Optimal Lockdown in a Commuting Network

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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 uniform 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, 25 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 (20 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 expenditure data

Model

- Planning problem

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

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

- % change in Susceptible:

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

  - $\lambda\left(i,j\right)$= pre-pandemic commute flows; ζ= fraction asymptomatic
  - Estimate $\beta_j = \frac{\beta}{\text{area}_j}$ from changes in flows and cases across locations

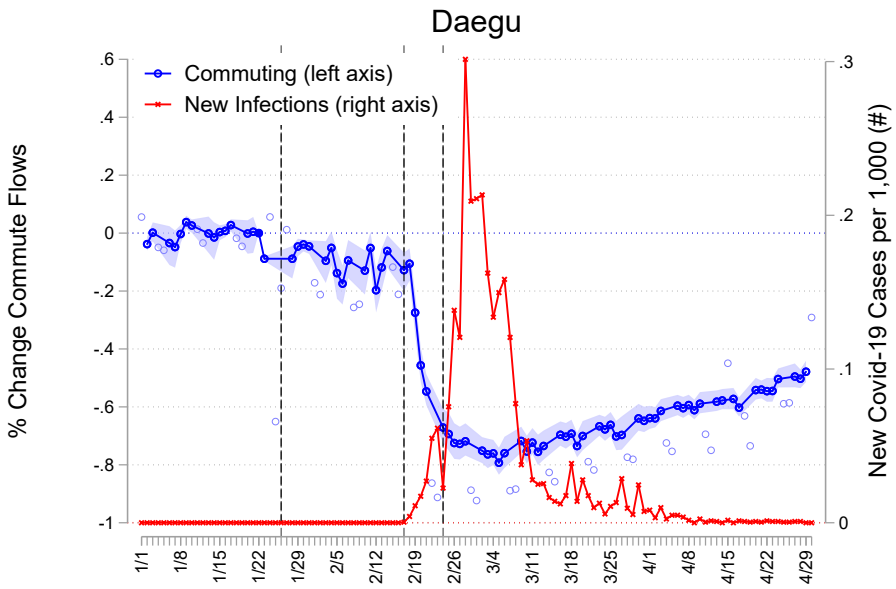
- Labor supply to location j:

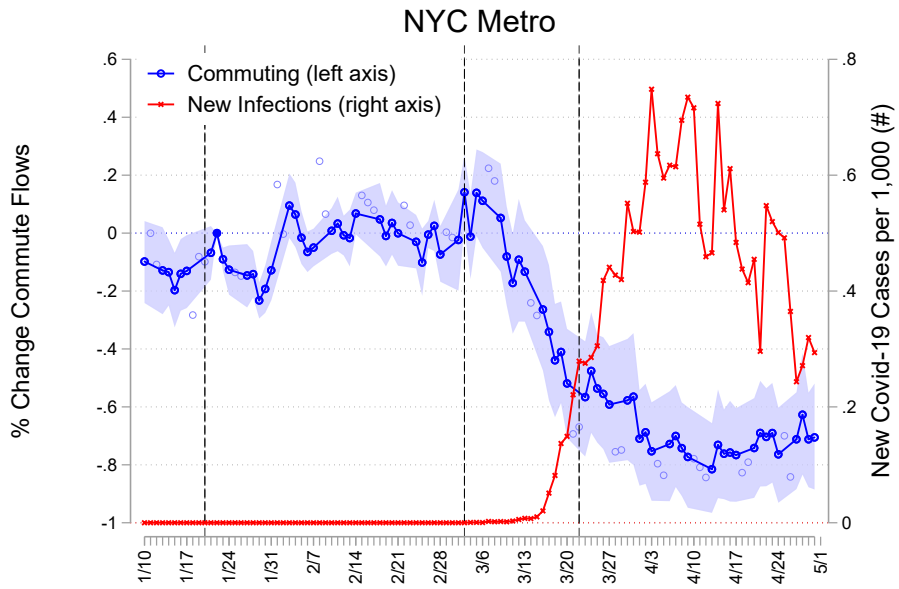
$$\sum_{u=S,E,I,R} \left[\chi\left(i,j,t\right) + \left(1 - \chi\left(i,j,t\right)\right) \delta_u \right] \lambda\left(i,j\right) N_u\left(i,t\right)$$

