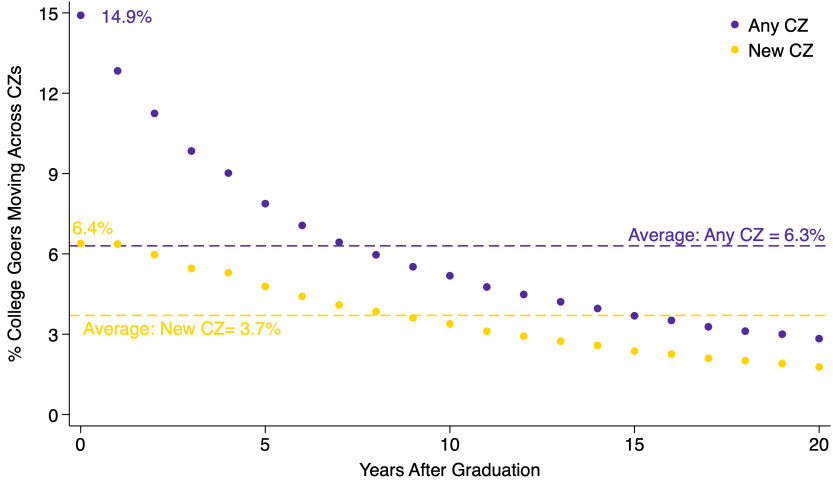
Back By College Loc Mobility Later Persistence

Mobility Around College Graduation



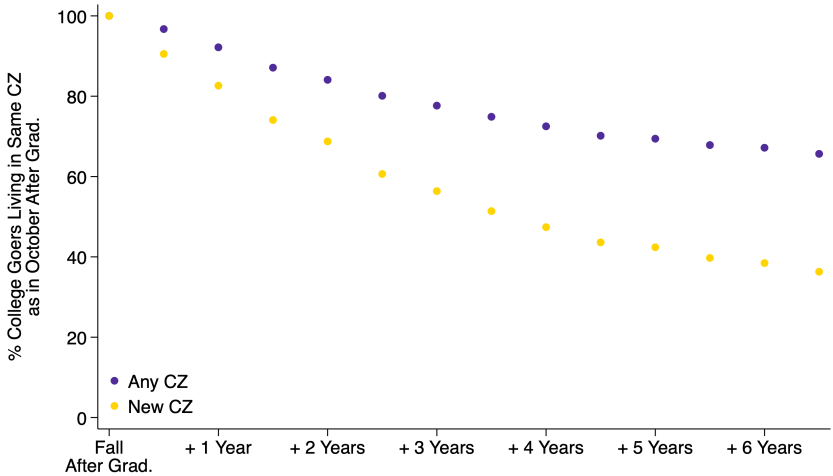
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Mobility In Years After College Graduation



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Persistence of Location Choices



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College Graduation Design

- Estimation equation

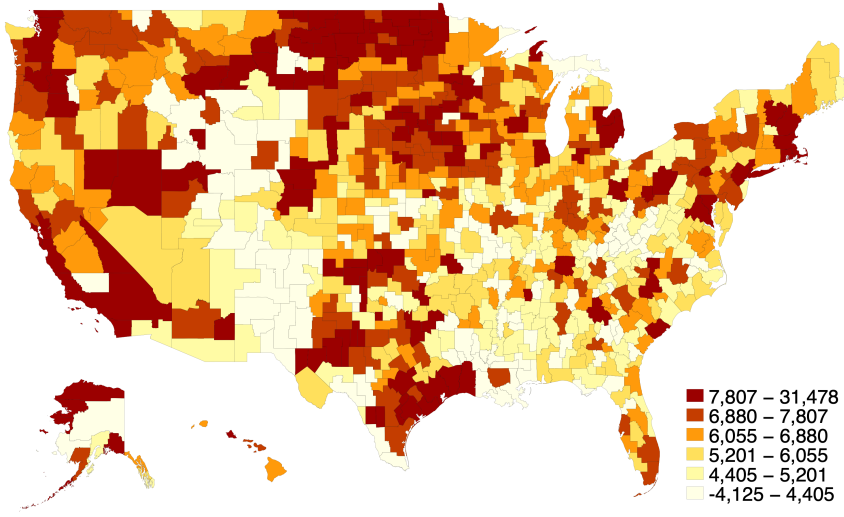
$$Y_{ikj,t^{grad}} = \sum_{t=t^{grad}-13}^{t^{grad}+12} \beta_t \Big[n_{ikj,t} - n_{ikj,t-1} \Big] + X_{ikj,t^{grad}} + u_{ikj,t^{grad}}$$

  - Restrict choice set to 50 biggest CZs Map $\rightarrow$ 50 rows per user
  - $X_{ikj,t^{grad}}$: childhood CZ $\times$ college CZ $\times$ friends $\times$ j FEs + control for $n_{ij,initial}$
  - t: three-months intervals
  - t^{grad}: October after graduation
  - 2017 - 2019 graduating cohorts
  - Focus on older friends made ≥ 1 year before graduation

- **Identifying assumption:** conditional on having friend(s) move to (or away from) j around one's graduation, the timing of such move is orthogonal to potential outcomes
  - Much weaker than assuming that friends' moves themselves exogenous

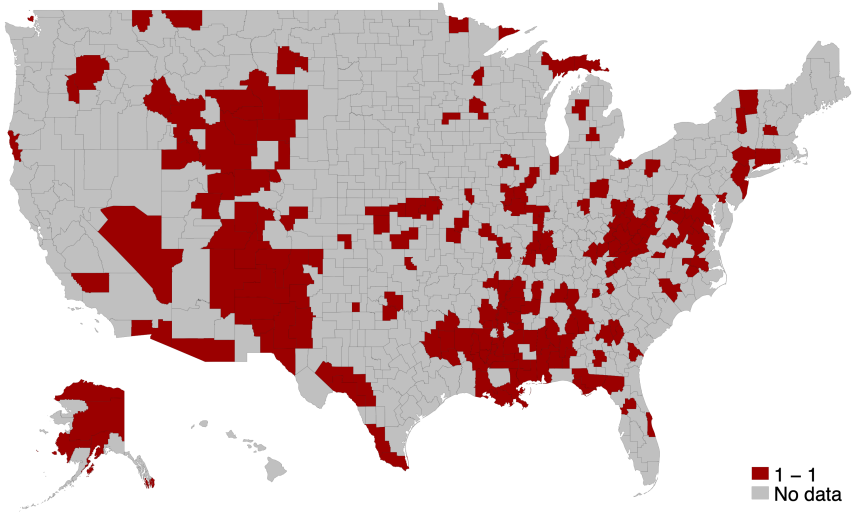
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Wage Growth Across CZs, 2010 to 2017



