A Online Appendix

A.1 Trade Flows and Mobility: Empirical Validation

Our model relies on the assumption that trade and mobility between states are positively correlated. To empirically assess this relationship, we perform a regression analysis where we regress bilateral trade volumes on mobility flows. Our analysis is performed using data before the pandemic. Specifically, we run the following regression:

$$Trade_{l,j} = \beta_0 + \beta_1(\gamma_{l,j} + \gamma_{j,l}) + \beta_2 X_l + \beta_3 X_j + \theta_l + \theta_j + u_{l,j} \tag{7}$$

The dependent variable $Trade_{l,j}$ corresponds either to bilateral trade flows or trade shares between states l and j. Trade data is from shipments data between states from the 2017 Commodity Flow Survey. The measure of mobility used in the regression analysis is the same used in the model calibration and explained in detail in section 3. γ's match the LEX index developed in Couture et al. (2020) using data from PlaceIQ. This index quantifies the share of cellphones present in a given state that have been in other states during the prior two weeks. We interpret this index as measuring the movement of people across different states. LEX index dev. corresponds to a standardization of the LEX index.

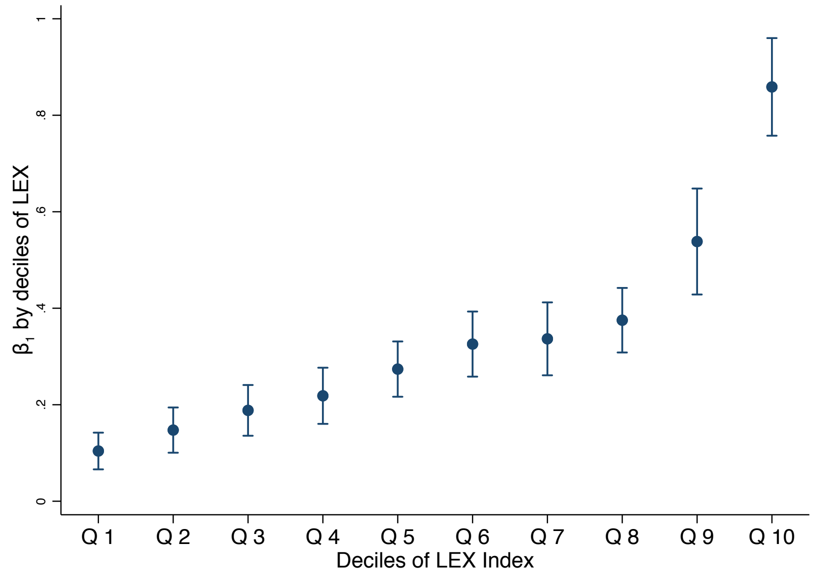
Table A.1: Trade Volume and Mobility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Trade Volumes				Trade Shares			
LEX Index dev.	0.0563***		0.0563***		0.281***		0.287***	
	(4.41)		(4.49)		(10.20)		(10.28)	
LEX Index		0.0565***		0.0558***		0.135***		0.138***
		(6.21)		(6.52)		(6.79)		(7.00)
N	2256	2256	2256	2256	2256	2256	2256	2256
R^2	0.395	0.410	0.483	0.495	0.673	0.320	0.717	0.369
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	No	No	Yes	Yes	No	No	Yes	Yes
Destination FE	No	No	Yes	Yes	No	No	Yes	Yes

Table A.1 reports the results of a regression where the volume of trade between any two pair of states is the dependent variable. The last four specifications contain control variables such as population in the origin and destination state, wages in service and consumption sector in the origin and destination state, and productivity in the origin and destination state. All the variables are standardized between 0 and 1.

Table A.1 reports the results for different specifications. We find that the correlation between LEX index and trade volumes ranges between 0.0563 and 0.0641 and is statistically significant at 99% confidence. The coefficients are very robust to the inclusion of state characteristics' controls as well as origin and destination fixed effects. The same happens

Figure A.1: Share of Trade and Mobility (LEX Index)



Note: The graph above reports the estimated coefficients of a quantile regression where the share of trade volume between any two pair of states is the dependent variable and the quantile of LEX index are the independent variables. We also control for variables such as population in the origin and destination state, wages in service and consumption sector in the origin and destination state, and productivity in the origin and destination state. All the variables are standardized between 0 and 1.

when we run the correlations with LEX index standardized in deviation from the mean where the correlation ranges between 0.0557 and 0.0565, and it is statistically significant at 99% in all cases. The same relationship holds when we use Trade Shares instead of trade volumes.

Moreover, to test whether the relationship between trade volumes and mobility index between states is monotone, we reproduce the same correlation for all the deciles of the LEX index. Figure A.1 reports the estimated coefficients for each decile of the LEX index and trade volumes. As we can see from the figure, the relationship is monotonically increasing. This suggests that the positive correlation is not driven by a specific part of the distribution of the LEX index.

