Optimal Lockdown in a Commuting Network

Pablo D. Fajgelbaum **Amit Khandelwal** **Wookun Kim** **Cristiano Mantovani** **Edouard Schaal**

UCLA/NBER, Columbia/NBER, SMU, Pompeu Fabra, CREI/CEPR

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Introduction

- Manhattan has as many daily commuters as residents, $\sim$1.6m people
  - Two months after lockdown, commutes down 49%
  - Was this reduction too large or not large enough?
- Lockdowns were fairly uniformly across bordering U.S. states (avg diff of 4 days)
  - But, Illinois lockdown more than two weeks before Missouri; variation across counties
  - Are there significant losses from spatially uniform or uncoordinated lockdown?

This Paper

- Optimal dynamic lockdown in a commuting network to fight a pandemic
- Framework:
  - Standard trade model (Armington)
  - Standard spatial epidemiology model
- Estimated with real-time commuting and credit-card expenditure data
  - Korea (Daegu and Seoul) and New York Metro
- Questions:
  - What are the optimal lockdown patterns over time and space?
  - How large are the benefits from optimal spatial targeting?
  - How do observed commuting reductions compare with optimal?

Data

- Korea
  - Seoul (largest city, 20 districts) and Daegu (largest outbreak, 8 districts)
  - Real-time commuting data (individual transport cards, Subway entry and exits)
  - Universe of credit-card transactions at physical shops from one of Korea's top-3 banks
  - Wages and population (National tax records)

- New York Metro (25 counties)
  - Cellphone mobility data (SafeGraph)
  - Wages and population (LEHD and Census)

- Estimate:
  - Decline in commuting relative to pre-pandemic period
  - Virus transmission rate using spatial structure of the model
  - Within-city trade frictions from credit card expenditures data

Model

- Planning problem

$$W = \max_{\chi(t)} \int_0^{\infty} e^{-(r+\nu)t} \sum_j \left[U\left(j,t,\chi\left(t\right)\right) + \frac{\nu}{r} \bar{U}\left(j,t\right) - \omega\gamma_D I\left(j,t\right) \right] dt$$

  - $\chi\left(t\right)$ fraction of commuting flows that can operate
  - $U\left(j,t,\chi\left(t\right)\right)$ is the general-equilibrium outcome of (Armington) trade model
  - SEIR spatial model determines flows Susceptible, Exposed, Infected, Recovered

- % change in Susceptible:

$$\frac{\dot{S}\left(i,t\right)}{S\left(i,t\right)} = -\sum_j \beta_j \chi\left(i,j,t\right) \lambda\left(i,j\right) \left[\zeta \sum_{i'} \chi\left(i',j,t\right) \lambda\left(i',j\right) I\left(i',t\right) \right]$$

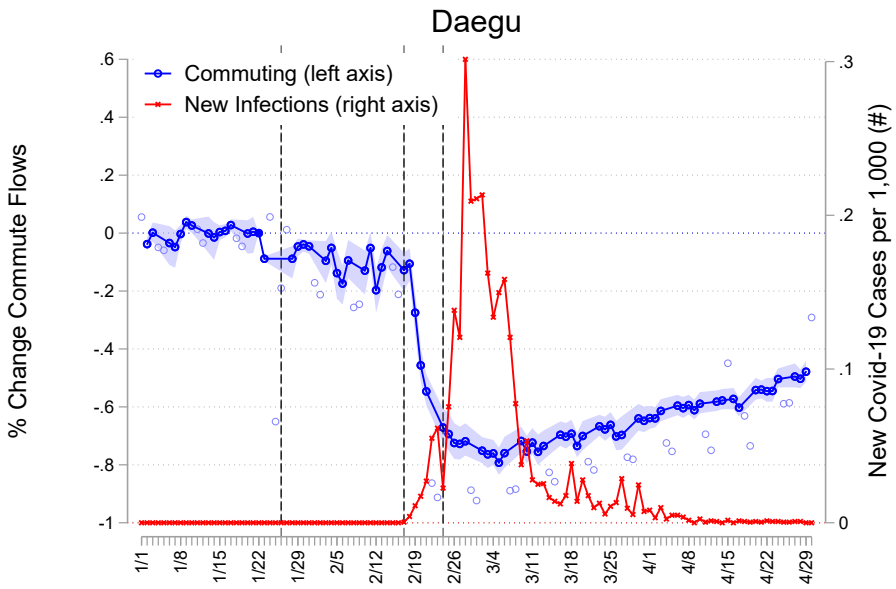
  - Estimate $\beta_j = \frac{\beta}{\text{area}_j}$ from observed commuting flows and infections