  - δ_u = fraction of telecommuters

parameters

Commute Responses and Disease Spread

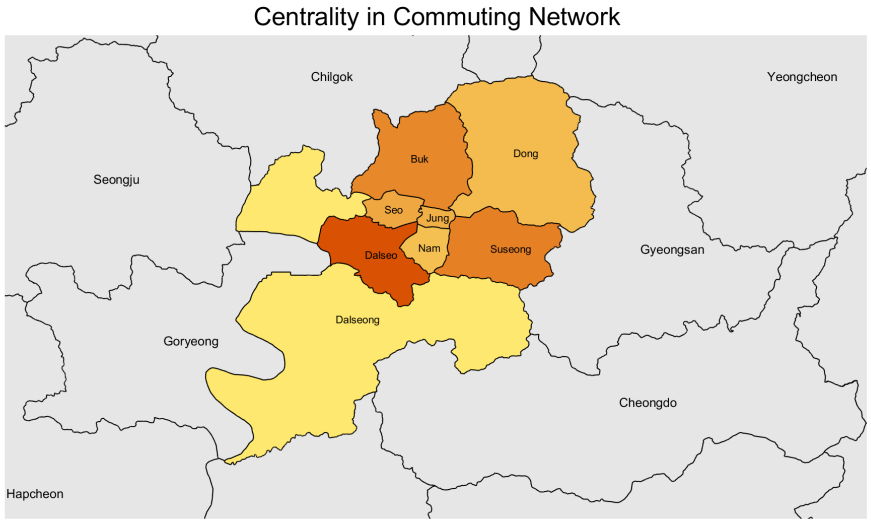


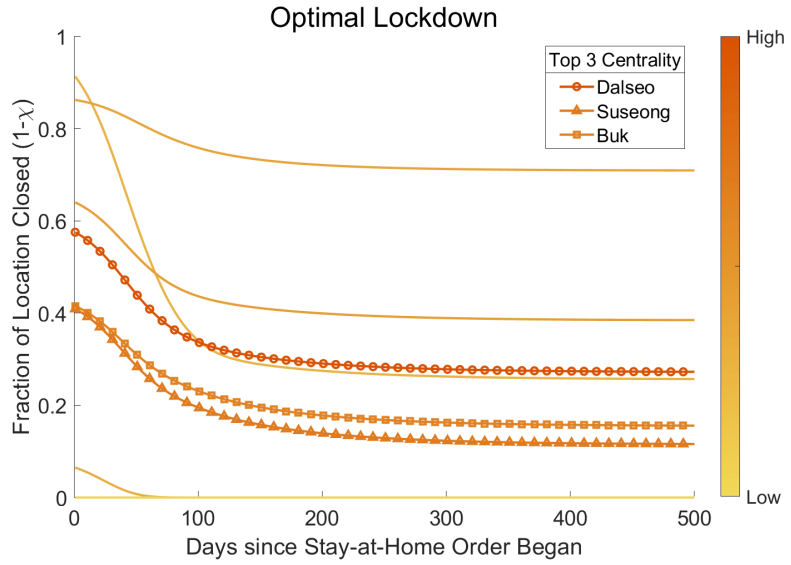


▶ Seoul

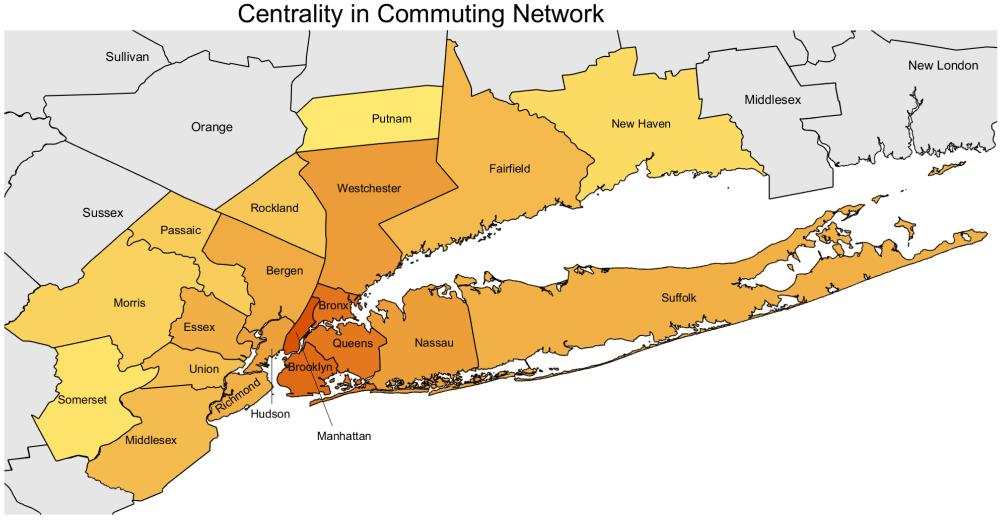