A.2 Optimization Problems

This section describes and solves the optimization problems faced by the agents of the economy. We start by discussing the consumption of regular goods from different regions. As widely known, the allocation of consumption across different varieties for a given level of expenditure is a static problem. An individual in location l, allocates the aggregate consumption of regular good, c_l, according to the following problem:

$$u(c_l) = \max_{\{c_{j,l}\}_{j=\{1,\ldots,L\}}} \left(\sum_{j=1}^{L} \alpha_{l,j} \tilde{c}_{l,j}^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}$$

$$s.t. \quad \sum_{j=1}^{L} (1+\tau^c_{l,j}) \tilde{p}_j \tilde{c}_{l,j} = p^c_l c_l$$

There first order conditions are:

$$c_l^{\frac{1}{1-\epsilon}} \alpha_{l,j} \tilde{c}_{l,j}^{-\frac{1}{\epsilon}} = \lambda (1+\tau^c_{l,j}) \tilde{p}_j$$

After some algebra and defining the aggregate regular good price index after taxes in location l as,

$$(1+\tau^c_l) p^c_l = \left[\sum_{j=1}^{L} \alpha_{l,j}{}^{\epsilon} \Big((1+\tau^c_{l,j}) \tilde{p}_j \Big)^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}},$$

we obtain that an agent in location l consumes from location j:

$$\tilde{c}_{l,j} = \left(\frac{(1+\tau^c_{l,j}) \tilde{p}_j}{\alpha_{l,j} (1+\tau^c_l) p^c_l} \right)^{-\epsilon} c_l$$

We are now left to solve for the aggregate consumption of regular and social good and hours worked for individuals of different health status, location and sectors across time.

Susceptible People A susceptible person s in location l in sector $k \in \{c, x\}$ at time t chooses consumption $c^{k,s}_{l,t}$ and $x^{k,s}_{l,t}$ and number of hours worked $n^{k,s}_{l,t}$ that solves the following optimization problem:

$$U^{k,s}_{l,t} = \max_{\left\{c^{k,s}_{l,t}, x^{k,s}_{l,t}, n^{k,s}_{l,t}\right\}} u\left(c^{k,s}_{l,t}, x^{k,s}_{l,t}, n^{k,s}_{l,t}\right) + \beta \left[\left(1 - h^k_{l,t}\right) U^{k,s}_{l,t+1} + h^k_{l,t} U^{k,i}_{l,t+1}, \right]$$

$$s.t. \quad (1+\tau^c_l) p^c_{l,t} c^{k,s}_{l,t} + (1+\tau^x_l) p^x_{l,t} x^{k,s}_{l,t} = w^k_{l,t} n^{k,s}_{l,t} + T^{k,s}_{l,t}$$

where $h^k_{l,t}$, the probability of becoming infected is defined in equation (2). We assume that susceptible people take aggregate variables as given, but they understand how their consumption and working decisions impact their own probability of becoming infected. However, they don't internalize how their decisions impact the aggregate variables, giving origin to infection externality.
The first-order conditions are:

$$u_1\left(c^{k,s}_{l,t}, x^{k,s}_{l,t}, n^{k,s}_{l,t}\right) = \lambda^{k,s}_{l,t} (1+\tau^c_l) p^c_{l,t} + \beta \left(U^{k,s}_{l,t+1} - U^{k,i}_{l,t+1} \right) \pi_1 \left(\lambda C^a_{l,t} + (1-\lambda) C^i_{l,t} \right) I_{l,t} / Pop_{l,t}$$

$$u_2\left(c_{l,t}^{k,s}, x_{l,t}^{k,s}, n_{l,t}^{k,s}\right)) = \lambda_{l,t}^{k,s}(1+\tau_l^c)p_{l,t}^x + \beta\left(U_{l,t+1}^{k,s} - U_{l,t+1}^{k,i}\right))\pi_2\left(\lambda X_{l,t}^a + (1-\lambda)X_{l,t}^i\right) I_{l,t}/Pop_{l,t}$$

$$\chi\left(n_{l,t}^s\right)^\theta = \lambda_{l,t}^{k,s} w_{l,t}^k - \beta\left(U_{l,t+1}^{k,s} - U_{l,t+1}^{k,i}\right)\pi_3\left[\frac{\left(\lambda N_{l,t}^{a,k} + (1-\lambda)N_{l,t}^{i,k}\right) I_{l,t}^k + \mathbb{1}_{(k=x)}\left(\lambda X_{l,t}^a + (1-\lambda)X_{l,t}^i\right) I_{l,t}}{Pop_{l,t}}\right]$$

where $\lambda_{l,t}^{k,s}$ is the Lagrangian multiplier associated with the budget constraint. As expected, the shadow price of each good is not only the market price but also the impact of one extra unit of consumption/leisure on the probability of becoming infected. This change in probability weights the forgone future utility of becoming infected which is given by $\beta(U_{l,t+1}^{k,s} - U_{l,t+1}^{k,i})$. This forward-looking component is the crucial element that makes the problem of the susceptible dynamic even in the absence of any asset.

Infected People Infected people solves the following problem:

$$U_{l,t}^{k,i} = \max_{\left\{c_{l,t}^{k,i}, x_{l,t}^{k,i}, n_{l,t}^{k,i}\right\}} u\left(c_{l,t}^{k,i}, x_{l,t}^{k,i}, n_{l,t}^{k,i}\right) + \beta\left[\left(1-\pi_r-\pi_d\right)U_{l,t+1}^{k,i} + \pi_r U_{l,t+1}^{k,r}\right]$$

$$s.t. \quad (1+\tau_l^c)p_{l,t}^c c_{l,t}^{k,i} + (1+\tau_l^x)p_{l,t}^x x_{l,t}^{k,i} = w_{l,t}^k \nu^i n_{l,t}^{k,i} + T_{l,t}^{k,i}$$