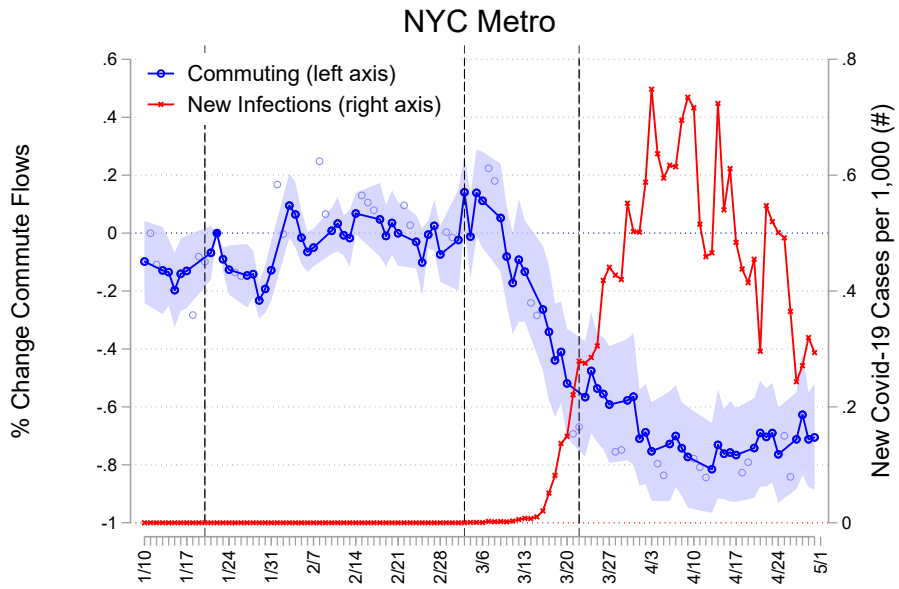
- Labor supply to location j:

$$\sum_{u=S,E,I,R} \left[\chi\left(i,j,t\right) + \left(1 - \chi\left(i,j,t\right)\right) \delta_u \right] \lambda\left(i,j\right) u\left(i,t\right)$$

