# 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

NBER ITI Covid Session, 07/08/2020

# 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 within cities and across bordering U.S. states (avg diff of 4 days)
  - But economic activity and potential for spread is not uniform
  - Are there significant losses from spatially uniform or uncoordinated lockdown?

# This Paper

- Optimal dynamic lockdown in a commuting network to fight a pandemic
- Framework integrates:
  - 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

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

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

- % change in susceptible population:

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

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

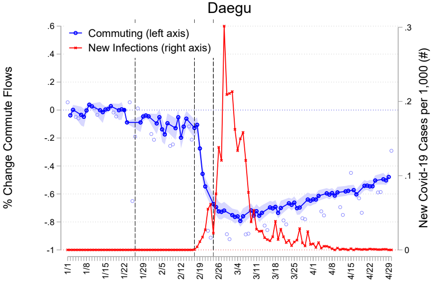
- Labor supply to location $j$:

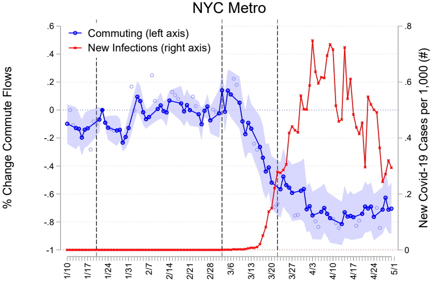
$$\sum_{u=S,E,I,R} \left[ \chi(i,j,t) + \left(1 - \chi(i,j,t)\right) \delta_u \right] \lambda(i,j) N_u(i,t)$$