Similarly to Eichenbaum et al. (2020), we implicitly assume that the cost of death is the foregone utility of life and that infected people don't take into consideration that they may infect other people. Therefore, the infected people's problem becomes static with the following first-order conditions:

$$u_1\left(c_{l,t}^{k,i}, x_{l,t}^{k,i}, n_{l,t}^{k,i}\right) = \lambda_{l,t}^{k,i}(1+\tau_l^c)p_{l,t}^c$$

$$u_2\left(c_{l,t}^{k,i}, x_{l,t}^{k,i}, n_{l,t}^{k,i}\right) = \lambda_{l,t}^{k,i}(1+\tau_l^x)p_{l,t}^x$$

$$\chi\left(n_{l,t}^i\right)^\theta = \lambda_{l,t}^{k,i}\nu^i w_{l,t}^k$$

Recovered People Similarly to infected people, the decisions of the recovered people are also static and satisfy the following problem:

$$U_{l,t}^{k,r} = \max_{\left\{c_{l,t}^{k,r}, x_{l,t}^{k,r}, n_{l,t}^{k,r}\right\}} u\left(c_{l,t}^{k,r}, x_{l,t}^{k,r}, n_{l,t}^{k,r}\right) + \beta U_{l,t+1}^{k,r}$$

$$s.t. \quad (1+\tau_l^c)p_{l,t}^c c_{l,t}^{k,r} + (1+\tau_l^x)p_{l,t}^x x_{l,t}^{k,r} = w_{l,t}^k n_{l,t}^{k,r} + T_{l,t}^{k,r}$$

where the first-order conditions resemble the ones from the infected people.

A.3 Parameters Values

Space We calibrate the model to US states. The decision to make a state-specific model is driven by the fact that several policies are implemented by state-level government rather than other units of geographies. We normalized the population in Alabama, the smallest state, to 1.

Preferences Regarding the labor supply, we set χ to 0.001275 and the Frisch elasticity θ to 1 as in Eichenbaum et al. (2020), which implies that all agents in the economy work 28 per week in the pre-pandemic steady state. Given our productivity calibration detailed below, the average weekly income is $\$58,000/52$. We also set the weakly discount factor β to be $0.965^{1/52}$ so that the average value of a life is 10.7 million dollars in the pre-epidemic steady state, which is consistent with the economic value of life used by US government agencies in their decisions process.

We consider that social consumption goods are the sum of healthcare expenditures, entertainment, food outside the house, education, apparel, personal services and personal care products and services, following a definition similar to that in Kaplan et al. (2020), and the rest fall into the category of regular consumption goods. We pin down ϕ by matching the share of expenditure in regular consumption goods from the 2018 Consumer Expenditure Survey.

Regarding the economic linkages across states, we set the elasticity of substitution across states, ϵ, to 5 as estimated by Ramondo et al. (2016). Following the trade literature, we parametrize $\alpha_{j,l}$ as a log-linear function of bilateral distance between states $\alpha_{j,l} = \alpha_0 dist^{\alpha_1}$ for $j \neq l$ and set $\alpha_{l,l} = 1$. This functional form implies a gravity equation on bilateral trade flows:

$$\log E_{j,l} = (\epsilon - 1)\alpha_1 \log(dist_{j,l}) + \delta_j + \delta_l + \eta_{j,l},$$

where $E_{j,l}$ is the expenditure of state l on state j's goods and δ_j and δ_l are the origin and destination fixed effects. Using between-states shipments data from the 2012 Commodity Flow Survey, we estimate $(\epsilon - 1)\alpha_1$ to be -1.31. α_0 is then chosen to match the expenditure share of tradable goods in each state coming from the other states.

Production We estimate the productivity by sector in each state, Z_l^c and Z_l^x, by matching the model implied wages in the pre-pandemic equilibrium with wage data from 2019 Quarterly Census of Employment and Wages. Symptomatic Infected people during the pandemic face a productivity loss of 30%, so $\nu^i = 0.7$.

SIR Following the CDC best estimated, we set the fraction of asymptomatic, λ, to 0.3. We assume a 1% death rate, which, taking into account that our model is weekly, implies π_d to be 0.00389, which is the equivalent of $7 \times 0.01/18$, where 18 is the average number of days that it takes to recover or die. Hence, the probability of recovery if infected is set to $7{\times}0.99/18$. π_d and π_r are within the range of the estimates reported by the CDC.

To estimate $\pi_{1,l}, \pi_{2,l}, \pi_{3,l}$ and $\pi_{4,l}$ in equation (2), we use a similar approach as in Eichenbaum et al. (2020). These parameters are jointly estimated to match different transmission rates across activities.

Table A.2: Parameter Values

Parameter	Interpretation	Internal	Value
Space			
N	Number of Locations	N	49
Preferences			
θ	Frisch elasticity	N	1
χ	Labor Disutility	N	0.001275
ϕ	Share consumption good c	Y	0.735
β	Discount factor	Y	$0.965^{1/52}$
ρ	Elast. substitution between c and s	N	0.5
$\alpha_{i,j}$	Share of c from other states	Y	
ϵ	Elast. substitution between c from diff. states	N	5
Technology			
z^s	Productivity in s	Y	*see Table A.3*
z^c	Productivity in c	Y	*see Table A.3*
ν^i	Symptomatic Productivity Adjustment	Y	0.7
SIR			
π_r	Probability of recovery	N	$7{\times}0.99/18$
π_d	Probability of dying	N	$7{\times}0.01/18$
λ	Asymptomatic Share	N	0.3
$\pi_{1,l}$	Infection Probability by X	Y	*see Table A.3*
$\pi_{2,l}$	Infection Probability by C	Y	*see Table A.3*
$\pi_{3,l}$	Infection Probability by Working	Y	*see Table A.3*
$\pi_{4,l}$	Infection Probability by General contact	Y	*see Table A.3*

Note: This table reports the parameters' values used in the calibration stating whether they are internal or externally calibrated. The model is calibrated at a weekly frequency.