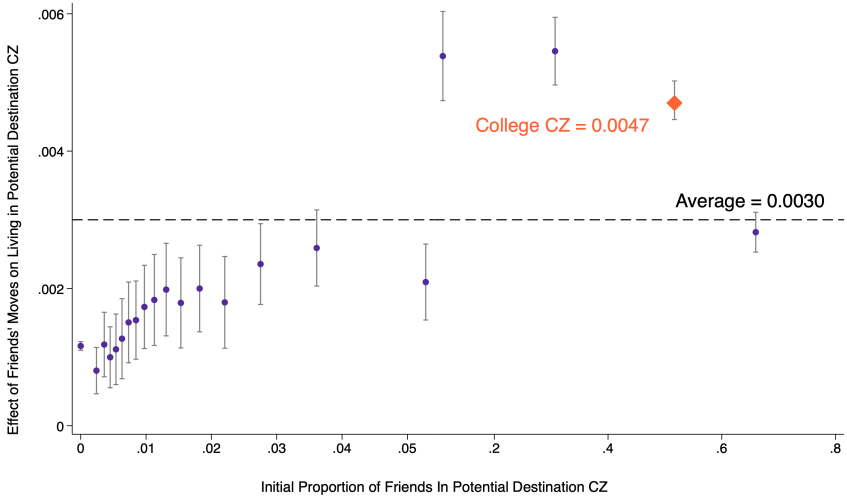
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Wage Growth Across CZs, 2010 to 2017



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Heterogeneity in Network Effects by Initial Connectedness



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Extensions

- "Dollar Valuation of a Friend" Details
- Placebo Tests Details
  - Sister CZs
  - Post-graduation friends
- External Validity Details
- Mechanisms Details
  - Information unlikely to be main driver XX
  - Social amenity value potentially important XX

Placebo Tests

- Common shocks have been big challenge for literature identifying network effects
  - Placebo checks to provide addtl. evidence against common shocks

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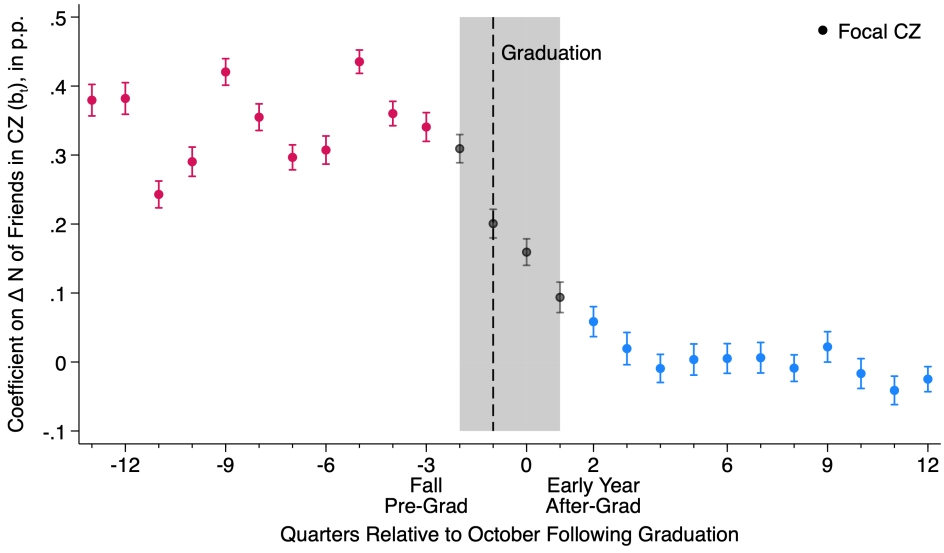
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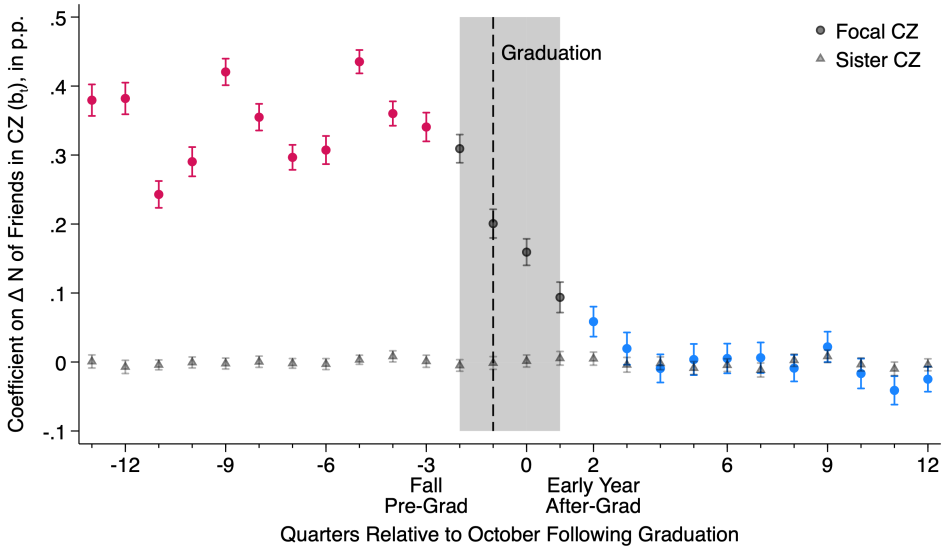
1. Sister CZs: how is living in given CZ (Detroit) affected by friends' moves to CZ with most similar industry composition (Cleveland)?
   - Nearest neighbor matching using 6-digit NAICS
   - Bartik IV lit.: sister CZs affected by local shocks in very similar way as focal CZ
     - First stage: 0.78 (recent growth)

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Placebo Tests



Placebo Tests



Placebo Tests

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   - Flat series of coefficients consistent with prior effects driven by network

2. Post-Grad. Friends: how is living in given CZ affected by moves to CZ among friends' made 4+ years after grad.?
   - Can serve as proxies for types of shocks graduates might respond to
   - If previous estimates driven by common shocks: expect to see "TE" as well
   - If driven by network effect: $\beta = 0$ for late friends $\rightarrow$ expect no "TE"

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   - If driven by network effect: $\beta = 0$ for late friends $\rightarrow$ expect no "TE"
   - Find no "TE": prior patterns likely reflect network effects Details

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General Sample

- Study effects outside of college graduation event among general sample

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- ID assumption stronger since no exogenous timing

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- Study effects outside of college graduation event among general sample
- ID assumption stronger since no exogenous timing
- Similar results Details
- Results robust to placebo tests

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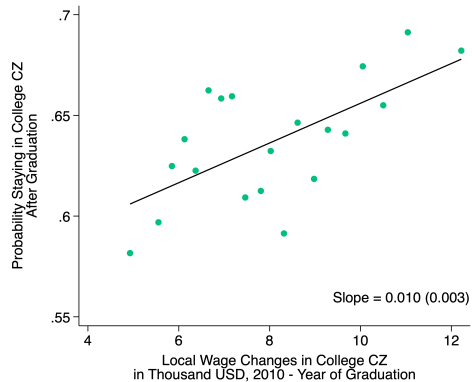
“Dollar Valuation of a Friend”

- How do effects compare to wage effects?