▸ parameters

Commute Responses and Disease Spread

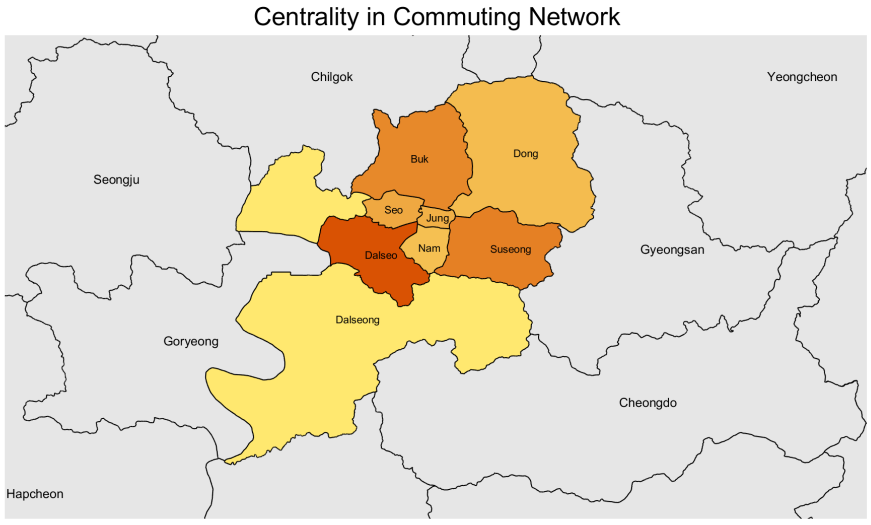


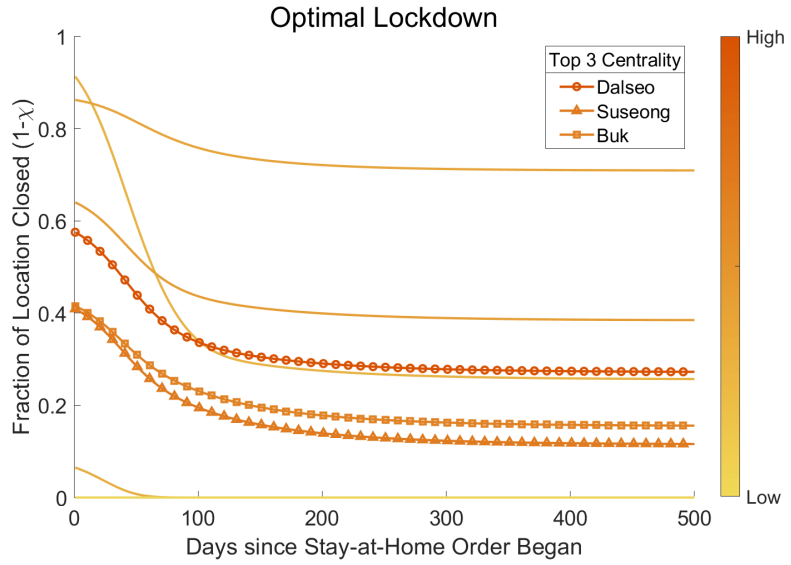


▶ Seoul

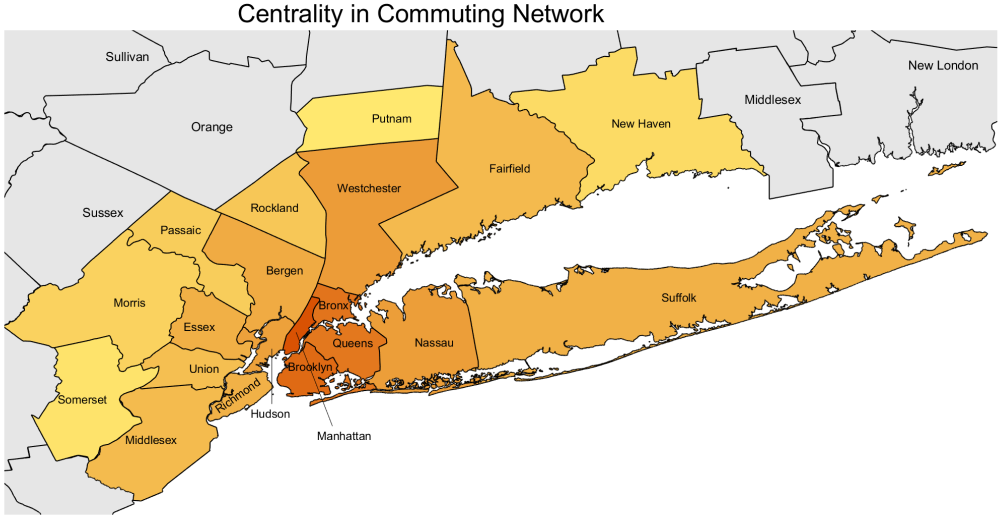
Centrality and Optimal Lockdown