Using the data from the Time Use Survey and the definition of "time-use in general community activities" of Eichenbaum et al. (2020), we find that 18% and 30% of the time spent on general community are used for the purchase of "goods and services" and "eating and drinking outside the home," respectively. Since according to Ferguson et al. (2006), 33% of virus transmission is likely to occur in the general community, we set the average number of infections originated by the consumption of regular good c to 6% (0.33×0.18) and those originated by the consumption of social good x to 10% (0.33×0.3).

Table A.3: Key Data Moments and Steady-State Values

	Data					Model							
State	Pop (10^6)	Labor share X	$\gamma_{l,l}$	$\mathcal{R}_0$	Deaths (%)	ϵ_0 (%)	π_1 (10^{-7})	π_2 (10^{-7})	π_3 (10^{-5})	π_4	Z^x	Z^c	Openness (%)
AL	3.53	0.45	0.98	1.35	0.01	0.14	8.50	1.68	2.51	0.33	19.58	22.50	0.16
AK	0.49	0.52	0.99	1.10	0.00	0.00	4.93	1.94	1.57	0.22	20.42	23.18	0.04
AZ	6.59	0.49	0.98	1.24	0.00	0.13	1.72	0.88	1.07	0.31	38.45	32.03	0.25
AR	1.90	0.46	0.97	1.13	0.00	0.06	7.96	2.08	2.18	0.26	18.17	18.37	0.12
CA	38.68	0.46	0.99	1.35	0.01	0.15	1.52	0.20	1.11	0.35	45.30	75.85	0.11
CO	5.04	0.46	0.98	1.60	0.02	0.31	5.50	0.71	2.22	0.40	25.85	39.56	0.09
CT	3.45	0.50	0.97	2.18	0.07	0.85	11.36	1.83	3.39	0.52	19.35	33.58	0.25
DE	0.74	0.50	0.94	1.53	0.01	0.11	11.27	2.85	2.78	0.23	16.29	19.09	0.37
DC	0.71	0.55	0.88	1.82	0.03	0.94	1.40	1.05	1.07	0.21	46.57	28.16	1.81
FL	20.17	0.53	0.99	1.39	0.01	0.16	0.90	0.77	0.78	0.36	52.64	41.57	0.09
GA	8.75	0.45	0.98	1.62	0.01	0.20	5.31	0.78	2.28	0.41	27.53	35.51	0.20
HI	0.98	0.58	0.98	1.06	0.00	0.00	1.05	3.07	0.66	0.22	38.66	21.93	0.06
ID	1.21	0.47	0.97	1.38	0.00	0.05	8.61	3.23	2.47	0.30	18.92	16.42	0.23
IL	11.08	0.46	0.98	1.80	0.02	0.37	5.46	0.71	2.40	0.47	28.03	42.27	0.16
IN	5.35	0.45	0.97	1.70	0.02	0.33	7.85	1.74	2.75	0.42	22.81	24.44	0.22
IA	1.87	0.45	0.97	1.38	0.01	0.16	13.31	2.27	3.09	0.31	15.80	19.42	0.15
KS	1.92	0.45	0.97	1.51	0.01	0.13	17.05	2.40	3.68	0.35	14.85	20.44	0.15
KY	2.67	0.46	0.96	1.52	0.01	0.11	7.87	2.15	2.55	0.35	21.16	20.46	0.17
LA	3.52	0.50	0.98	1.96	0.05	0.77	8.17	2.62	2.77	0.47	21.75	25.28	0.14
ME	0.80	0.56	0.96	1.32	0.01	0.00	3.02	5.33	1.27	0.25	26.30	15.13	0.16
MD	5.73	0.51	0.97	1.79	0.02	0.29	3.28	1.18	1.70	0.45	32.30	31.85	0.46
MA	6.86	0.52	0.97	1.99	0.05	0.79	2.33	0.59	1.50	0.51	39.51	51.74	0.28
MI	8.16	0.47	0.98	2.01	0.05	0.64	6.11	1.21	2.62	0.52	27.36	34.03	0.09
MN	4.20	0.48	0.98	1.47	0.01	0.19	4.48	0.81	1.89	0.37	26.88	35.89	0.10
MS	1.40	0.49	0.97	1.49	0.01	0.06	8.65	4.53	2.50	0.32	18.89	14.83	0.13
MO	4.57	0.49	0.97	1.53	0.01	0.15	4.69	1.45	1.92	0.38	26.03	26.94	0.16
NE	1.19	0.45	0.97	1.26	0.00	0.01	12.20	2.69	2.85	0.28	15.88	17.20	0.08
NV	2.80	0.59	0.95	1.49	0.01	0.21	0.86	2.23	0.71	0.30	50.22	23.67	0.86
NH	1.01	0.53	0.94	1.79	0.01	0.00	4.47	2.34	1.88	0.33	26.43	21.78	0.78
NJ	8.88	0.48	0.97	2.20	0.09	1.04	6.48	0.93	2.77	0.55	27.22	39.69	0.62
NM	1.41	0.53	0.96	1.50	0.01	0.18	4.48	2.83	1.73	0.28	24.38	19.33	0.28
NY	18.09	0.52	0.98	2.26	0.01	0.54	2.02	0.36	1.50	0.59	45.33	70.31	0.35
NC	7.66	0.47	0.98	1.34	0.00	0.09	4.80	0.95	1.89	0.34	25.26	30.86	0.18
ND	0.38	0.46	0.96	1.26	0.01	0.09	16.63	3.35	3.18	0.21	13.26	15.58	0.21
OH	9.49	0.48	0.98	1.45	0.01	0.22	4.16	1.02	1.81	0.37	27.64	31.53	0.12
OK	2.68	0.47	0.98	1.40	0.01	0.13	7.85	1.93	2.40	0.33	20.02	22.38	0.17
OR	3.32	0.48	0.98	1.18	0.00	0.08	3.33	1.01	1.45	0.29	27.68	27.57	0.39
PA	10.84	0.50	0.98	1.81	0.02	0.33	2.90	1.14	1.63	0.46	34.89	34.73	0.25
RI	1.06	0.56	0.95	1.86	0.01	0.00	6.55	6.19	2.21	0.37	21.32	16.73	0.63
SC	4.03	0.47	0.97	1.22	0.01	0.14	5.22	1.35	1.85	0.30	22.94	22.82	0.29
SD	0.43	0.51	0.95	1.66	0.00	0.00	11.97	10.92	2.96	0.28	16.24	11.53	0.09
TN	5.09	0.47	0.97	1.15	0.00	0.11	2.50	0.87	1.28	0.29	32.29	27.63	0.15
TX	25.86	0.45	0.99	1.28	0.00	0.08	4.09	0.41	1.76	0.33	27.55	51.27	0.07
UT	2.86	0.44	0.98	0.85	0.00	0.05	4.28	0.78	1.46	0.21	22.35	24.81	0.16
VT	0.22	0.57	0.90	1.88	0.02	0.00	6.91	11.37	2.24	0.12	20.54	11.42	0.44
VA	7.45	0.47	0.97	1.74	0.01	0.11	5.97	0.73	2.40	0.44	25.72	38.40	0.28
WA	6.73	0.46	0.99	1.47	0.01	0.29	3.12	0.53	1.65	0.38	33.20	44.97	0.20
WV	1.02	0.55	0.95	1.61	0.00	0.00	4.60	4.14	1.76	0.30	24.09	15.97	0.22
WI	4.28	0.45	0.98	1.48	0.01	0.14	7.59	1.49	2.53	0.37	21.87	25.26	0.18