  - $\delta_u$ = fraction of telecommuters

parameters

# Commute Responses and Disease Spread

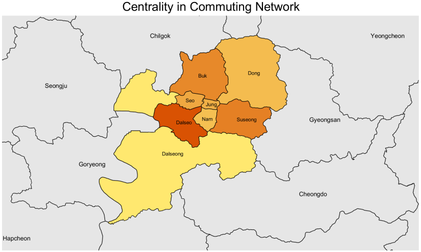


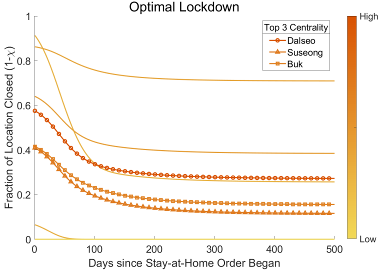




Seoul

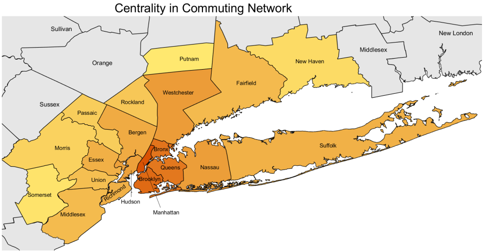
# Centrality and Optimal Lockdown

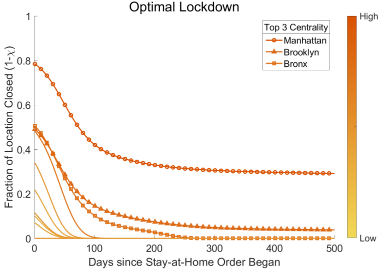
## Daegu




## NY Metro

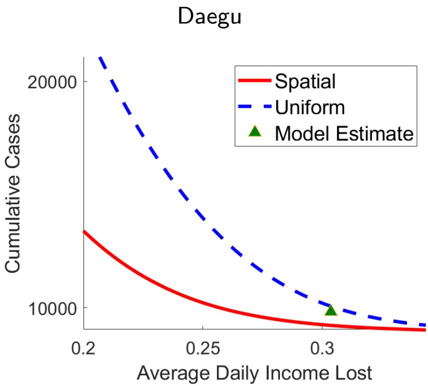


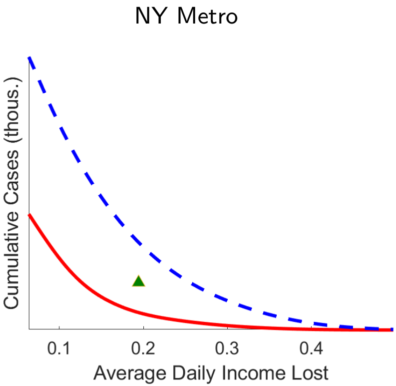




▸ Seoul

## “Pareto” Frontier: Cases versus Income

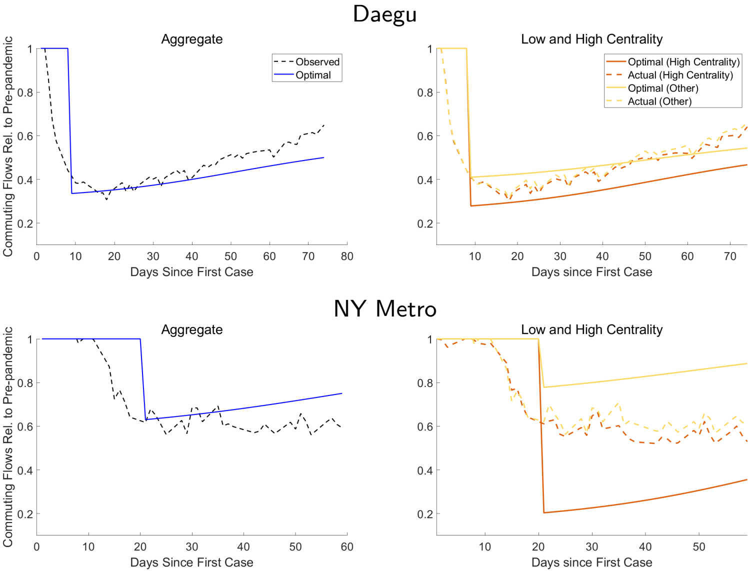
Cumulative cases and lost income (across values of life) by April 30




Seoul

# Optimal and Observed Changes in Commuting Flows

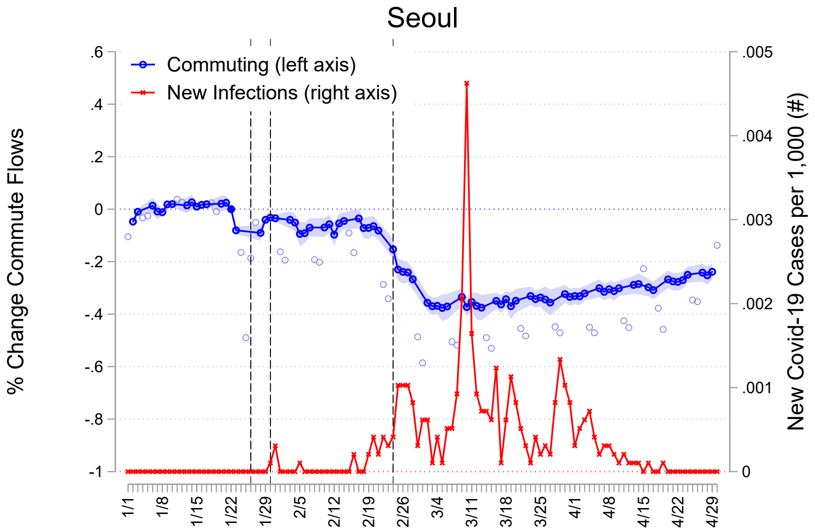



▸ Seoul

# Conclusion

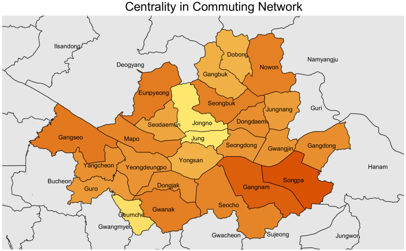
- Integrate spatial epidemiology and trade model, estimated on 3 cities
- Results
  1. Optimal spatial lockdowns have much smaller economic costs than uniform lockdowns
  2. Not easily approximated by simple centrality-based rules
  3. Commute responses were too weak in NYM's and Daegu's central nodes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