Centrality and Optimal Lockdown

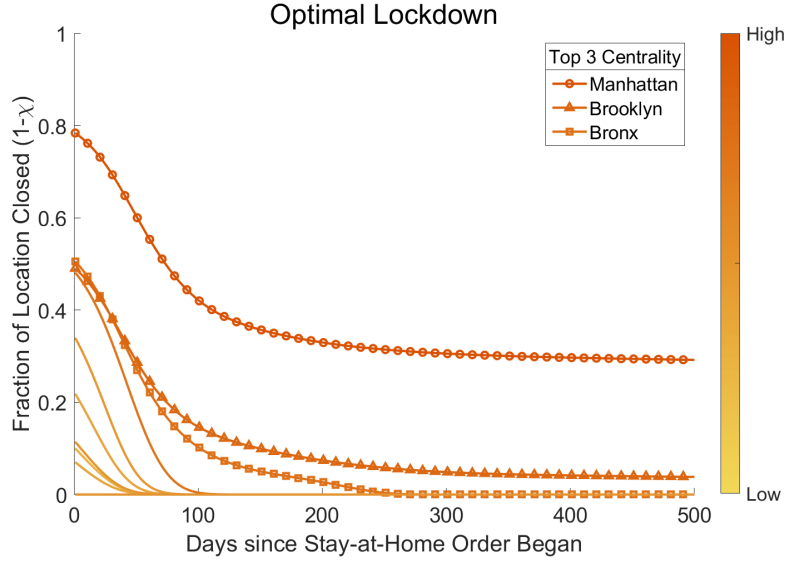
Daegu





NY Metro

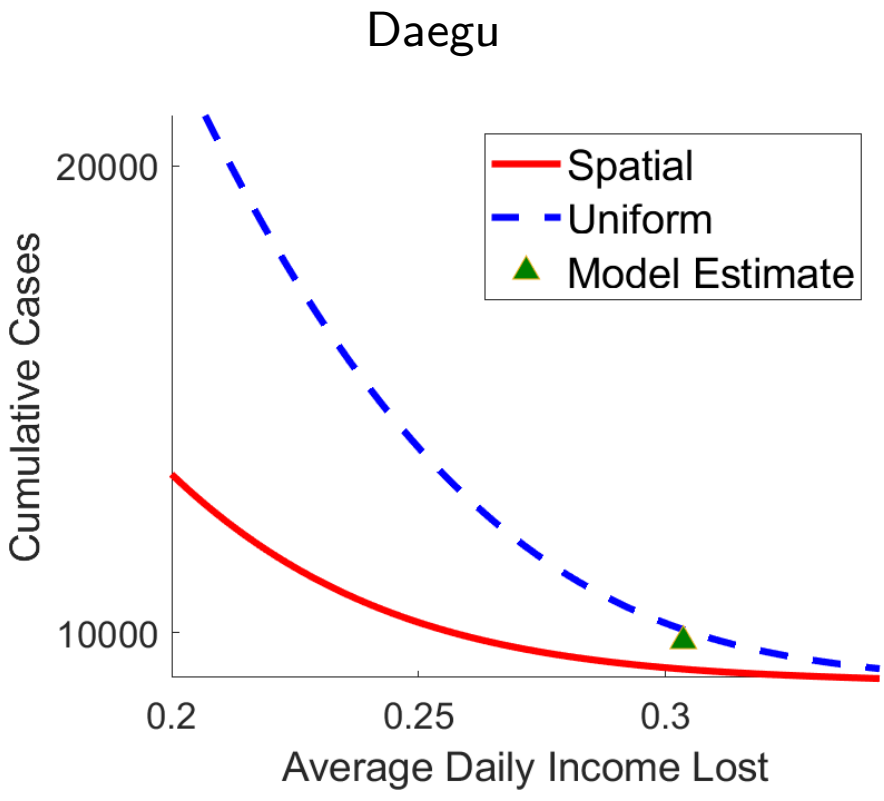


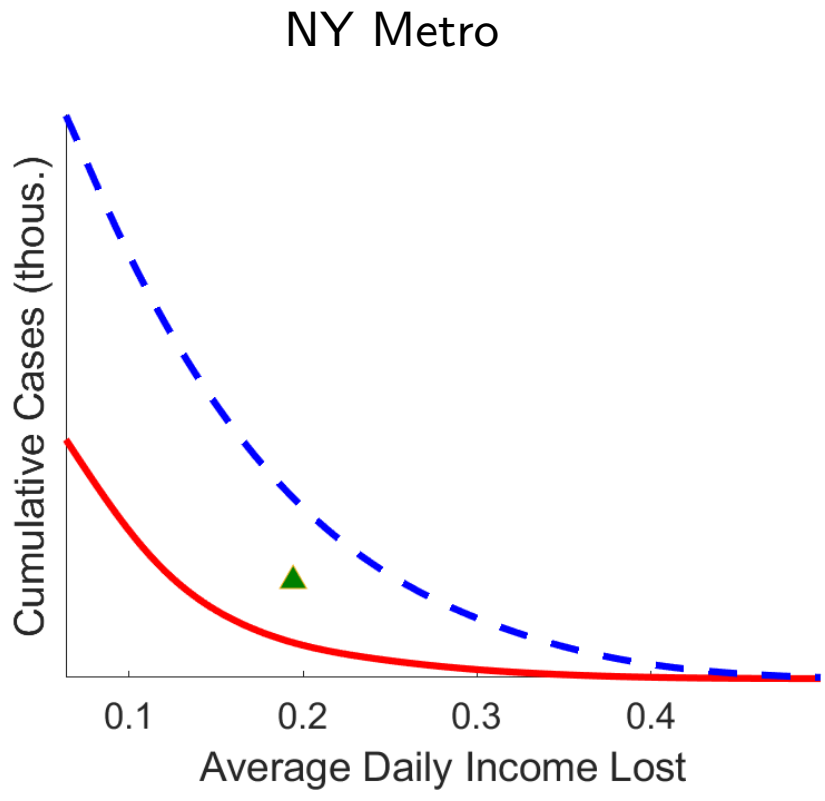


▶ Seoul

"Pareto" Frontier: Cases versus Income