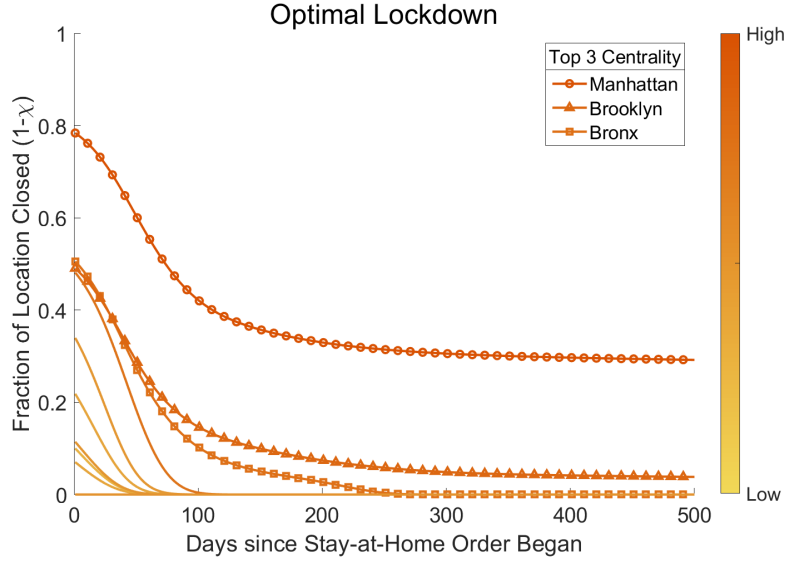
Daegu





NY Metro

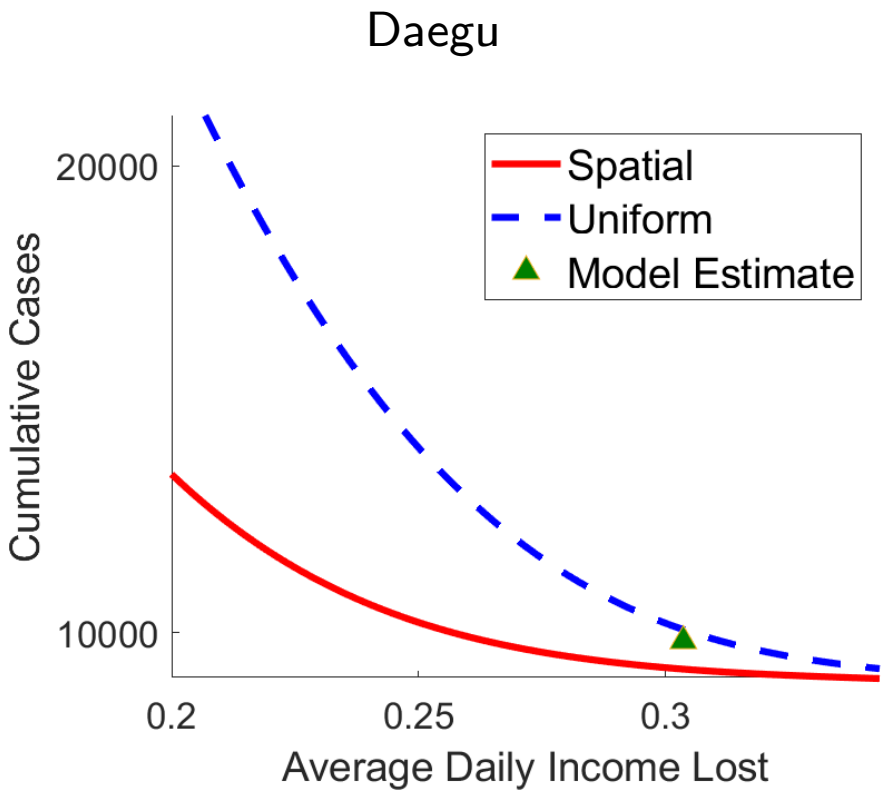


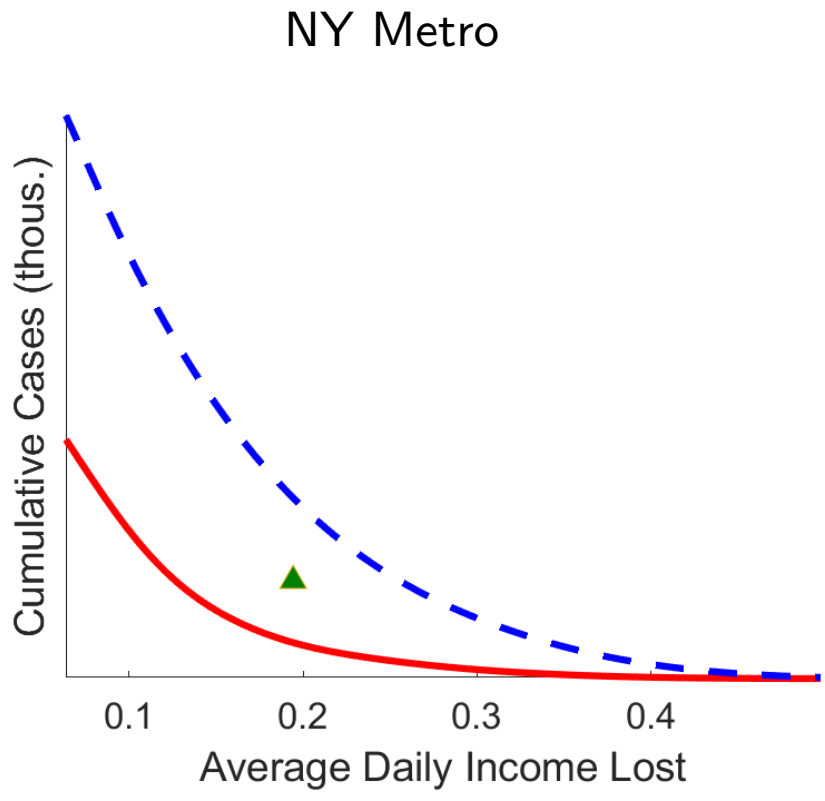


▶ Seoul

"Pareto" Frontier: Cases versus Income