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"Dollar Valuation of a Friend"

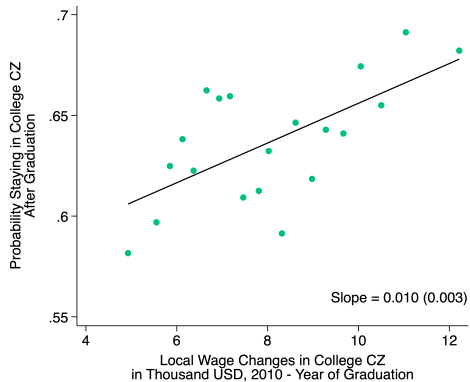
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- \$ 1,000 ↑ in avg. wages in college CZ leads to 1.0p.p. ↑ in prob. to stay



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"Dollar Valuation of a Friend"

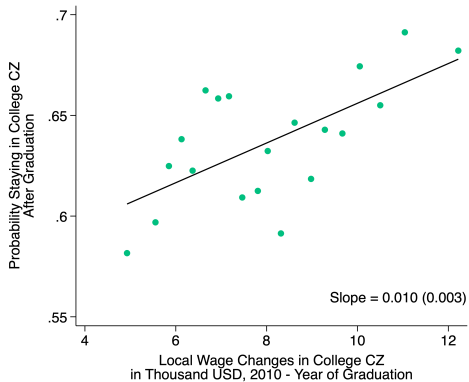
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- $\beta = 0.0047$ for college CZ Details



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"Dollar Valuation of a Friend"

- How do effects compare to wage effects?
- \$ 1,000 ↑ in avg. wages in college CZ leads to 1.0p.p. ↑ in prob. to stay
- $\beta = 0.0047$ for college CZ Details
- One more friend living in college CZ $\approx$ \$ 470 ↑ in local wages Survey evidence



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Mechanisms

- What drives large network effects?

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  - Off-platform survey (N = 500) about role of local networks for decision where to live

Mechanisms

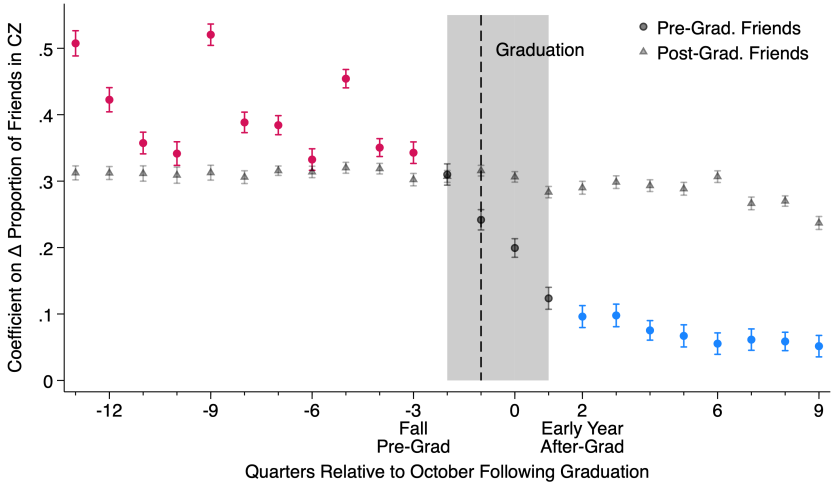
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- **Quasi-Monetary Benefits vs. Amenity Value**
  - Off-platform survey (N = 500) about role of local networks for decision where to live
  - Responses suggest importance of social amenity value Leisure Help limited Enjoy company

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Placebo: Post-Graduation Friends



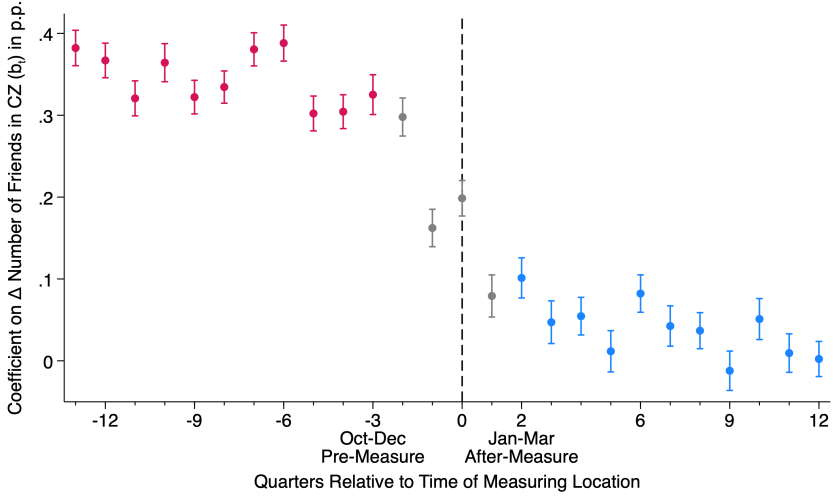
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General Sample

- Study effects for general sample outside of college graduation event
- Measure location twice, with 3.5 years in between
  - E.g., 2015 vs. 2018
- Compare two similar individuals *Charlotte* and *David* living in same CZ in 2015
- *Charlotte*'s friend moves to j pre-2018, but *David*'s friend moves after 2018
- **Identifying assumption:** conditional on having friend(s) move to (or away from) j, the timing of such move is orthogonal to potential outcomes
  - Similar assumption but stronger in this context: no exogenous timing
  - Can't distinguish between *Charlotte* choosing where to live in response to friend's moves vs. *Charlotte* and her friend moving at the same time pre-2018 due to common shock

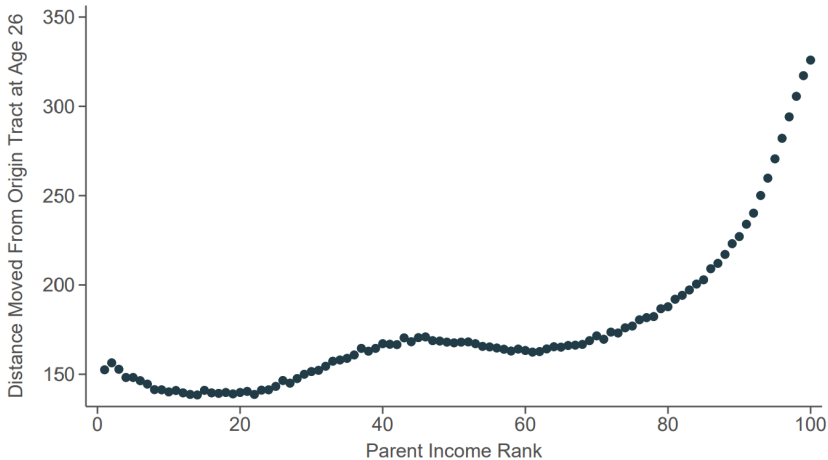
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General Sample