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

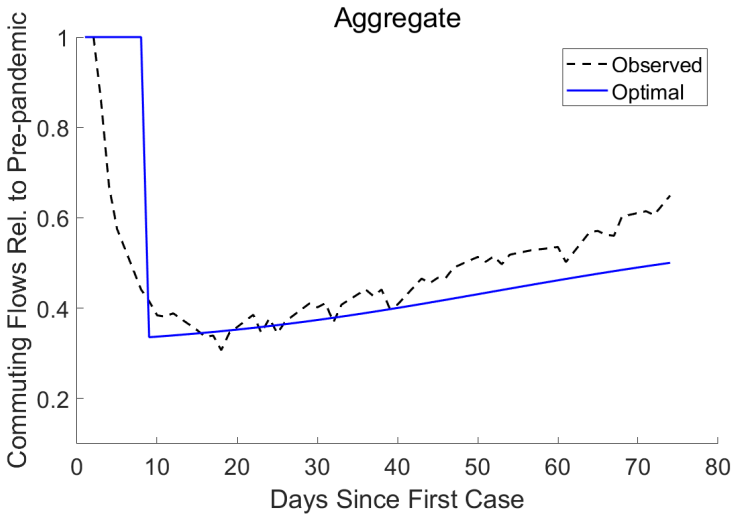


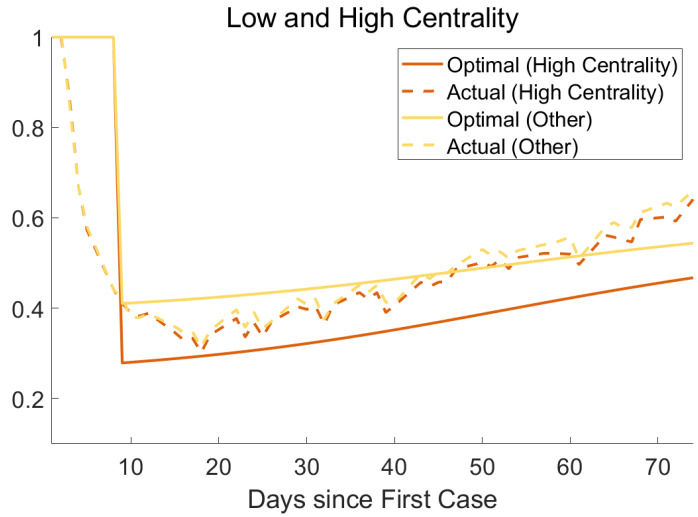


▸ Seoul

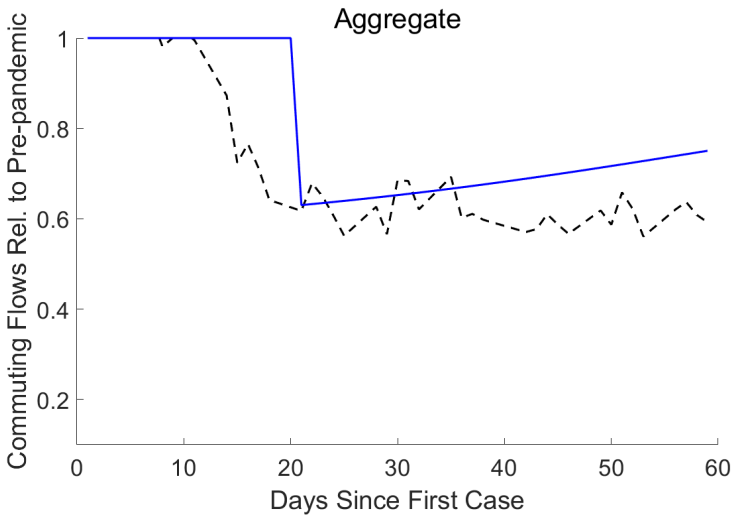
Optimal and Observed Changes in Commuting Flows