Pop stands for population residing in an urban area (MSA) in 2019. *Labor Share X* stands for the share of employment in the social good sector. $\gamma_{l,l}$ is the daily average of the share of cell phones in state l that did not ping in a different state in the previous 14 days. Data from Couture et al. (2020) from January 20, 2020, to February 15, 2020. Basic reproduction number, $\mathcal{R}_{0,l}$, are the basic reproduction numbers at the beginning of the pandemic estimated by Fernandez-Villaverde and Jones (2020). *Deaths* is the COVID-19 related death rate at April 1, 2020, for New York and May 1, 2020, for all the other states. ϵ_0 is the model-implied initial infection rate. π_1, π_2, π_3 and π_4 are defined in equation (2). Z^x and Z^c are the estimated productivity measures for state x and c, respectively. *Openness* stands for the degree of openness in the pre-pandemic equilibrium as defined in equation (6).

We also follow Eichenbaum et al. (2020) and assume that 17% of infections occur in the workplace. The functional form assumed in 2 generates higher transmission rates while working in the social sector than in the regular good sector.

Finally, most of the transmissions occur at home or by randomly meeting people in activities not related to consumption or working. We depart from the literature in arguing that the likelihood of getting infected depends not only on the number of infected people in the region but also on the likelihood of contact with an infected person from another state. Traveling for leisure, regular commuting and the performance of professional duties, such as meeting with clients, attending conferences or simply transporting goods, generate a large flow of people across regions. Given the assumed functional form, in the pre-pandemic equilibrium the number of people moving across states depends solely on γ's. Thanks to this property of the model, we calibrate γ's to match the pre-pandemic mobility flows between any two pair states. These mobility flows are pinned down using cell phone tracking data as in Couture et al. (2020). Among the smartphones that pinged in a given state on a certain day, this data reports the share of those devices that pinged in each of the other 50 states at least once during the previous 14 days. Since we want to calibrate to the pre-pandemic equilibrium, we consider cross-state cell phone data from January 20, 2020, to February 15, 2020. Specifically, we set γ to the daily average for that period. For simplicity, we assume that the elasticity between gross flows of people and trade for any pair of states is equal to 1. Data limitations prevent us from obtaining an unbiased estimate of such elasticity. Nevertheless, we find an estimate of 0.919 when we regress gross mobility flows on gross trade after controlling for several covariates and state-fixed effects. The main economic and health outcomes are not very sensitive to an elasticity different from 1.

