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 were down 49%
- Lockdowns were fairly uniform within cities and across bordering U.S. states
  - Avg diff of 4 days, s.d 3.5 days
  - NY, NJ, and Connecticut: almost simultaneous lockdown
  - There is also some variation
    - Illinois, more than two weeks before Missouri
    - Variation in county-level policies
- But economic activity and potential for virus spread is not uniform in space
- So, potentially, there could be gains from targeting lockdown in space

This Paper

- Optimal dynamic lockdown in a commuting network
- Framework integrates:
  - Standard trade model (Anderson and Van Wincoop (2003))
  - Standard spatial epidemiology model (Arino and Van den Driessche (2003))
- Estimated with real-time commuting and credit-card expenditure data
  - Korea (Daegu and Seoul) and New York Metro
    - ⋆ Daegu and NYM: Large shocks
- Questions:
  1. What are the optimal lockdown patterns over time and space?
  2. How do observed commuting reductions compare with optimal?
  3. How large are the benefits from optimal spatial targeting?

Main Results

- Optimal lockdown patterns
  - NYM and Daegu: strict initial lockdown of some central places, which remain partially closed for a long time
  - Actual commuting reductions were too weak in central locations in Daegu and NYM, and too strong across Seoul

- Spatial lockdowns achieve substantially smaller income losses than uniform
  - Spatial targeting vs. Uniform (space-blind): 20%, 32%, and 58% lower economic costs in Daegu, Seoul, and NYM (given the number of infections)
  - Gains can be largely achieved with spatially targeted business lockdowns

Literature Review

- Optimal control of epidemics in single-location economic models
  - Pre-Covid: Goldman and Lightwood (2002), Rowthorn and Toxvaerd (2012)
  - Covid: Atkeson (2020), Alvarez et al. (2020), Jones et al. (2020), Piguillem and Shi (2020), Rowthorn (2020), Rowthorn and Toxvaerd (2020),...
  - Heterogeneity: Acemoglu et al. (2020), Baqaee et al. (2020), Glover et al. (2020),...
- Transport networks and disease diffusion
  - Pre-Covid: Adda (2016), Viboud et al. (2006)
  - Covid: Tian et al. (2020), Fang et al. (2020), Kissler et al. (2020) , Hsiang et al. (2020), Flaxman et al. (2020)...
- Spatial SIR: Rvachev and Longini Jr (1985), Bolker and Grenfell (1995), Rowthorn et al. (2009)
  - Targeted policies: Germann et al. (2006), Eubank et al. (2004), Drakopolous and Zheng (2017)
  - Covid 19: Azzimonti et al. (2020), Chinazzi et al. (2020), Birge et al. (2020), Giannone et al. (2020), Argente et al. (2020)

Spatial SEIR Model

- $j = 1, .., J$ locations
  - Exogenous pre-pandemic population with commuting flows $\lambda(i, j)$
  - Policy $\chi(i, j, t)$ = Fraction of commutes (=jobs) allowed from i to j at time t
    - Flows are turned on and off (no reallocations)
- States: susceptible, exposed, infected, or recovered: $S(j,t)$, $E(j,t)$, $I(j,t)$, and $R(j,t)$
- % change in susceptible population (new infections):

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

  - $\beta_j = \frac{\beta}{\text{area}_j}$ estimated from changes in flows and cases across locations
  - ζ= fraction asymptomatic
  - Contagion happens in i or in j (not along route)
- Transitions across other states:

$$\begin{aligned}
\dot{\mathbf{E}}(t) &= -\dot{\mathbf{S}}(t) - \gamma_I \mathbf{E}(t) \\
\dot{\mathbf{I}}(t) &= \gamma_I \mathbf{E}(t) - (\gamma_R + \gamma_D) \mathbf{I}(t) \\
\dot{\mathbf{R}}(t) &= \gamma_R \mathbf{I}(t)
\end{aligned}$$

Trade Model

- Standard Armington trade model where lockdown policies affect labor supply and trade costs