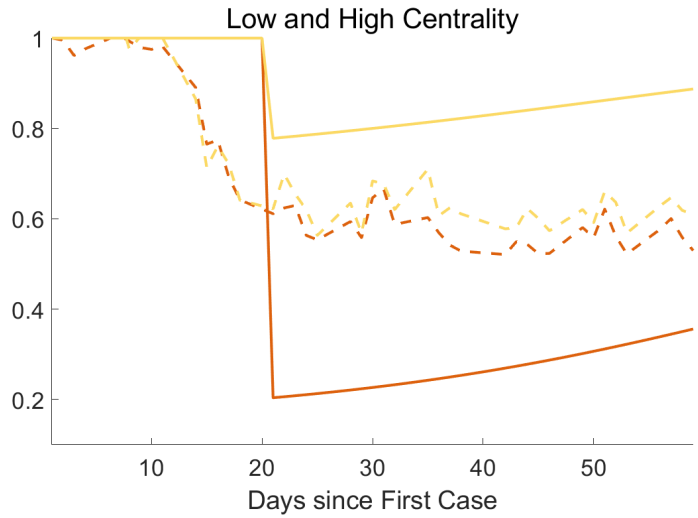
Daegu





NY Metro

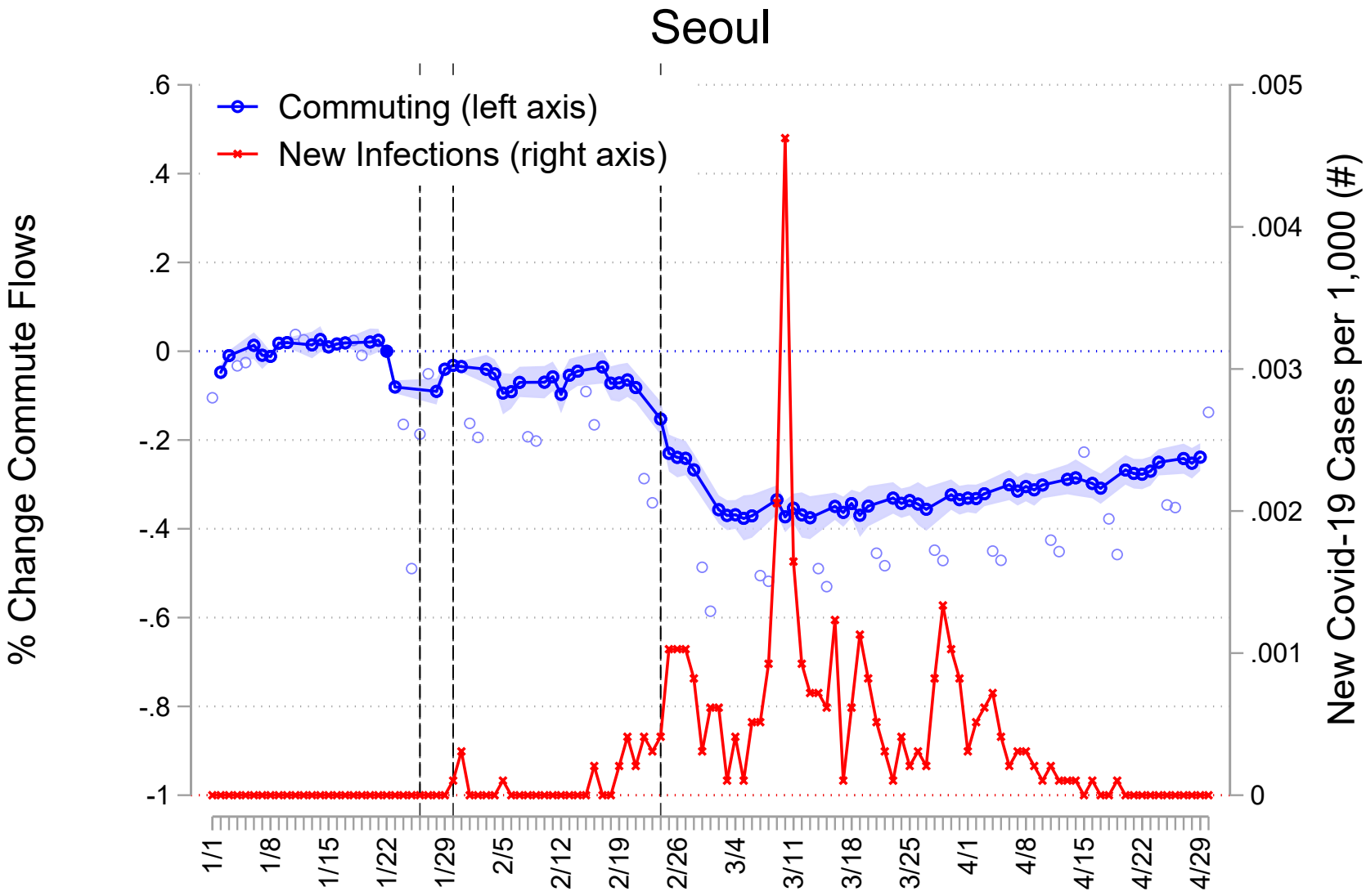




Conclusion

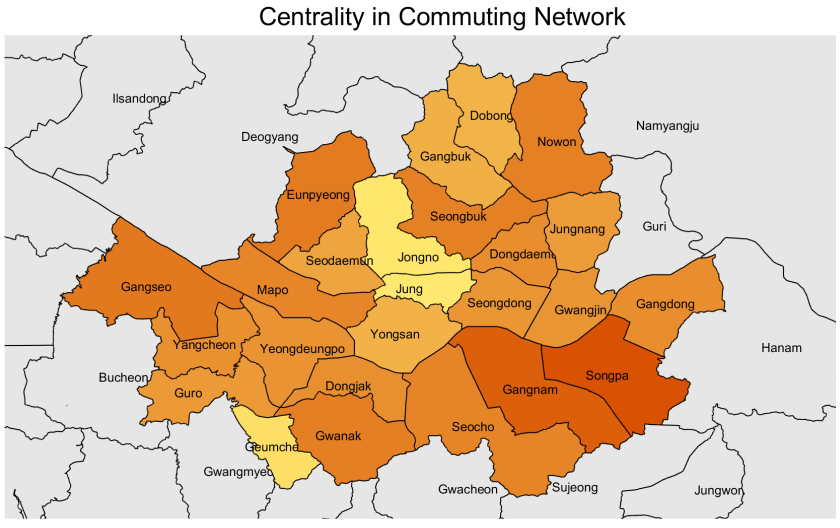
- Integrate spatial epidemiology and trade model, estimated on 3 cities
- Results
  1. Optimal spatial lockdowns have much smaller economic costs than uniform lockdowns