We also match the state-level basic reproduction number, $\mathcal{R}_{0,l}$, at the beginning of the pandemic estimated by Fernandez-Villaverde and Jones (2020).[25] Finally, to initialize the model, we take into consideration the heterogeneity in the evolution of the pandemic across states. To this end, we select each state's initial infection rate, $\epsilon_{0,l}$, to match the April 1, 2020, death rate for New York and the May 1, 2020, death rate for other states in the data, such that $D_{l,0} = \pi_d \epsilon_{l,0} Pop_l$.

To sum up, $\pi_{1,l}, \pi_{2,l}, \pi_{3,l}$ and $\pi_{4,l}$ are chosen to satisfy

$$\frac{\pi_{1,l} C_l^2}{H_l} = 0.06$$

$$\frac{\pi_{2,l} X_l^2}{H_l} = 0.1$$

[25] Fernandez-Villaverde and Jones (2020) does not report $\mathcal{R}_{0,l}$ for Montana and Wyoming, so those two states are excluded from our analysis.

$$\pi_3 \frac{\left(\frac{Pop_l^c}{Pop_l}\right)(N_l^c)^2 + \left(\frac{Pop_l^x}{Pop_l}\right)\left[(N_l^x)^2 + N_l^x X_l\right]}{H_l} = 0.17$$

$$R_{0,l} = \frac{\frac{H_l}{I_{l,0}}}{\pi_d + \pi_r}$$

where

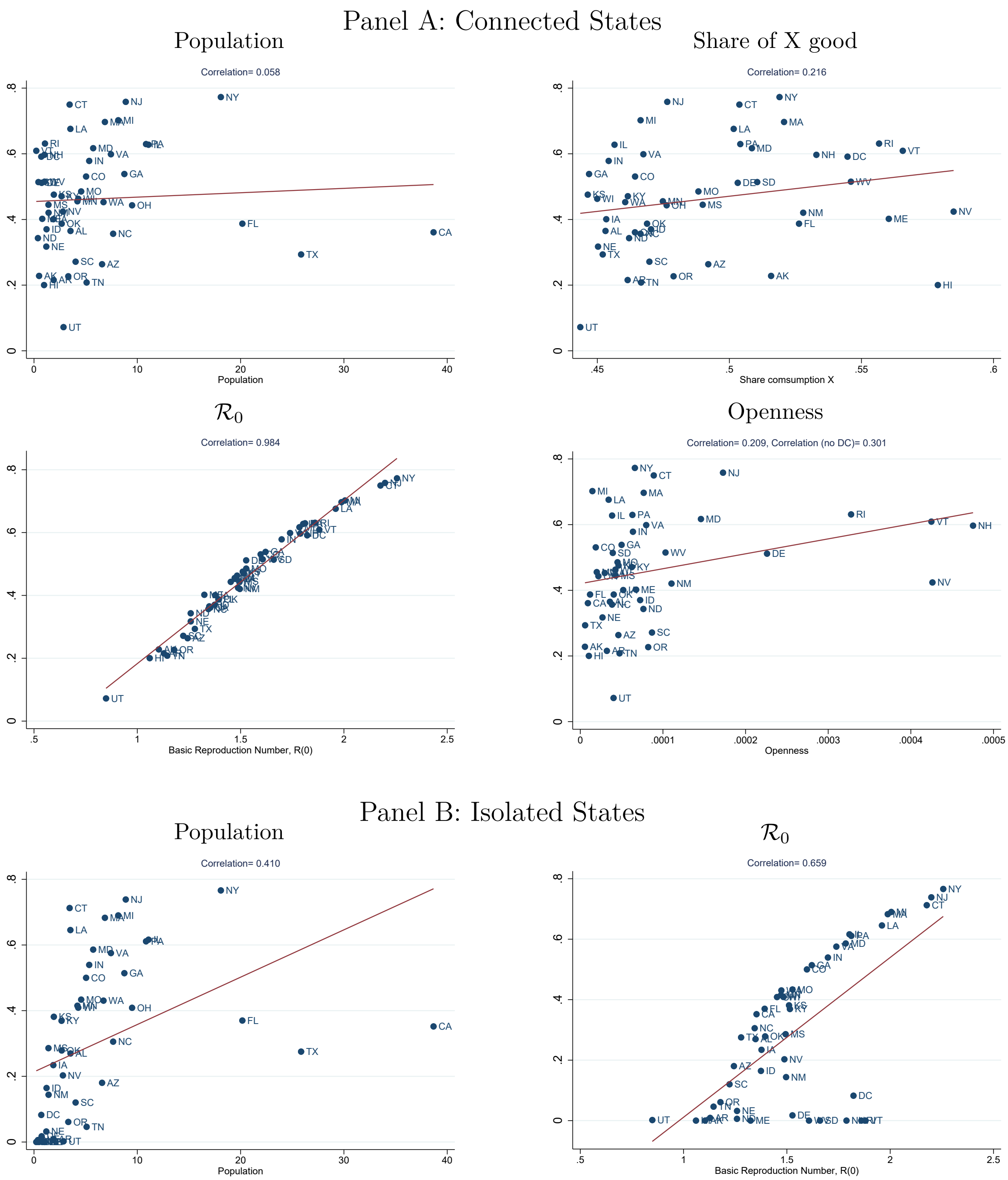
$$H_l = \pi_{1,l} X_l^2 + \pi_{2,l} C_l^2 + \pi_{3,l} \left(\left(\frac{Pop_l^c}{Pop_l}\right)(N_l^c)^2 + \left(\frac{Pop_l^x}{Pop_l}\right)\left[(N_l^x)^2 + N_l^x X_l\right]\right) + \pi_{4,l}\left(\gamma_{l,l} + \sum_{j \neq l} (\gamma_{l,j} + \gamma_{j,l}) \frac{I_{j,0}}{I_{l,0}}\right)$$

$$I_{l,0} = \epsilon_{l,0} Pop_{l,0}$$

All allocations and population refer to the pre-pandemic equilibrium. Parameters are summarized in Table A.2, and state-level parameters and moments can be found in Table A.3.