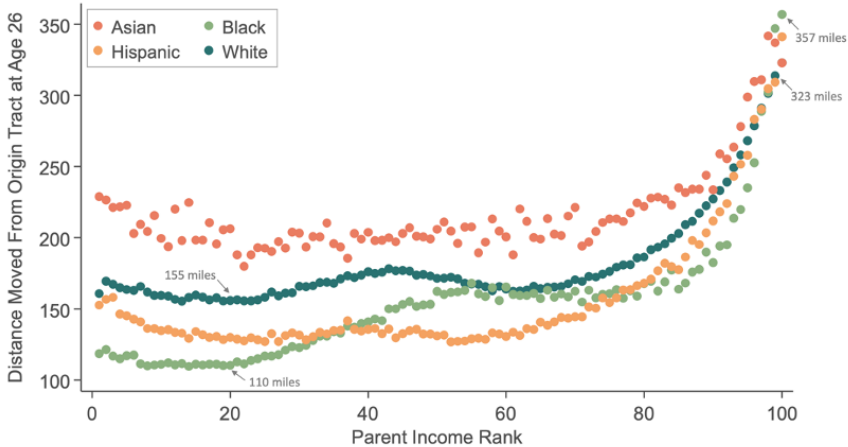
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Moving vs. Parent Income Rank



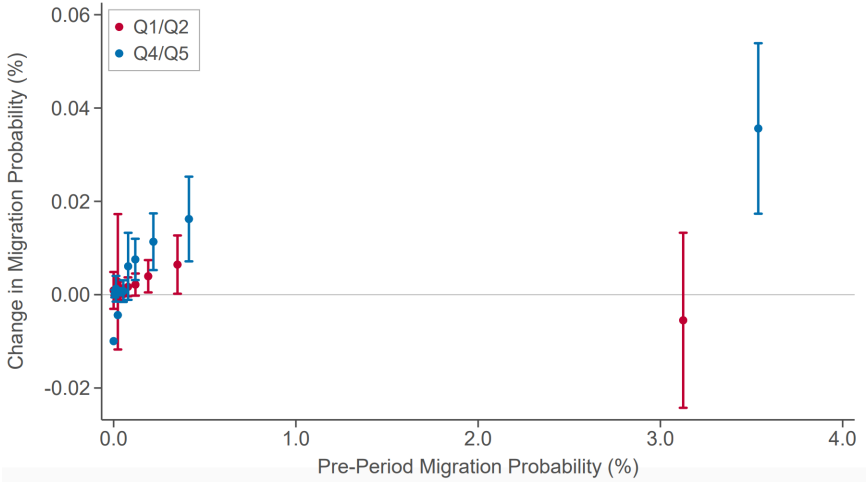
Source: Sprung-Keyser, Hendren and Porter (2022) Back

Moving vs. Parent Income Rank and Race



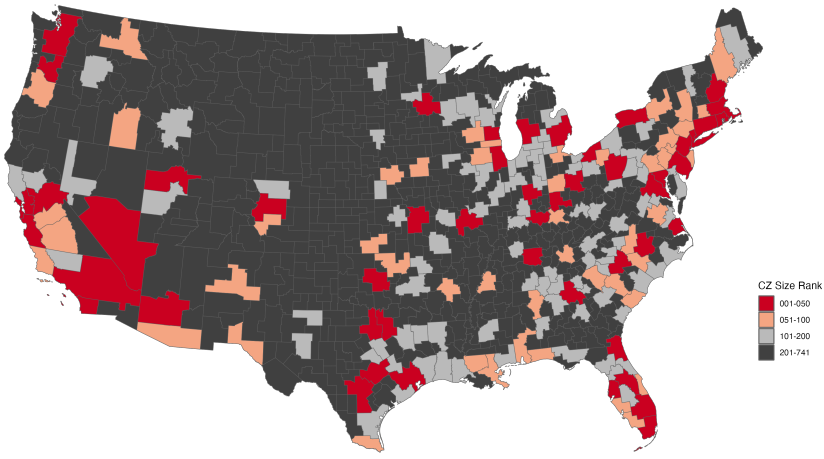
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Responsiveness to Destination Wage Changes



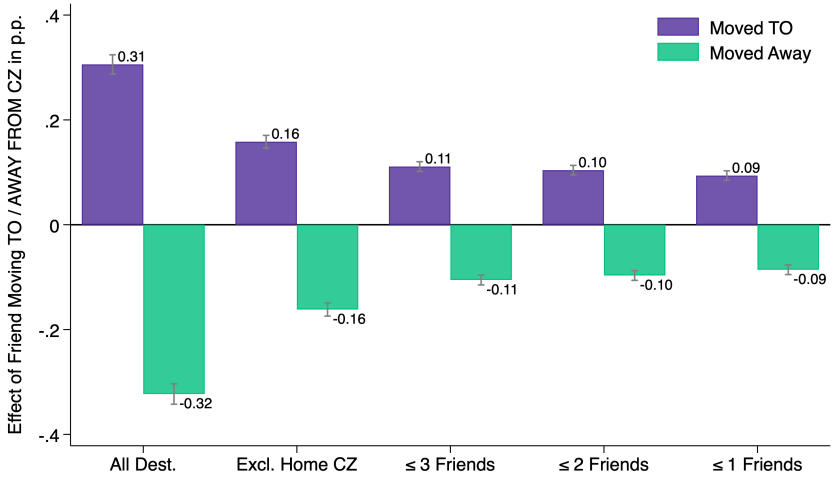
Source: Sprung-Keyser, Hendren and Porter (2022) Back

Largest CZs



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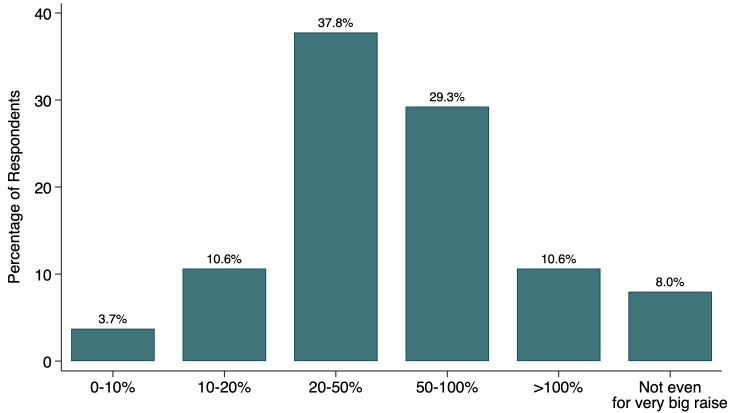
Role of Information



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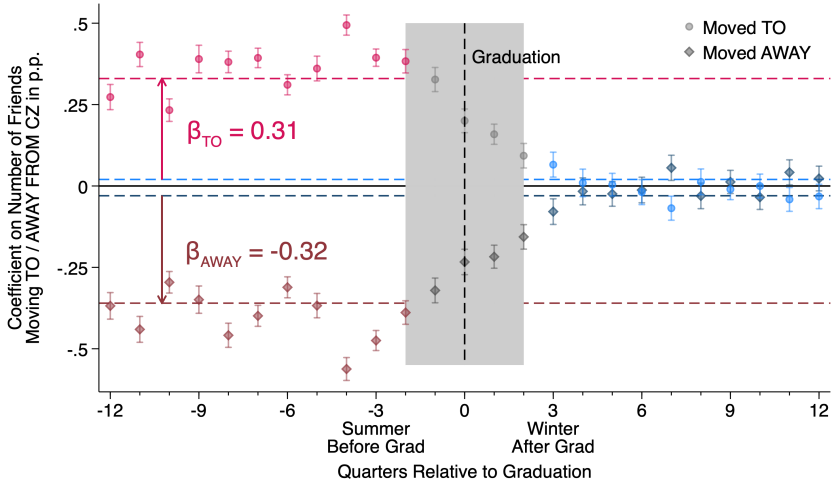
Pay Raise to Move to City without Friends

- "How high would a pay raise have to be in order for you to move to a city where you don't know anybody?"