Cumulative cases and lost income (across values of life) by April 30

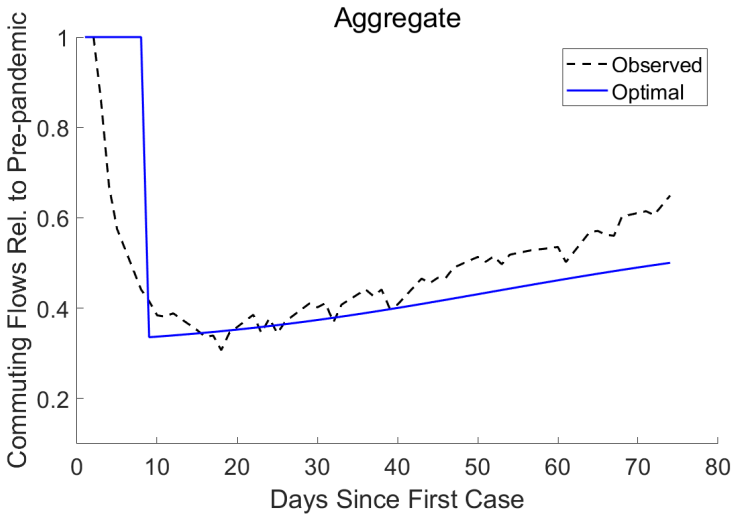


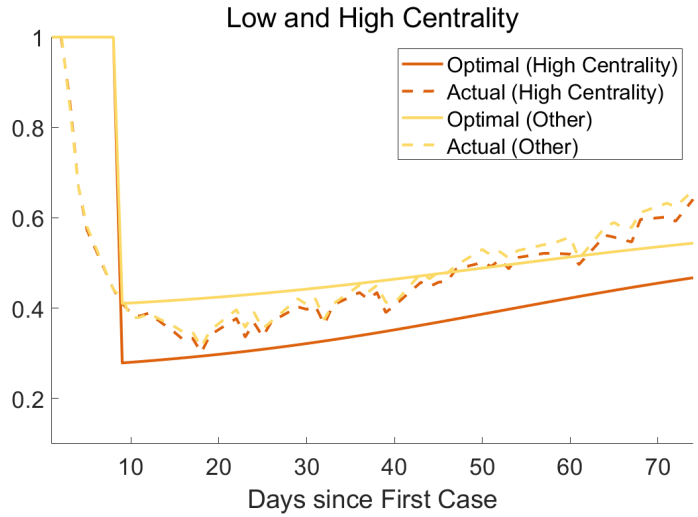


▸ Seoul

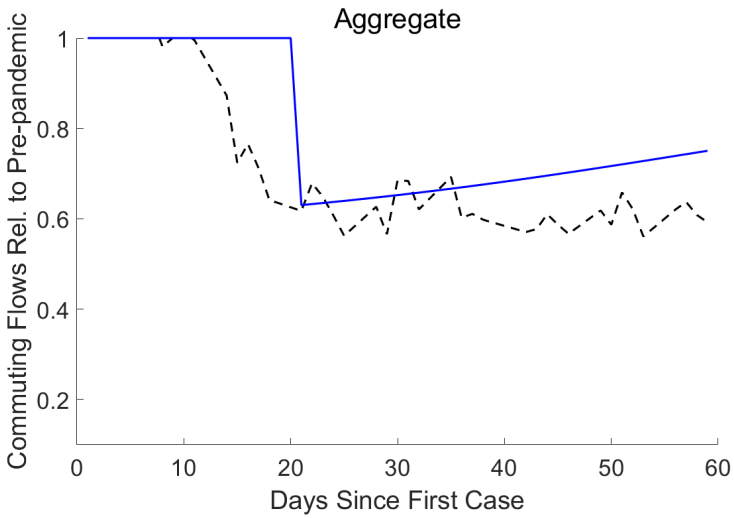
Optimal and Observed Changes in Commuting Flows