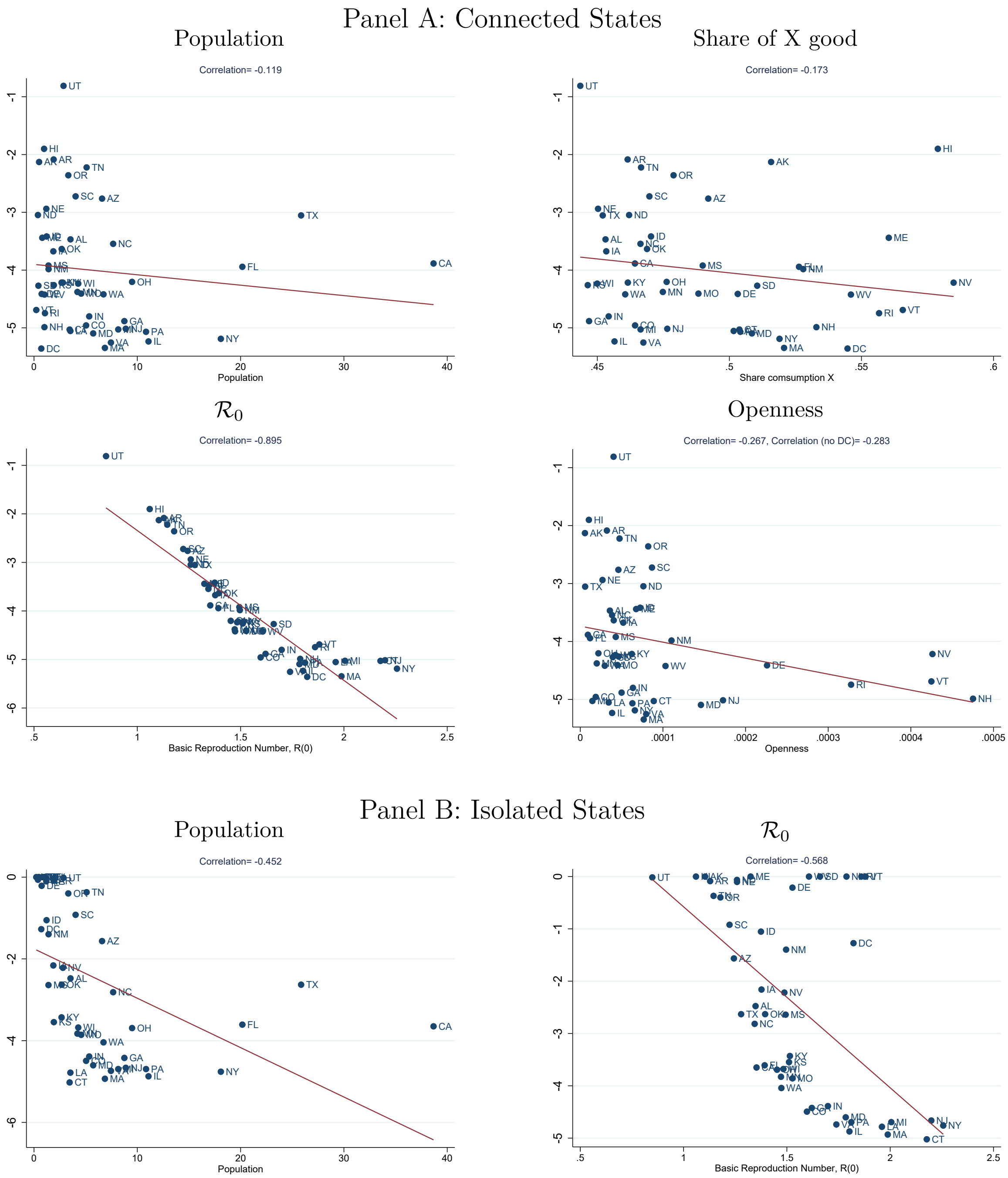
A.4 Pandemic and State Characteristics

Figure A.2: Correlations between Deaths and State Characteristics



This figure reports the correlation between the model implied deaths as result of COVID-19 and some key state characteristics. *Openness* is defined in equation (6). We exclude DC from the plot regarding *Openness*, but we report the correlations with and without DC.

Figure A.3: Correlations between Consumption Drop and State Characteristics



This figure reports the correlation between the average decline in aggregate consumption over the first two years of the pandemic and some key state characteristics. *Openness* is defined in equation (6). We exclude DC from the plot regarding *Openness*, but we report the correlations with and without DC.

A.5 Robustness

In this section, we perform a series of robustness exercises in which we vary some key parameters of the model. Table A.4 reports some key statistics for each of these exercises.