- Labor supply of type $u = S, E, I, R$ from location i to$j$:

$$N_u(i,j,t) = u(i,t)\,\lambda(i,j)\zeta_u\left[\chi(i,j,t) + (1-\chi(i,j,t))\,\delta\right]$$

  - ζ_I = fraction of asymptomatic infected (= 1 for other types)
    - Infected with symptoms do not work
  - δ = fraction of telecommuters

- Real Income $U(i,t) = \frac{Y(i,t)}{P(i,t)}$, where
  - Income: $Y(i,t) = \sum_u \sum_j N_u(i,j,t)\,w(j,t)$
  - Wages: $w(j,t)\sum_u \sum_i N_u(i,j,t) = \sum_i s(i,j,t)\,Y(i,t)$
  - Expenditure shares: $s(i,j,t) \equiv \left(\frac{\tau(i,j,t)}{P(i,t)}\frac{w(j,t)}{z(j)}\right)^{1-\sigma}$

- Residents of i face costs $\tau(i,j,t) \equiv \kappa_0 distance(i,j)^{\kappa_1}\,\chi(i,j,t)^{-\varepsilon} > 1$ when shopping in j

- In paper: virus diffusion through shopping

Planning Problem

- In reduced form, trade model gives:

$$U(j,t,\chi(t)) \equiv U(j,\mathbf{S}(t),\mathbf{E}(t),\mathbf{I}(t),\mathbf{R}(t),\chi(t))$$

- Vaccine becomes available at rate ω, instantaneous switch to:

$$\bar{U}(j,t) \equiv U(j;0,0,0,\mathbf{S}(t)+\mathbf{E}(t)+\mathbf{I}(t)+\mathbf{R}(t),\mathbf{1}_{J\times J})$$

- Planning problem:

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

subject to how the $\mathbf{S}(t),\mathbf{E}(t),\mathbf{I}(t),\mathbf{R}(t)$ dynamics depend on $\chi(t)$

- We use as initial condition the SEIR distribution at the the lockdown date

FOC

- Assume multiplicative matching function:

$$M_j\left(\tilde{I},\tilde{S}\right)=\beta_j\tilde{I}\tilde{S}$$

- FOC over $\chi(i,j,t)$ given wage $w(j)$ (i.e., no GE through trade model):

$$\begin{aligned}(1-\delta)\,w(j)=\Delta(i,t)\,\frac{S(i,t)}{N(i,t)}\beta_j\sum_{i'}\zeta I\left(i',t\right)\lambda\left(i',j\right)\chi\left(i',j,t\right)\\ +\frac{\zeta I(i,t)}{N(i,t)}\beta_j\sum_k\Delta(k,t)\,S(k,t)\,\lambda(k,j)\,\chi(k,j,t)\,,\end{aligned}$$

  where

  - $\Delta(i,t)\equiv\mu_S(i,t)-\mu_E(i,t)$, the difference between the co-states $S(t)$ and $E(t)$
  - $N(i,t)$ is the surviving population of i at time t

Data

- Korea
  - Seoul (largest city, 25 districts) and Daegu (largest outbreak, 8 districts)
  - Commuting data (individual transport cards in Seoul, subway entry and exits in Daegu)
  - Credit-card district-to-district transactions at physical shops in Seoul (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 (β)
  - Spatial frictions (κ, ε)