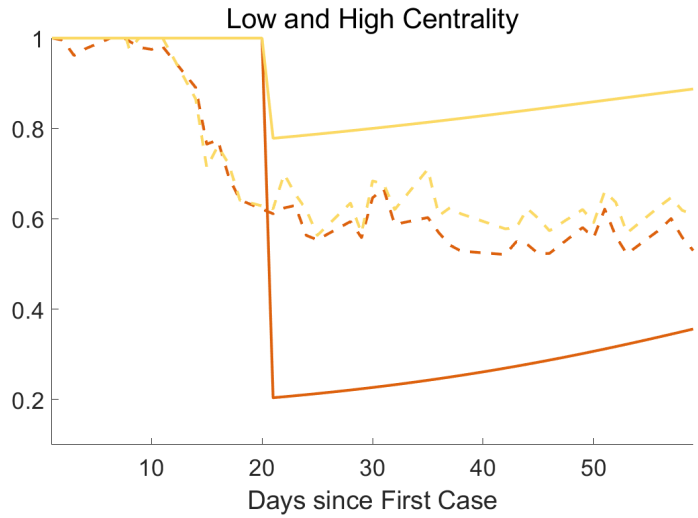
Daegu





NY Metro

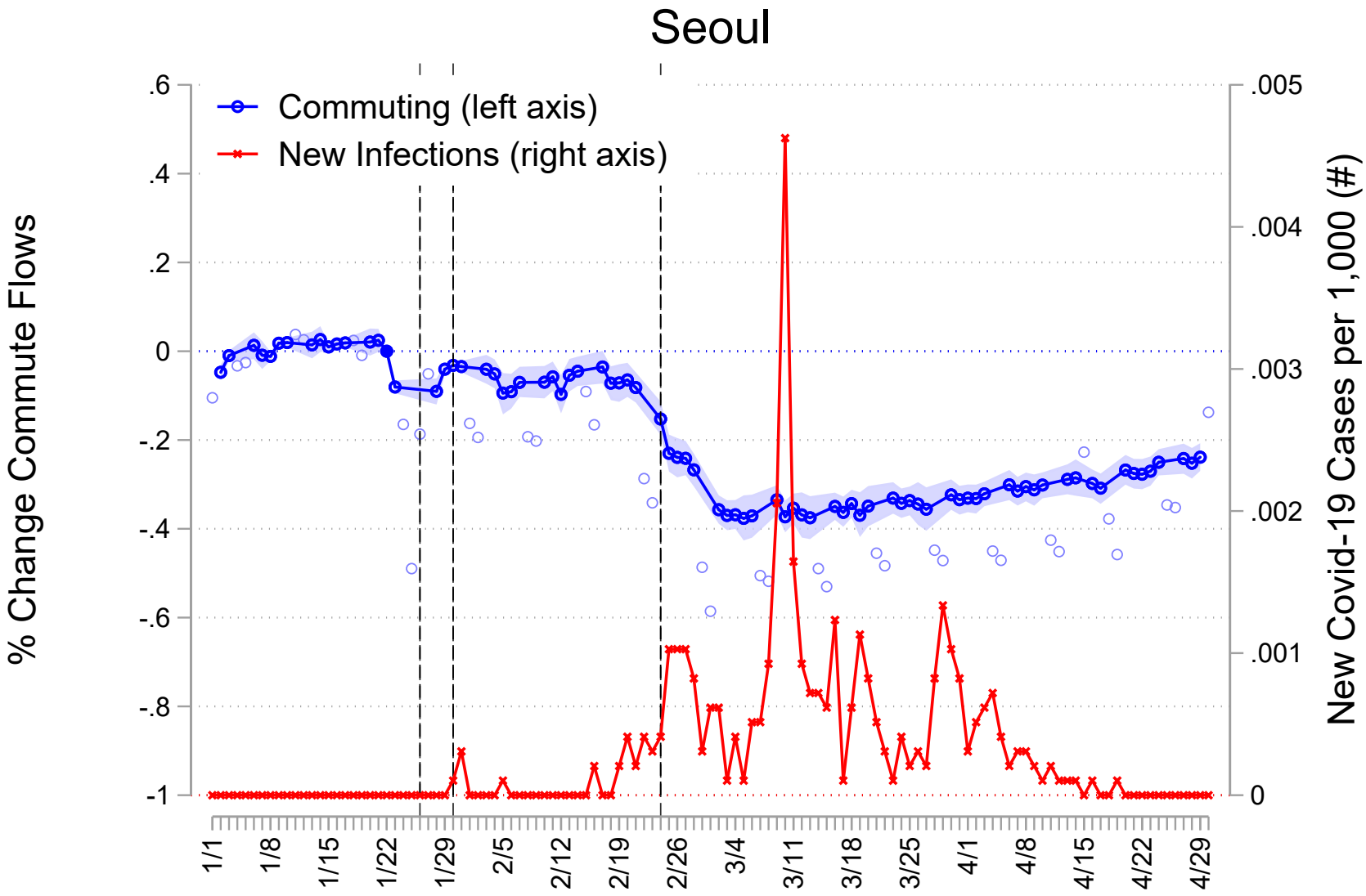




Conclusion

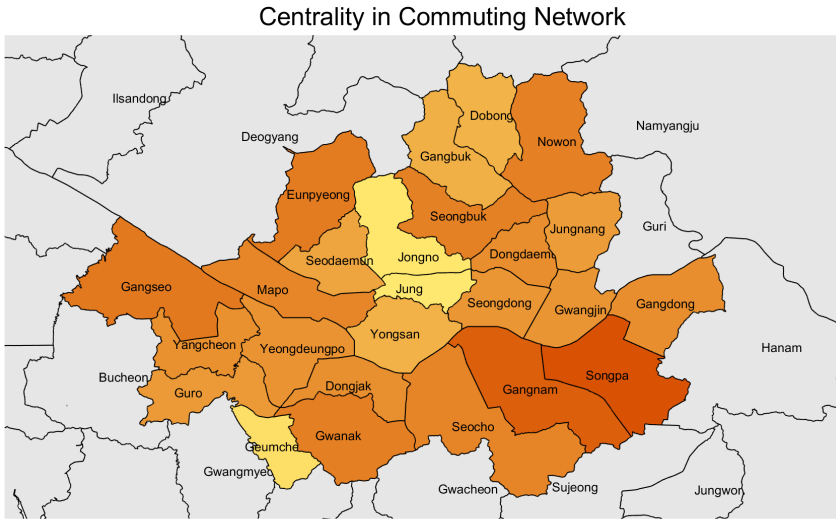
- Integrate spatial epidemiology and trade model, estimated on 3 cities
- Results
  1. Optimal spatial lockdowns have much smaller economic costs than uniform lockdowns
  2. Not easily approximated by simple centrality-based rules
  3. Commute responses were too weak in NYM's and Daegu's central nodes (too strong across Seoul)
- Possible extensions
  - Other spatial scales
  - Optimal deployment of vaccine
  - Disease transmission through shopping/leisure consumption
  - Endogenous job reallocations