  2. Not easily approximated by simple centrality-based rules
  3. Commute responses were too weak in NYM's and Daegu's central nodes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

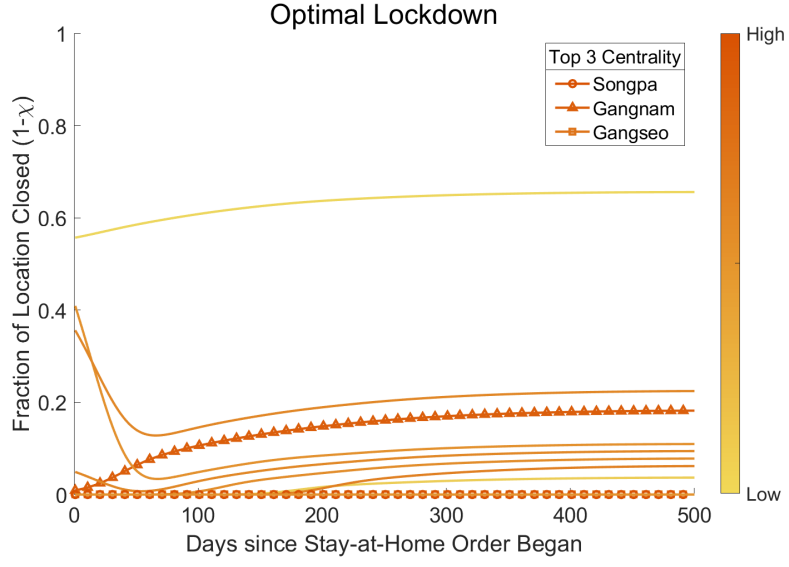
Commute Responses and Disease Spread: Seoul