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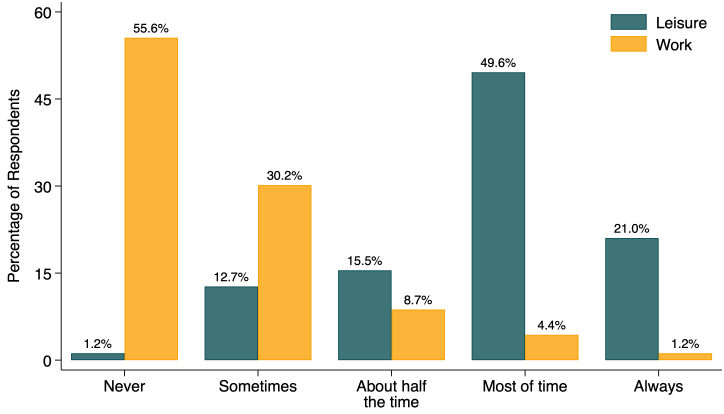
Role of Information



Back By Initial Connections

What Do Local Social Ties Do?

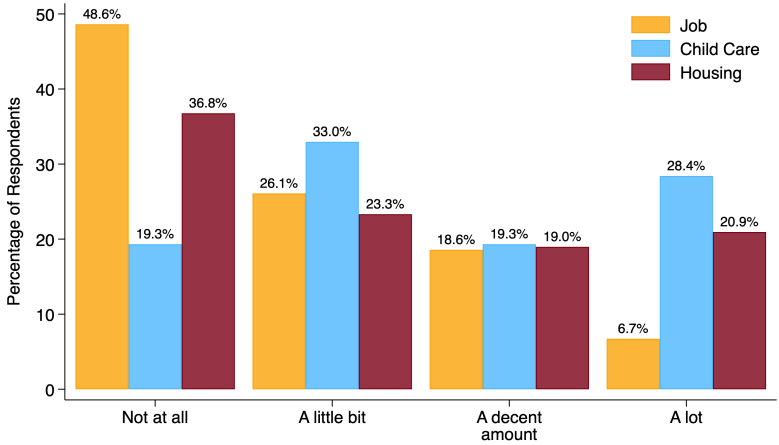
- "What is the primary purpose for you to see the people that are most important for you to live in [current city]?"



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What Do Local Social Ties Do?

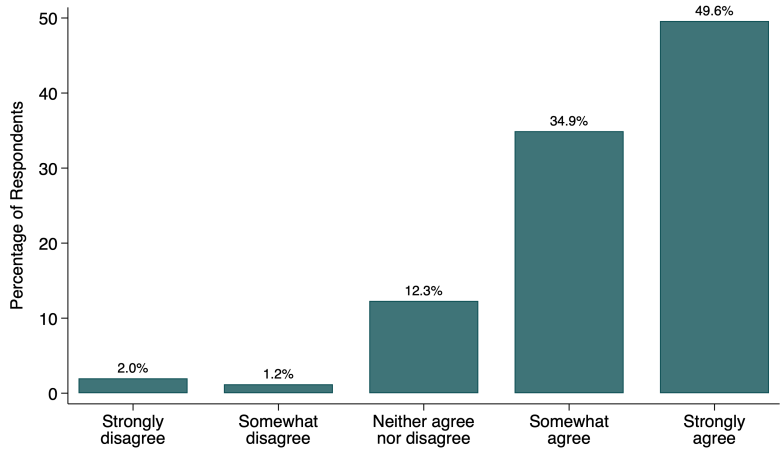
- "How much did those people help you with the following in recent years?"



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What Do Local Social Ties Do?

- "I enjoy their company, much more than I need their help with anything."



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Model Setup - Production and Housing

- Production Details :
  - In each CZ j representative, perfectly competitive firm produces local Y_j

$$Y_j = \theta_j K_j^{\alpha^Y} N_j^{1-\alpha^Y}$$

  - CZ-specific productivities θ_j generate differences in wages c.p.
  - Perfectly competitive natl. firm produces consumption goods Y out of Y_j purchased at p_j
  - N_j: all residents of j inelastically supply 1 unit of labor

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- Housing Details
  - Supply: Natl. housing supply elasticity + CZ-specific shifter

$$H_j^S = \nu_j r_j^{\eta^H}$$

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- Find θ_j and ν_j to match 2019 local wages (skill-adj.) and rents (2br)

Model Setup - Production

- In each CZ j representative, perfectly competitive firm produces local good:

$$Y_j = \theta_j K_j^{\alpha^Y} N_j^{1-\alpha^Y}$$

  - K_j supplied at $\rho = 0.025$ (Zabek, 2024)
  - $\alpha^Y = 0.33$ same everywhere (Zabek, 2024)
  - θ_j differs across CZs

- Perfectly competitive national firm produces consumption goods out of local goods purchased at price p_j:

$$Y = \left[\sum_{j' \in J} (Y_{j'})^{\frac{\eta^Y - 1}{\eta^Y}} \right]^{\frac{\eta^Y}{\eta^Y - 1}}$$

  - $\eta^Y = 4$ (Feenstra et al. 2018): Armington elasticity of substitution

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Model Setup - Production

- Local wages:

$$w_j = (1 - \alpha^Y)(p_j \theta_j)^{\frac{1}{1-\alpha^Y}} \left[\frac{\alpha^Y}{\rho} \right]^{\frac{\alpha^Y}{1-\alpha^Y}}$$

- Find local productivities θ_j given 2019 wages (skill-adjusted) and population levels
  - Define Dallas as reference CZ
  - Skill-adjusted wages: re-weight education-specific wages using national distribution of education levels
  - Population: Facebook user count

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Model Setup - Housing

- Local housing supply:

$$H_j^S = \nu_j r_j^{\eta^H}$$

  - $\eta^H = 2$ (Saiz, 2010): national housing supply elasticity
  - ν_j: CZ-specific housing supply shifter (e.g., local land and construction productivity)

- Housing demand: workers spend constant fraction of income (w_j) on housing

$$H_j^D = \left[\frac{\alpha_h}{\alpha_h + \alpha_w} w_j N_j\right] / r_j$$

- Local rent:

$$r_j = \left[\frac{\alpha_h}{\alpha_h + \alpha_w} \frac{w_j N_j}{\nu_j}\right]^{\frac{1}{1+\eta^H}}$$

- Find local housing supply shifter ν_j given 2019 two-bedroom rents, wages (skill-adjusted) and populations

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Matching Model to Data

- Goal: Find α_w, α_h, A_j to match populations (N_j), networks (n_{ij}), observed wage elasticity (ϵ_w^{obs}) to data
  - Given: wages (w_j), rents (r_j), network effect (β^{logit}, δ^{logit})