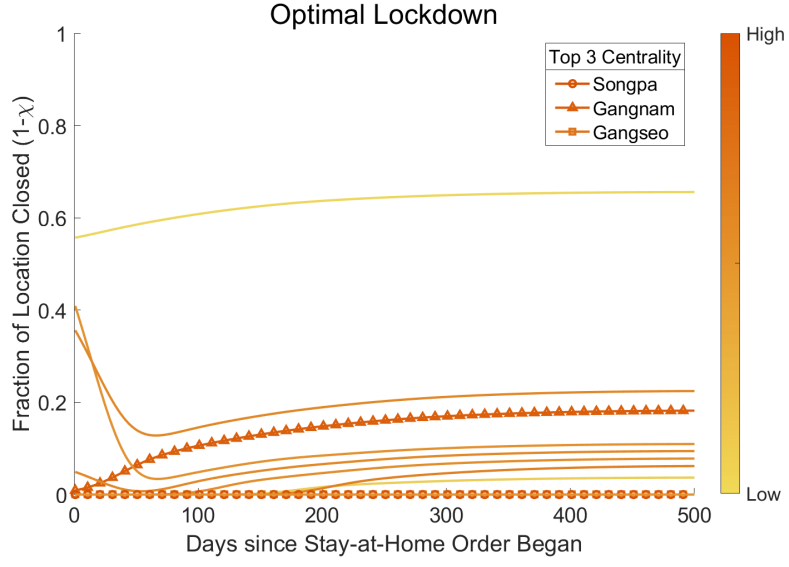
Commute Responses and Disease Spread: Seoul



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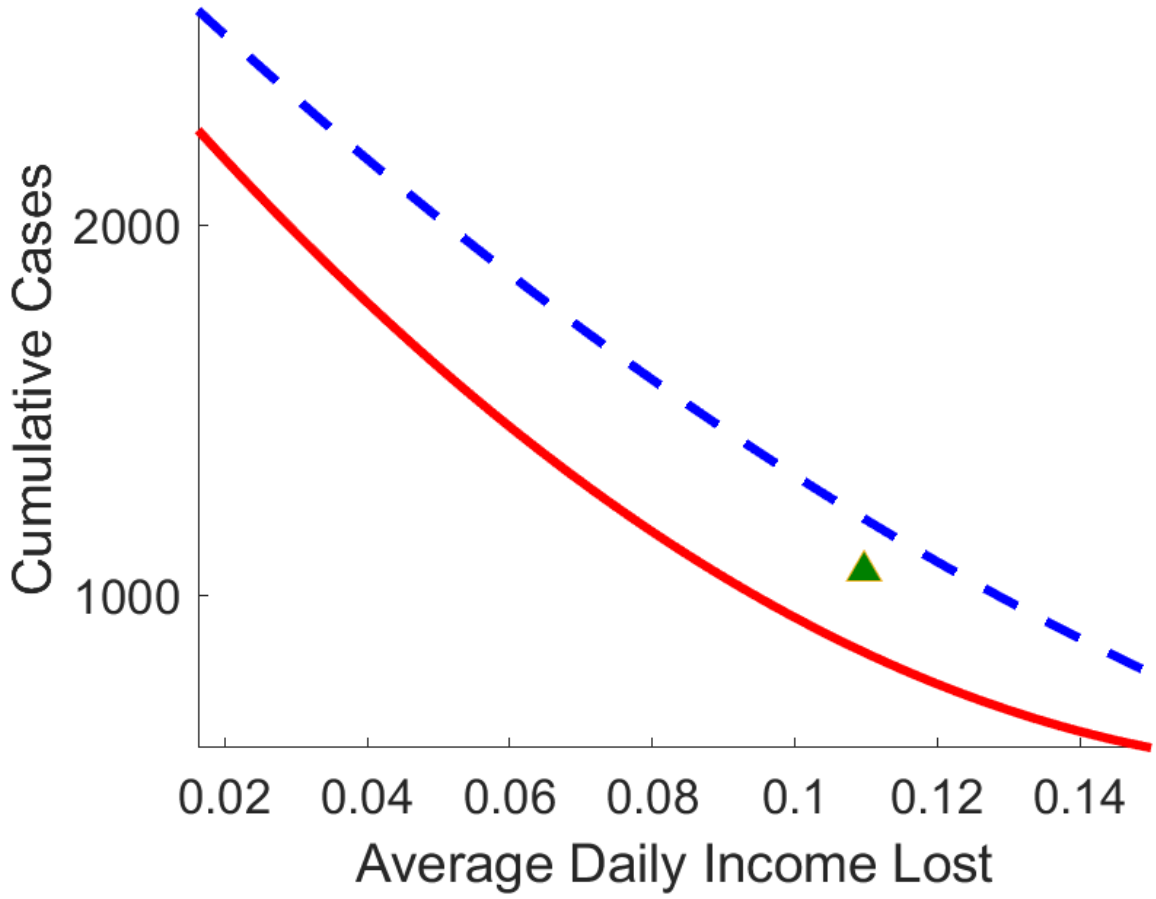
Centrality and Optimal Lockdown: Seoul