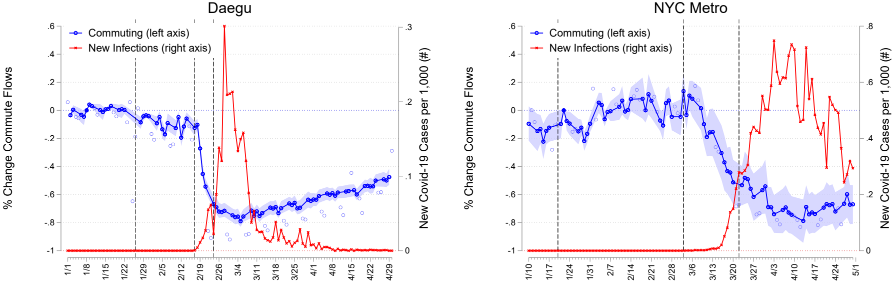
Summary Statistics

	Daegu	Seoul	NYC Metro
Population	2,438,031	9,729,107	19,467,622
# Districts	8	25	20
Sample Period	Jan 1, 2018–Apr 30, 2020	Jan 1, 2018–Apr 30, 2020	Jan 1, 2020–Apr 30, 2020
Data Source	Subway ridership	Subway/bus ridership	Mobile phones
Flow Type	Turnstile	Bilateral	Bilateral
First Case	Feb 17, 2020	Jan 30, 2020	Mar 3, 2020
Lockdown Date	Feb 24, 2020	Feb 24, 2020	Mar 22, 2020
# Cumulative Cases	6,778	354	389,603

Notes: Table reports summary statistics for the Daegu, Seoul, and NYC Metro data. Administrative units within the two Korean cities are called districts with an average population of 368,701 and an average land area of 45 km^2. Administrative units within NYC Metro are counties with an average population of 1,232,768 and an average land area of 690 km^2. Cumulative Covid-19 cases are as of April 30 2020.

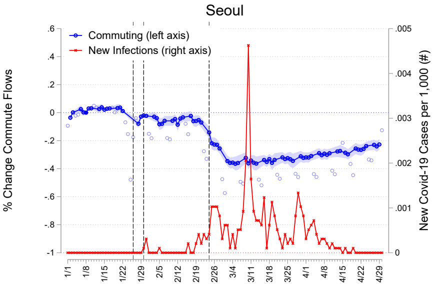
Daegu and NYM: Commute Responses and Disease Spread

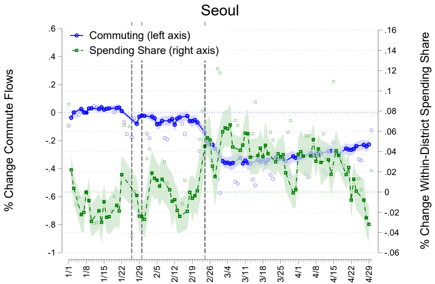
Report π_t from: $\frac{N_{ijt}}{\bar{N}_{ij,\tau(t)}} = \pi_t + \epsilon_{ijt}$ (NYM) and $\frac{E_{it}}{\bar{E}_{i,\tau(t)}} = \pi_t + \epsilon_{it}$ (Daegu)



Seoul: Commute Responses, Disease Spread, and Spending

$$\text{Report } \pi_t \text{ from: } \frac{N_{ijt}}{\bar{N}_{ij,\tau(t)}} = \pi_t + \epsilon_{ijt}$$





Transmission Rate β

1. $S(i,t)$ and $I(i,t)$ are recovered from data on new infections and calibrated transition rates $(\gamma_I, \gamma_R, \gamma_D)$
2. Estimate β to fit diffusion after the peak:

$$\Delta S(i,t) = -\beta \sum_j \frac{1}{\text{area}_j} \left[\lambda(i,j) S(i,t) \chi(i,j,t)\right] \left[\zeta \sum_{i'} I(i',t) \lambda(i',j) \chi(i',j,t)\right] + \varepsilon(i,t)$$

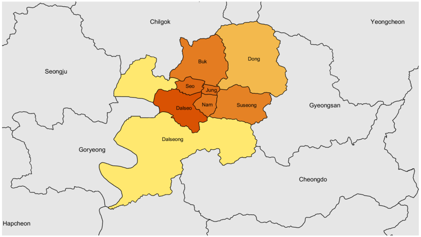
- Model-implied city-level reproduction number during first week: 1.32 in Seoul, 1.32 in Daegu, and 2.94 in NYM
- Suggestive evidence: commuting and new daily cases link