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  - $\epsilon_w^{obs} = 0.93$ from Bartik-IV Details

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- Workers optimize asynchronously, i.e. no coordination / anticipation

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- Solve iteratively since no closed form solution for n_{ij} Details
- Workers optimize asynchronously, i.e. no coordination / anticipation
- Similarly, find $\tilde{\alpha}_w$, $\tilde{\alpha}_h$, $\tilde{A}_j$

Matching Model to Data

- Goal: Find α_w, α_h, A_j to match populations (N_j), networks (n_{ij}), observed wage elasticity (ϵ_w^{obs}) to data given wages (w_j), rents (r_j), network effect (β^{logit}, δ^{logit})
  - α_h assumed to be $\frac{\alpha_w}{2}$ (spend $\frac{1}{3}$ on housing)

- Solve iteratively since no closed form solution for n_{ij}

- Four steps:
  1. Guess $\alpha_w \longrightarrow$ find A_j so that observed N_j's match model implied N_j's
     - Take observed n_{ij} as fixed
  2. Given A_j, find implied n_{ij} and let workers re-optimize asynchronously to find EQ
     - Confirm new EQ N_j, w_j, r_j n_{ij} "similar" to observed values
  3. Simulate local productivity shocks, find new EQ and compare implied ϵ_w to observed value
  4. Iterate over steps 1.-3. until condition in 3. satisfied

- Find $\tilde{\alpha}_w$, $\tilde{\alpha}_h$, $\tilde{A}_j$ (no network parameters) by repeating 1., 3., and 4.

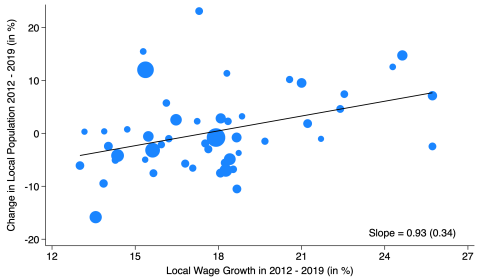
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Empirical Wage Elasticity ϵ_w^{obs}

- Construct Bartik-IV using 6-digit NAICS
- Predict CZ-level wage growth 2012-2019 in largest 50 CZs
- Ask: how is migration among users in model sample affected by wage growth?

Empirical Wage Elasticity ϵ_w^{obs}

- Construct Bartik-IV using 6-digit NAICS
- Predict CZ-level wage growth 2012-2019 in largest 50 CZs
- Ask: how is migration among users in model sample affected by wage growth?
- $\epsilon_w^{obs} = 0.93$



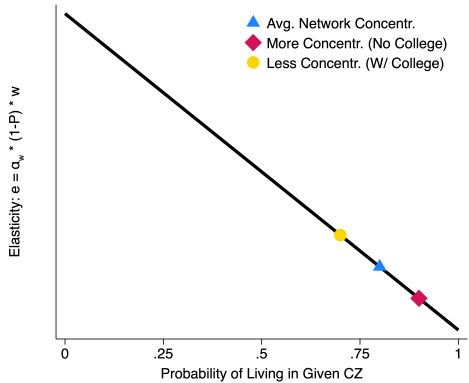
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Where does Difference in Elasticity Come From?

- Logit framework:

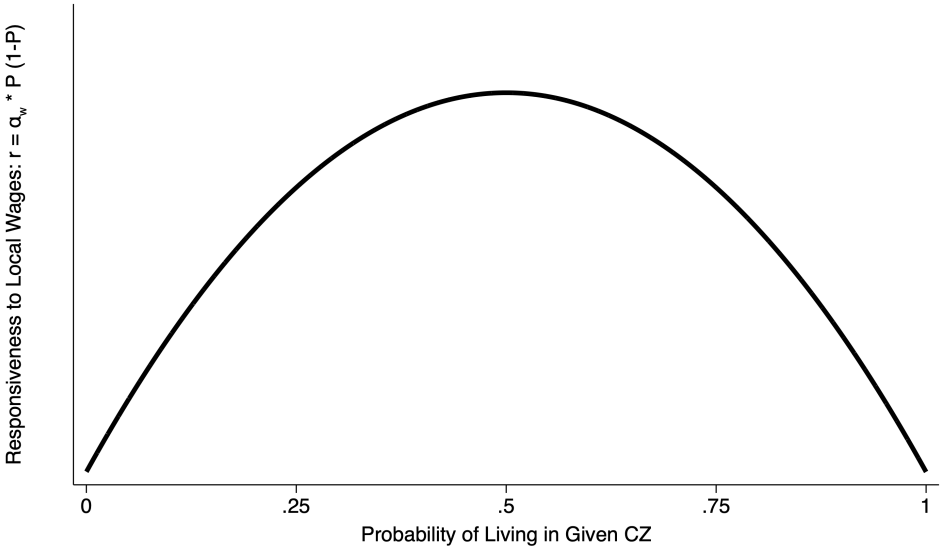
$$\epsilon_w = \alpha_w * (1 - P) * w$$

- $P =$ prob. living in given CZ
- $\frac{\partial P}{\partial n_{ij}} > 0 \forall \beta > 0$
- $\uparrow n_{ij}$: $\downarrow \epsilon_w$
- Supporting empirical evidence Details