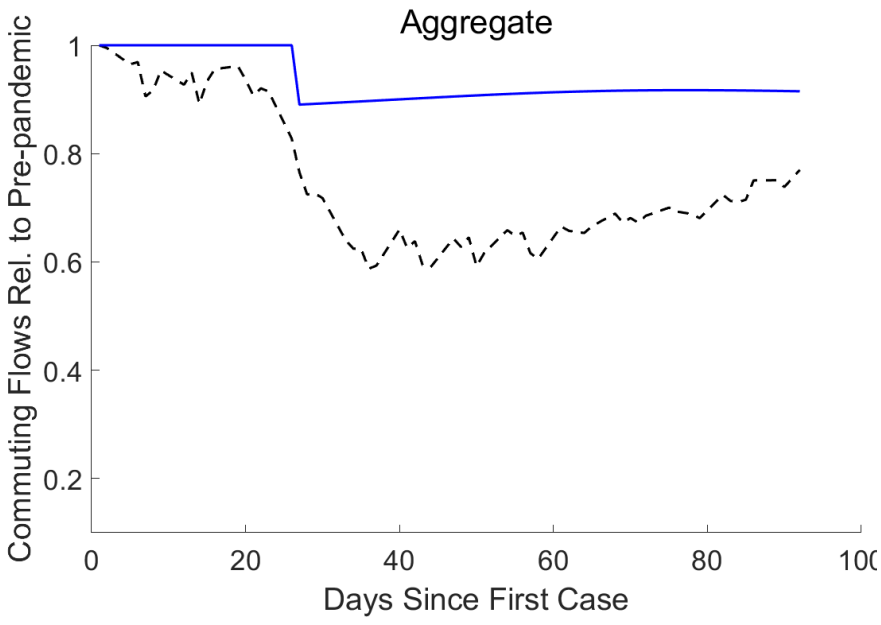
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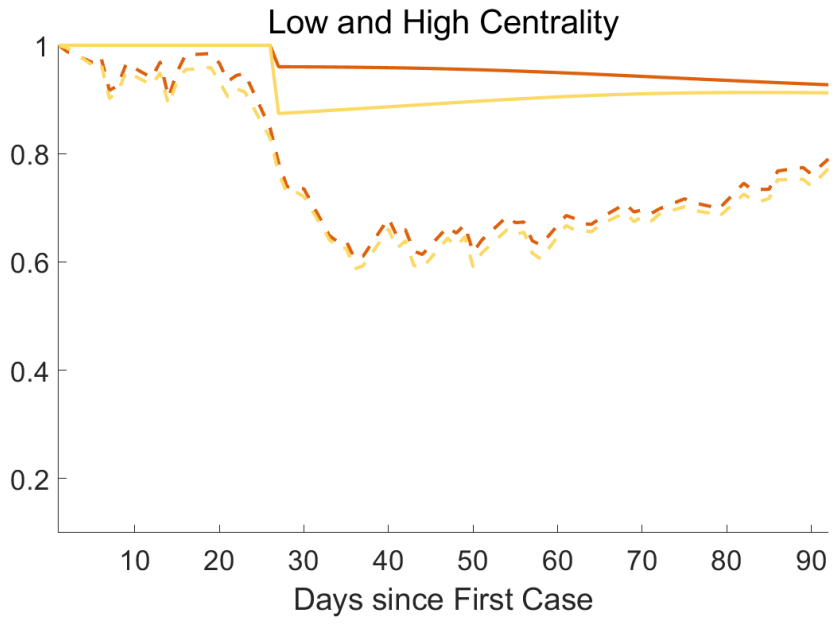
"Pareto" Frontier: Seoul



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Optimal and Observed Changes in Commuting Flows: Seoul





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Parameters

Parameter	Definition	Value	Source
Disease Dynamics			
γ_I	Exposed to Infected Rate	{1/5.1, 1/4.2}	Ferguson et al. (2020), Sanche et al. (2020)
γ_R	Infected to Recovered Rate	{1/18, 1/10}	Wang et al. (2020)
γ_D	Infected to Death Rate	{0.0005, 0.0002} (see Table note)	Ferguson et al. (2020), Hall et al. (2020)
ζ_I	% asymptomatic	{0.545, 0.272}	Alamian et al. (2019)
Matching Function			
β	Transmission Rate	Daegu: 0.58 Seoul: 1.58 NYM: 0.16	Case Data and Commuting
Trade Model			
κ_1	Distance-Trade Cost Elasticity	0.37	
κ_0	Scale of Trade Costs	Daegu: 0.69 Seoul: 1.23 NYM: 0.62	Credit Card Expenditures
σ	Demand Elasticity	5	Ramondo et al. (2016)
Other Parameters			
δ_I	Telecommuting Rate	Korea: 0.62 NYM: 0.46	Job Korea Dingel and Neiman (2020)
v	Probability of Vaccine	1/(365*1.5)	Expected time of 1.5 years until vaccine
ω	Value of Life	{1/100,..,100}*10 Million USD	
ρ	Discount rate	0.04/365	

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