Parameters

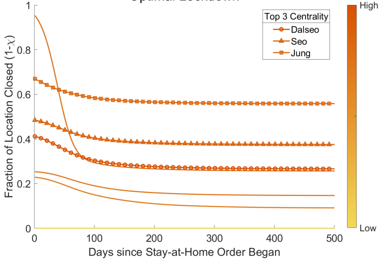
Parameter	Definition	To match	Source
Disease Dynamics			
γ_I	Exposed to Infected Rate	Incubation period of 5.1 (robustness: 4.2 days)	Ferguson et al. (2020), Sanche et a
γ_R	Infected to Recovered Rate	Recovery of 18 days (robustness: 10 days)	Wang et al. (2020)
γ_D	Infected to Death Rate	Infection-Fatality ratio 0.9% (robustness: 0.3%)	Ferguson et al. (2020), Hall et al. (
ζ_I	% asymptomatic	36% (robustness: 18%)	Alamian et al. (2019)
Matching Function			
β	Transmission Rate	Daegu: 1.58 Seoul: 4.17 NYM: 0.55	Case Data and Commuting
Gravity: $\ln X(i,j,t) = \psi(j) + \eta(i) - (\sigma-1)\kappa_1 \ln(distance(i,j)) + (\sigma-1)\varepsilon \ln(\chi(i,j,t)) + \epsilon(i,j,t)$			
κ_1	Distance-Trade Cost Elasticity	$(\sigma-1)\kappa_1 = 1.53$	
κ_0	Scale of Trade Costs	Same-district expenditure share: 55%	Credit Card Expenditures
ε	Lockdown-Trade Cost Elasticity	$(\sigma-1)\varepsilon = 0.45$	
σ	Demand Elasticity	5	Ramondo et al. (2016)
Other Parameters			
δ	Telecommuting Rate	Korea: 62% NYM: 46%	Job Korea Dingel and Neiman (2020)
v	Probability of Vaccine	Expected time of 1.5 years	
ω	Value of Life	14.5 years x \$185,000	Hall et al. (2020)
ρ	Discount rate	4% Annually	

Daegu

Centrality in Commuting Network

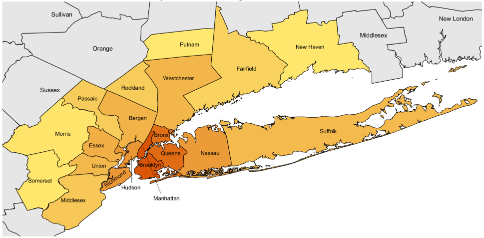


Optimal Lockdown

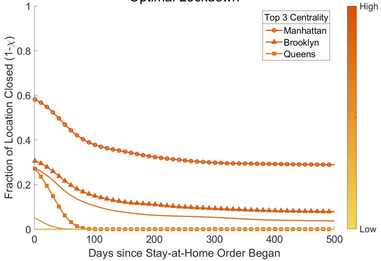


NY Metro

Centrality in Commuting Network



Optimal Lockdown



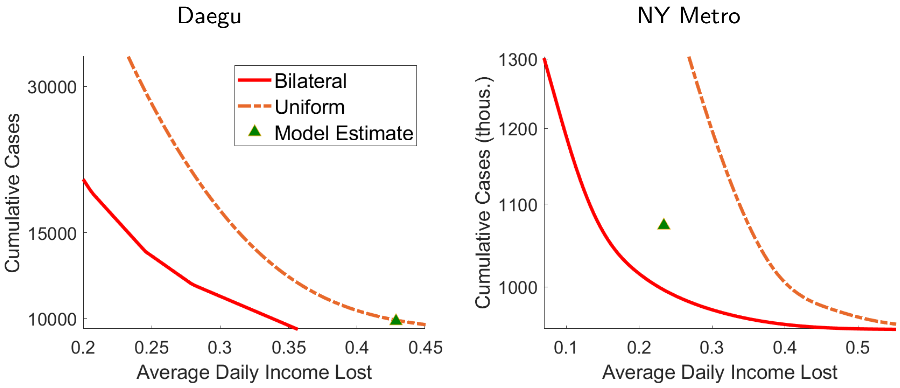
Note: Centrality: Largest eigenvalue of the viral spread matrix at time 0. Right panel shows inflow lockdown.