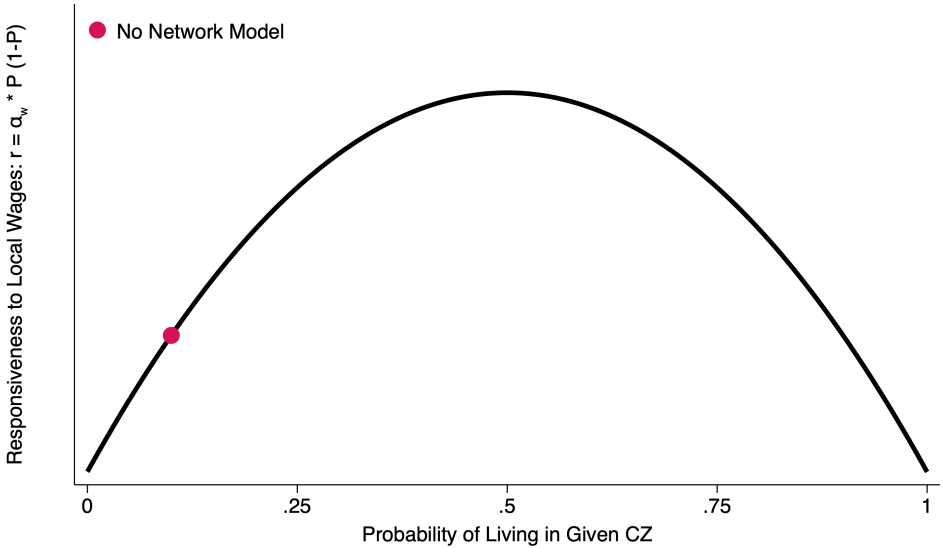


Back

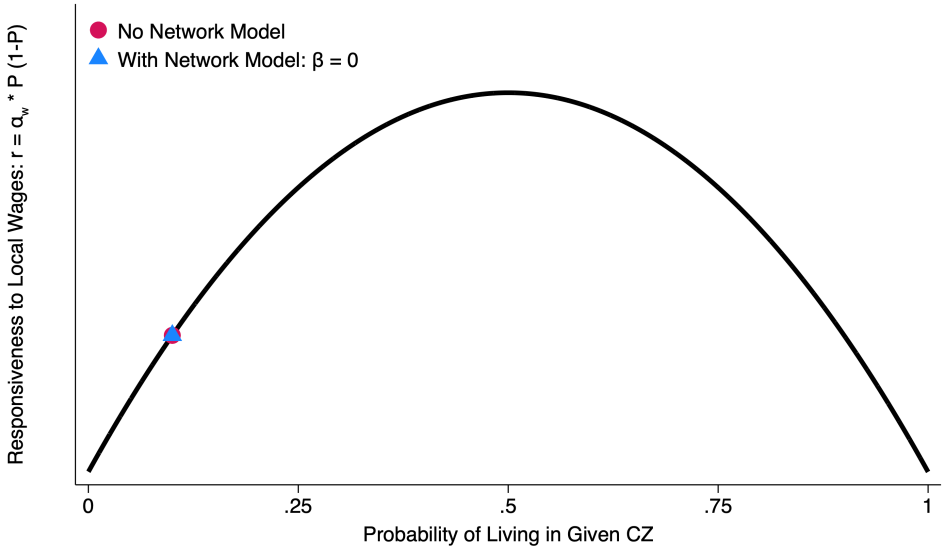
Where Do Differences in Responsiveness Come From?



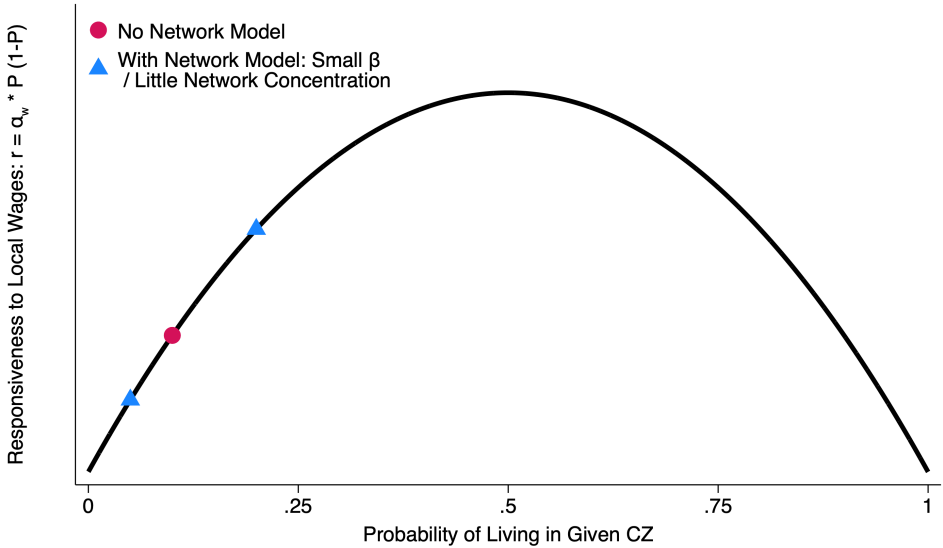
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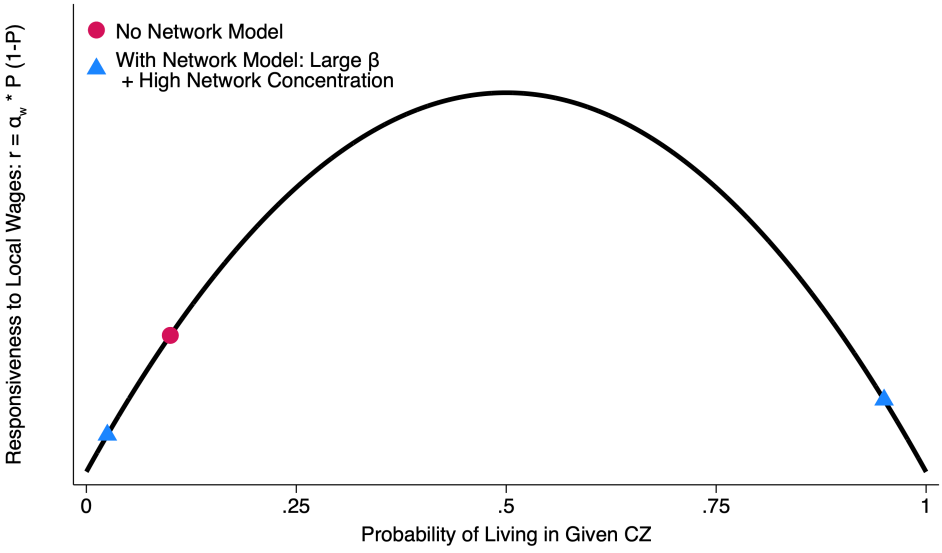
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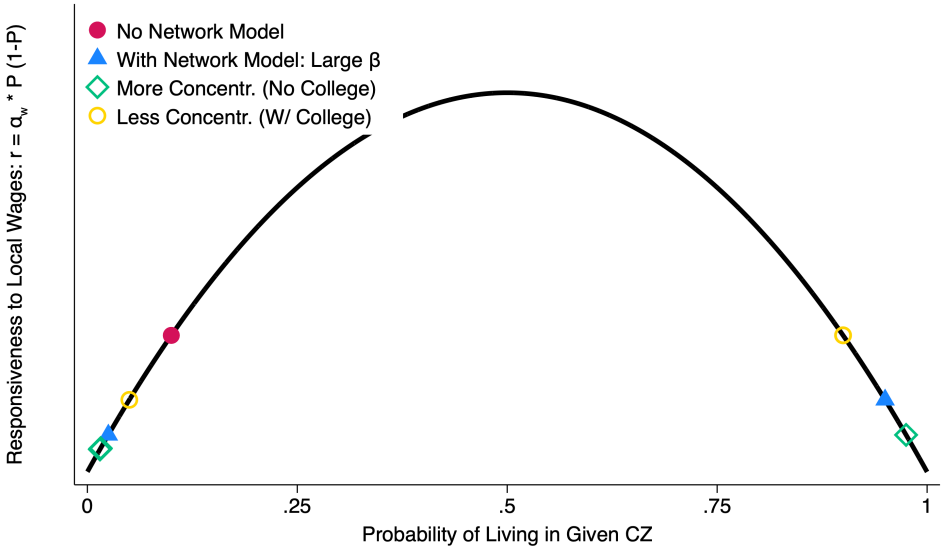
Where Do Differences in Responsiveness Come From?



Where Do Differences in Responsiveness Come From?



Where Do Differences in Responsiveness Come From?