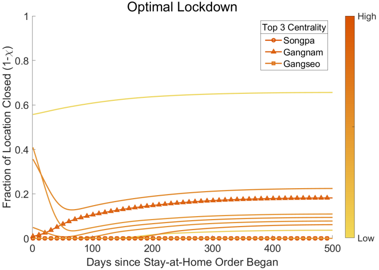
# Commute Responses and Disease Spread: Seoul




return

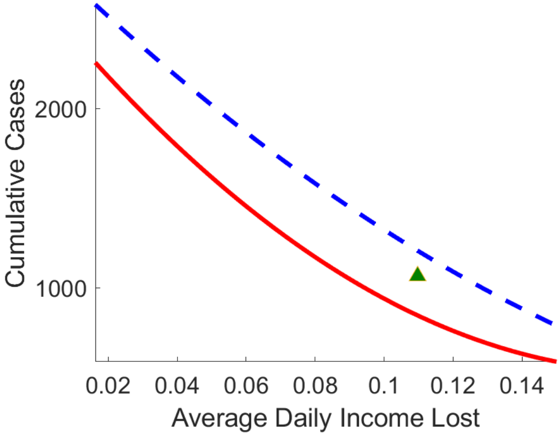
# Centrality and Optimal Lockdown: Seoul



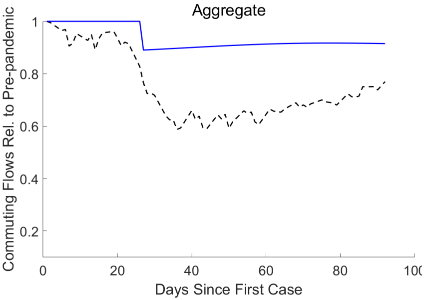

return

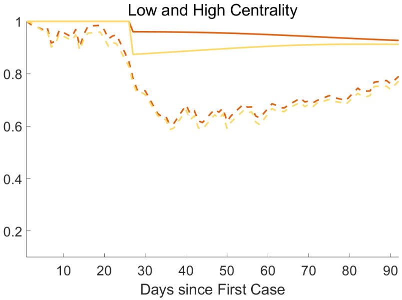
# "Pareto" Frontier: Seoul




return

# Optimal and Observed Changes in Commuting Flows: Seoul




return

# Parameters

| Parameter | Definition | Value | Source |
|---|---|---|---|
| Disease Dynamics | | | |
| $\gamma_I$ | Exposed to Infected Rate | $\{1/5.1, 1/4.2\}$ | Ferguson et al. (2020), Sanche et al. (2020) |
| $\gamma_R$ | Infected to Recovered Rate | $\{1/18, 1/10\}$ | Wang et al. (2020) |
| $\gamma_D$ | Infected to Death Rate | $\{0.0005, 0.0002\}$ (see Table note) | Ferguson et al. (2020), Hall et al. (2020) |
| $\zeta_I$ | % asymptomatic | $\{0.545, 0.272\}$ | Alamian et al. (2019) |
| Matching Function | | | |
| $\beta$ | Transmission Rate | Daegu: 0.58<br>Seoul: 1.58<br>NYM: 0.16 | Case Data and Commuting |
| Trade Model | | | |
| $\kappa_1$ | Distance-Trade Cost Elasticity | 0.37 | Credit Card Expenditures |
| $\kappa_0$ | Scale of Trade Costs | Daegu: 0.69<br>Seoul: 1.23<br>NYM: 0.62 | |
| $\sigma$ | Demand Elasticity | 5 | Ramondo et al. (2016) |
| Other Parameters | | | |
| $\delta_I$ | Telecommuting Rate | Korea: 0.62<br>NYM: 0.46 | Job Korea<br>Dingel and Neiman (2020) |
| $v$ | Probability of Vaccine | 1/(365*1.5) | Expected time of 1.5 years until vaccine |
| $\omega$ | Value of Life | $\{1/100,..,100\}$*10 Million USD | |
| $\rho$ | 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.