▸ Seoul

“Pareto” Frontier: Cases versus Income

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

- Bilateral: unconstrained $\chi(i, j, t)$
- Uniform: $\chi(i, j, t) = \chi(t)$ for all i, j

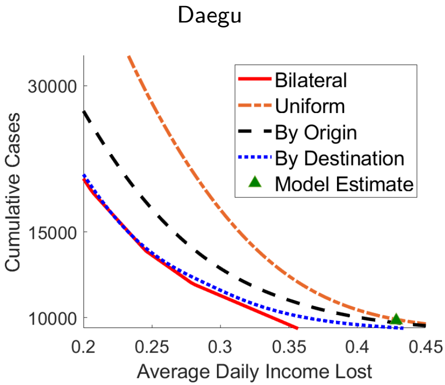


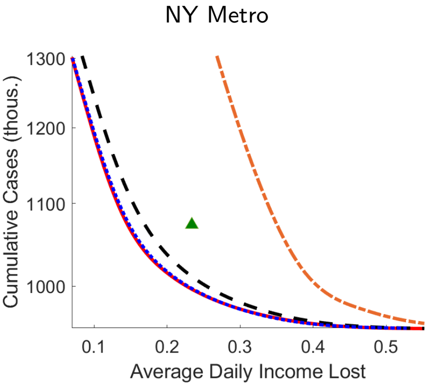
Seoul

"Pareto" Frontier: Cases versus Income

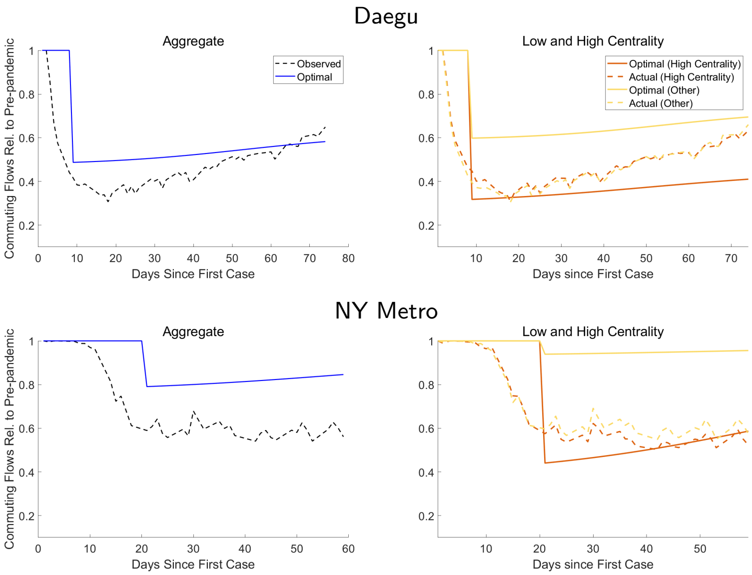
Cumulative cases and lost income, across values of life, by April 30

- By Origin: $\chi(i,j,t) = \chi(i,t)$ for all j
- By Destination: $\chi(i,j,t) = \chi(j,t)$ for all i





Optimal and Observed Changes in Commuting Flows



Seoul

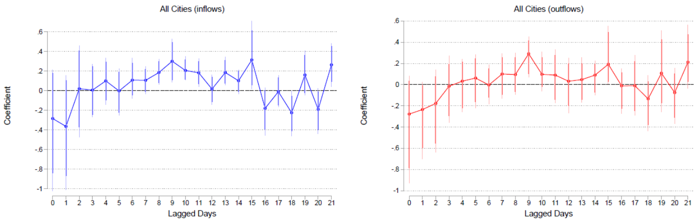
Conclusion

- Integrate spatial epidemiology and trade model, estimated on 3 cities
- Results
  1. Optimal lockdown targets some central locations for an extended period
  2. Commute responses were too weak in NYM's and Daegu's central nodes (too strong across Seoul)
  3. Optimal spatial lockdowns have much smaller economic costs than uniform lockdowns
     - ★ Spatially targeted business lockdowns may be enough to reap the benefits of spatial targeting
- Possible extensions
  - Other spatial scales
  - Endogenous job reallocations
  - Optimal deployment of vaccine