This Paper

1. Social networks drive residential choices [Partial Equilibrium]
   - Having one more friend in given CZ increases odds of living there by 0.3 p.p.
   - Effect similar to $470 increase in local wages

2. Networks explain puzzles of migration and residential choice [General Equilibrium]
   - Generalizing spatial choice model to include networks greatly reduces large, opaque residuals
   - Helps to explain why low-skilled less responsive to local shocks than high-skilled

3. **Effects have implications for policies promoting moves across the country**
   - Use model from (2) to demonstrate how results impact effects of policy

Policy Implications of Network Effects

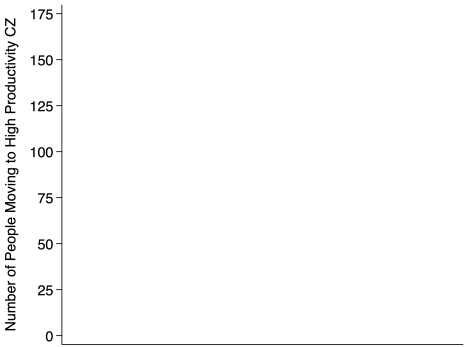
- Hypothetical policy: $\$10k$ living subsidy to first 100 movers from least productive (bottom quintile) CZs to most productive (top quintile) CZs
  - Productivities defined based on θ_j
  - Low productivity: e.g., New Orleans, Oklahoma City, Louisville
  - High productivity: e.g., Houston, Boston, Chicago

Policy Implications of Network Effects

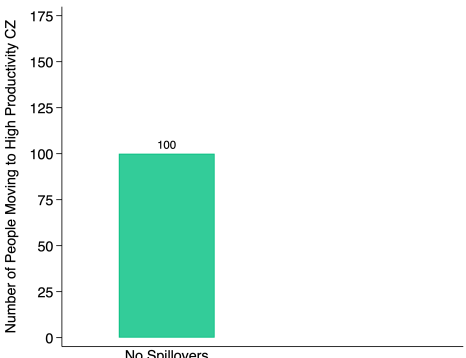
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  - Low productivity: e.g., New Orleans, Oklahoma City, Louisville
  - High productivity: e.g., Houston, Boston, Chicago

- Motivation
  - CZ-level MTO
  - Companies (e.g., Google, Amazon, Tesla) and local governments (e.g., Tulsa Remote, Vermont Remote Worker Grant Program, St. Clair County) offer relocation bonuses
  - $\uparrow$ GDP by employing workers where they are most productive (Hornbeck and Moretti, 2024)

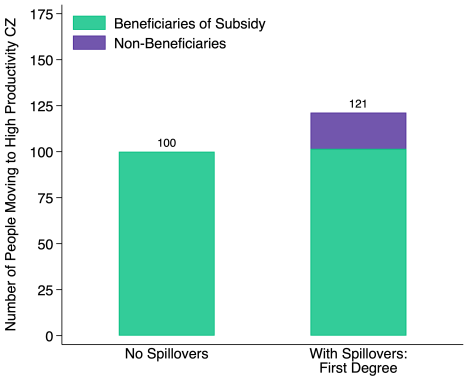
Effects of Moving Subsidy



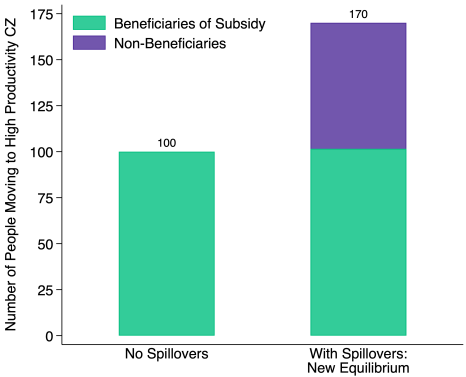
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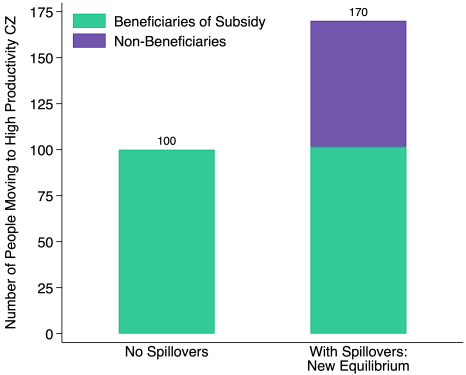
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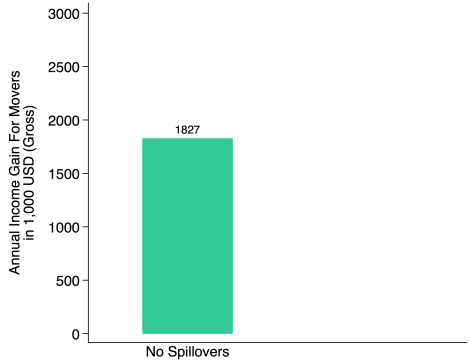


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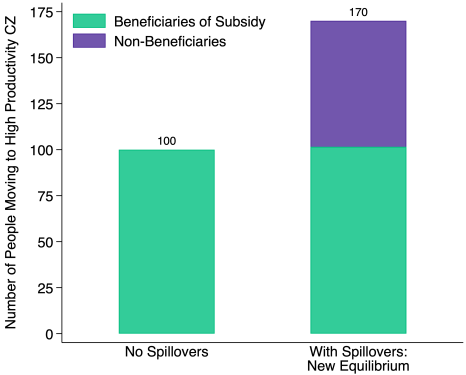


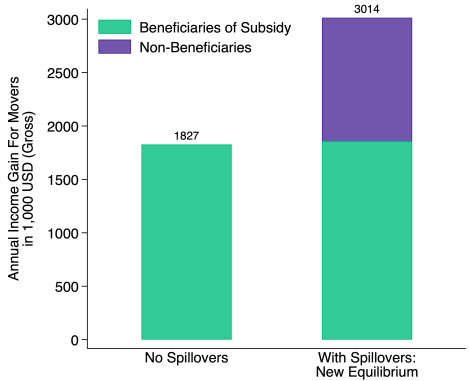
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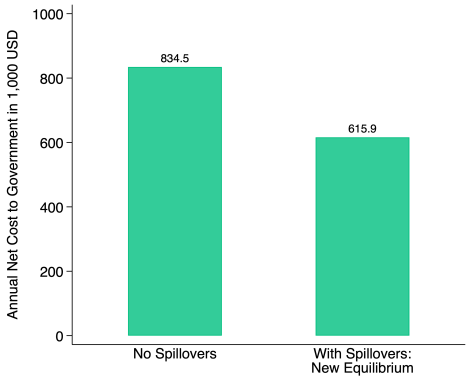


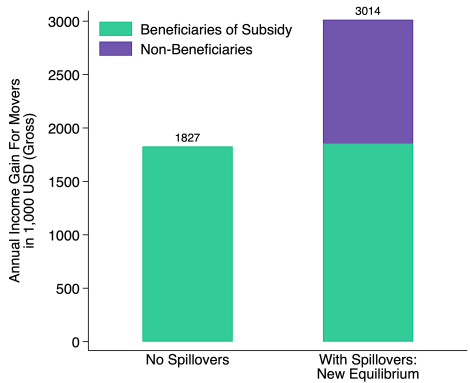
Effects of Moving Subsidy





Effects of Moving Subsidy





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