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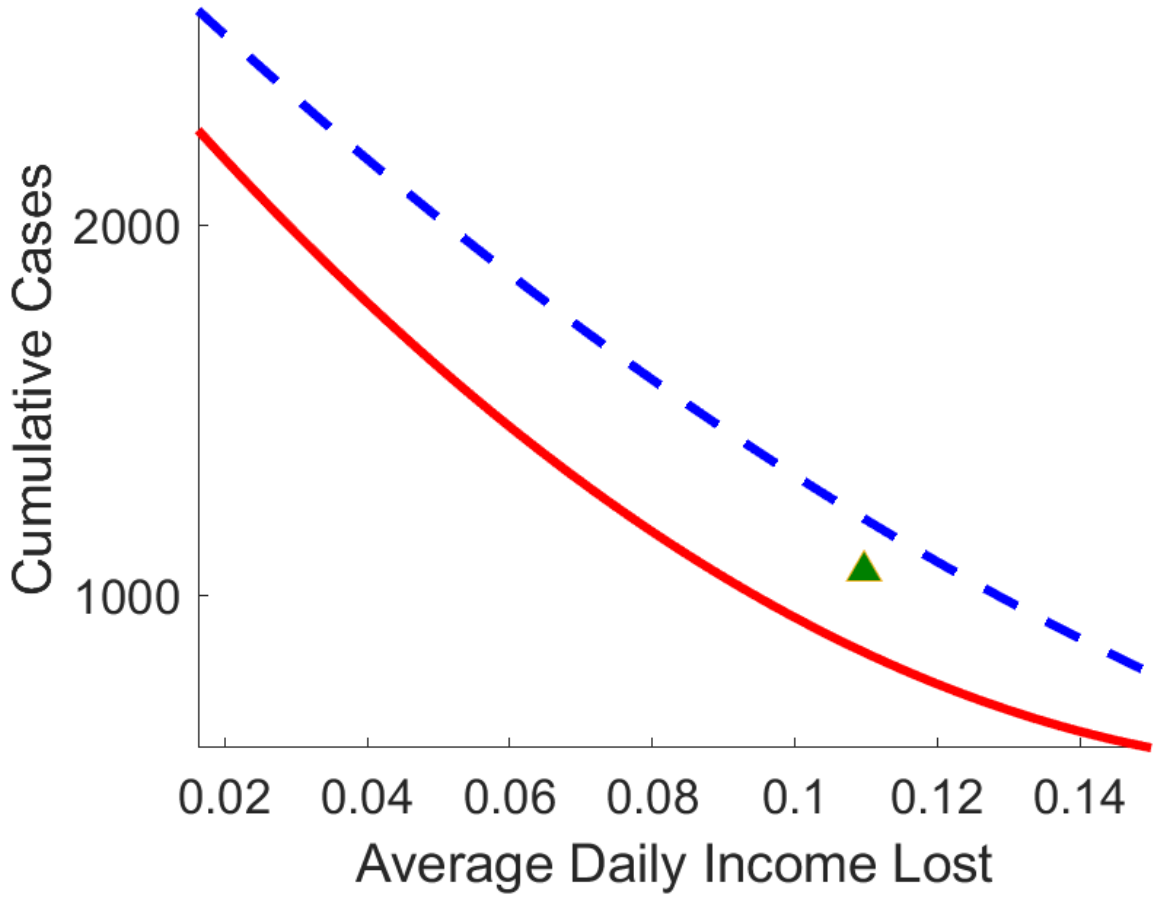
Centrality and Optimal Lockdown: Seoul