Suggestive Evidence: Commuting and New Daily Cases

$$\ln(1 + \text{new cases}_{it}) = \alpha_i + \gamma_{city(i),t} + \sum_{k=0}^{21} \delta_k \ln(flow_{i,t-k}) + \epsilon_{it}$$

Figure A.4: Commuting and New Daily Cases



Note: The figure plots the coefficients from equation (A.15). The left panel reports results using inflows as the independent variable. The right panel reports outflows as the independent variable. The regression pools over the three cities and applies weights so that each city contributes equally. The regression uses data since January 22 2020. Error bars show 90 percent (thick) and 95 percent (thin) confidence intervals. Standard errors are clustered by using the block bootstrap to account for a small number of clusters.

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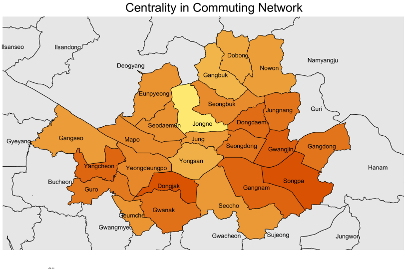
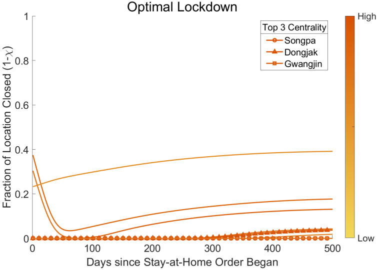
Centrality and Optimal Lockdown: Seoul





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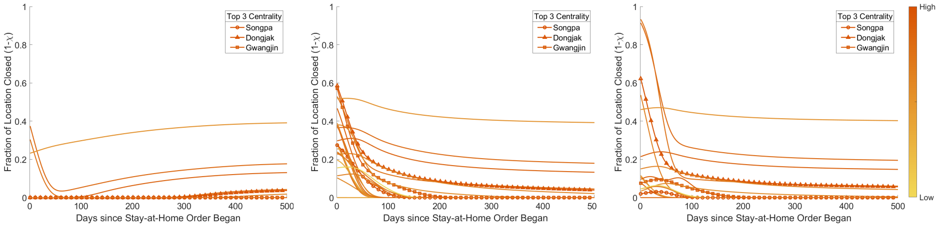
Seoul: Baseline and Alternative Parametrizations

Figure: Seoul: Optimal Lockdown in Baseline and Alternative Scenarios

(a) Baseline (b) Large Shock (c) High Value of Life



Note: The three panels show the results for Seoul under the baseline calibration (left panel), a large shock infecting 1% of the population (middle panel) and a value of life that is 100 times the benchmark (right panel).

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"Pareto" Frontier: Seoul

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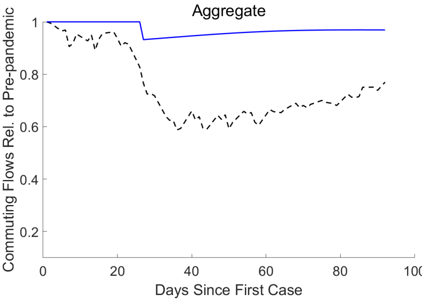
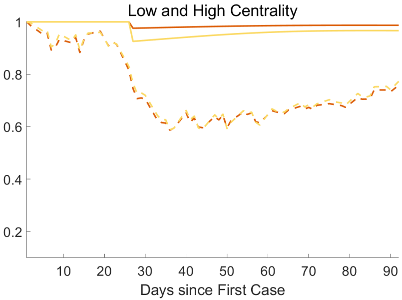
Optimal and Observed Changes in Commuting Flows: Seoul





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