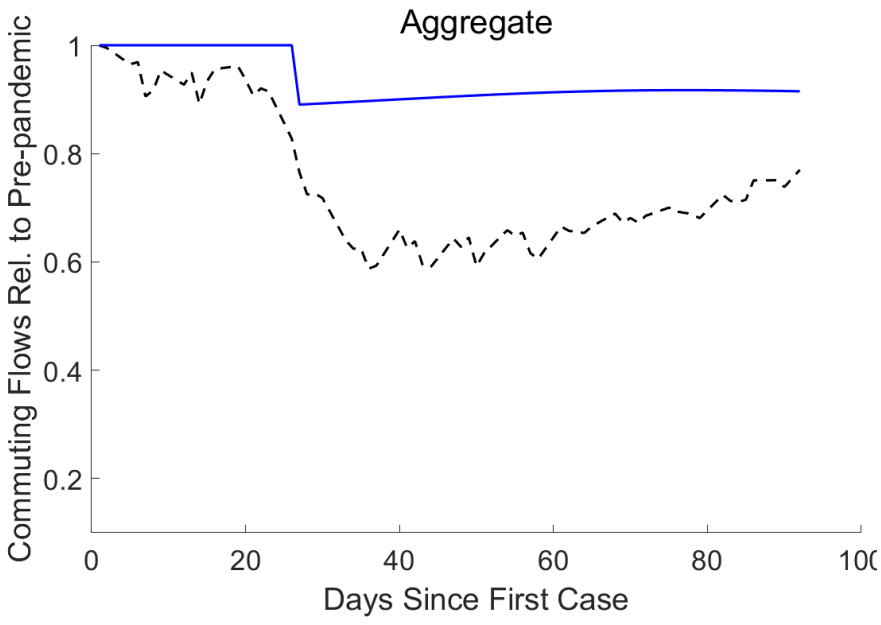
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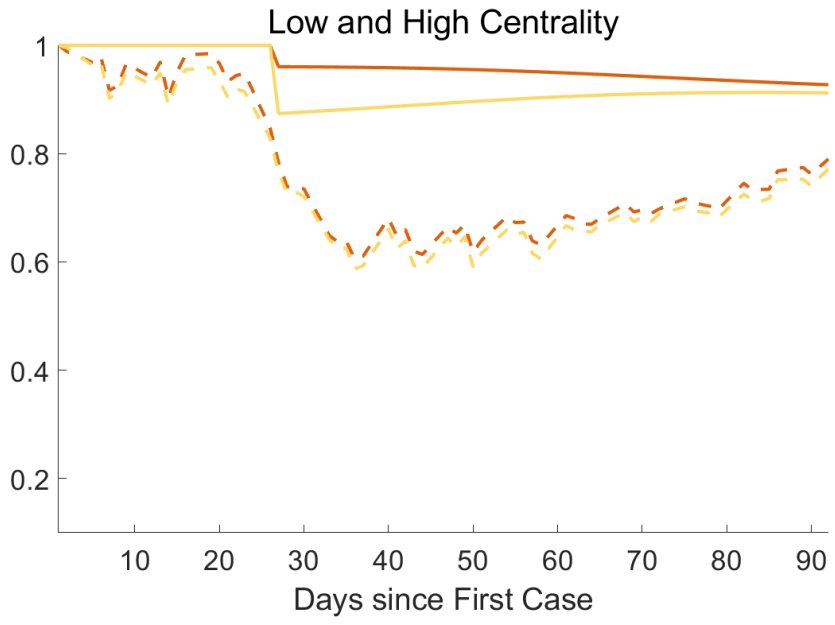
"Pareto" Frontier: Seoul



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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	

return

References I

Alamian, A., S. Pourbakhsh, A. Shoushtari, and H. Keivanfar (2019). Seroprevalence investigation of newcastle disease in rural poultries of the Northern Provinces (Golestan, Gilan, and Mazandaran) of Iran. *Archives of Razi Institute 74*(4), 365–373.

Dingel, J. I. and B. Neiman (2020). How many jobs can be done at home? Technical report, NBER Working Paper 26948.

Ferguson, N., D. Laydon, G. Nedjati Gilani, N. Imai, K. Ainslie, M. Baguelin, S. Bhatia, A. Boonyasiri, Z. Cucunuba Perez, G. Cuomo-Dannenburg, et al. (2020). Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Technical report, Imperial College.

Hall, R. E., C. I. Jones, and P. J. Klenow (2020). Trading off consumption and COVID-19 deaths. Technical report, NBER Working Paper 27340.

Ramondo, N., A. Rodríguez-Clare, and M. Saborío-Rodríguez (2016). Trade, domestic frictions, and scale effects. *American Economic Review 106*(10), 3159–84.

Sanche, S., Y. T. Lin, C. Xu, E. Romero-Severson, N. Hengartner, and R. Ke (2020). Early release-high contagiousness and rapid spread of severe acute respiratory syndrome coronavirus 2. *Emerging Infectious Diseases 26*, 1470–1477.

Wang, H., Z. Wang, Y. Dong, R. Chang, C. Xu, X. Yu, S. Zhang, L. Tsamlag, M. Shang, J. Huang, et al. (2020). Phase-adjusted estimation of the number of coronavirus disease 2019 cases in Wuhan, China. *Cell discovery 6*(1), 1–8.