In our baseline economy, the productivity of a symptomatic infected agent drops 30%. We now analyze the cases where productivity drop 40% ($\nu^i = 0.6$) and 20% ($\nu^i = 0.8$). The higher the productivity loss (lower ν^i), the smaller the number of cases and deaths and the smaller the economic downturn. In our model, higher productivity losses resemble forced lockdown for infected agents, as lower income induces lower hours worked and lower consumption, which reduces the likelihood of infecting others. Lower productivity also impacts the behavior of susceptible people. On the one hand, becoming infected is more costly, so susceptible and asymptomatic drop consumption by more. On the other hand, as the shopping intensity of infected people is lower, the probability of being infected decreases, so susceptible people consume more. Overall, we find that consumption decreases by more for higher ν^i.

The household discount factor, β, is crucial to determine the value of life. In the baseline economy, $\beta = 0.965^{1/52}$ is associated with a value of life of 10.7 million. We now consider $\beta = 0.96^{1/52}$ and $\beta = 0.97^{1/52}$, which imply a value of life of 9.4 and 12.6 million, respectively. Although the results do not vary much with β, a higher discount factor is associated with lower infections and deaths, but a higher drop in labor, consumption and openness. Overall, welfare losses induced by the pandemic are slightly lower when the value of life is higher because the reduction in deaths more than compensates for the worse economic outcomes.

The mortality rate has a non-linear effect in our framework. In the baseline economy $\pi_d = 1\%$. We now consider two other cases: $\pi_d = 0.5\%$ and $\pi_d = 2\%$. The higher the mortality rate, the higher the cost of becoming infected. In reaction, individuals reduce hours worked and consumption and consequently openness. Despite the number of cases dropping because less economic activity reduces the probability of becoming effect, overall deaths still rise. Because the number of deaths and economic downturn is exacerbated with higher fatality rates, welfare losses increase substantially.

In our baseline calibration, we match the state-specific basic reproduction number, $\mathcal{R}_{0,l}$, estimated by Fernandez-Villaverde and Jones (2020), which implies a population-weighted average reproduction number, $\bar{\mathcal{R}}_0$, of 1.57 and 43% of the population either recovers from the infection or dies. In Table A.4, we report two robustness exercises regarding $\mathcal{R}_0$. First, we increase all the state-specific $\mathcal{R}_0$ estimated by Fernandez-Villaverde and Jones (2020) by 1, which implies that $\bar{\mathcal{R}}_0 = 2.57$ and that 82.76% of the population gets infected. Second, we increase $\mathcal{R}_0$ by 1 for states below-median $\mathcal{R}_0$ and by 0.5 for states above the median. This case implies $\bar{\mathcal{R}}_0 = 2.85$ and a cumulative infection rate of 87.92% of the pre-pandemic population. A higher basic reproduction number is associated with more infections and deaths. On the economic side, higher $\mathcal{R}_0$ implies larger peak drops in labor, consumption and openness (not reported) as agents endogenously change behavior in response to large infection peaks. Simultaneously, $\mathcal{R}_0$ speeds up the evolution of the pandemic and the infection peak tends to occur earlier. Although it generates larger peaks, the recovery is faster and therefore the average drop in labor, consumption and openness over the first two years of the pandemic tend to decrease with $\mathcal{R}_0$. Nevertheless, welfare losses undoubtedly increase with higher $\mathcal{R}_0$.

Table A.4: Robustness in the Model without Containment

	Cases %	Deaths %	Deaths mil.	Peak weeks	Labor %	Consumption %	Openness %	Welfare %
Baseline	47.39	0.47	1.31	17	-4.06	-4.21	-3.58	-0.49
Isolated	42.11	0.42	1.17	16	-3.42	-3.66		-0.435
Non-behavioral	51.86	0.52	1.44	17	0.00	-0.26	-0.65	-0.512
					Infected Productivity			
$\nu^i = 0.6$	45.34	0.45	1.26	17	-3.69	-3.89	-3.41	-0.468
$\nu^i = 0.8$	49.30	0.49	1.37	16	-4.42	-4.52	-3.73	-0.511
					Discount Factor			
$\beta = 0.96^{52}$	47.82	0.48	1.33	17	-3.60	-3.75	-3.26	-0.492
$\beta = 0.97^{52}$	46.86	0.47	1.30	17	-4.67	-4.81	-3.98	-0.486
					Mortality rate			
$\pi_d = 0.5\%$	49.15	0.25	0.68	17	-2.17	-2.34	-2.08	-0.254
$\pi_d = 2\%$	44.96	0.90	2.49	17	-7.45	-7.65	-6.05	-0.938
					Basic Reproduction Number			
$\bar{\mathcal{R}}_0 = 2.57$	82.76	0.83	2.29	15	-3.93	-4.45	-4.12	-0.852
$\bar{\mathcal{R}}_0 = 2.85$	87.92	0.88	2.44	13	-3.53	-4.04	-4.03	-0.901
					Share of Asymptomatics			
$\lambda = 0.15$	46.94	0.47	1.30	17	-3.72	-3.94	-3.36	-0.485
$\lambda = 0.7$	48.42	0.48	1.34	17	-4.99	-4.94	-4.23	-0.502
					Symptomatic Stay-Home			
$\zeta = \zeta^\tau = 0.8$	30.31	0.30	0.84	19	-1.59	-1.69	-1.50	-0.307
$\zeta = \zeta^\tau = 0.5$	37.58	0.38	1.04	18	-2.53	-2.64	-2.35	-0.383
$\zeta = 0$, $\zeta^\tau = 0.8$	45.10	0.45	1.25	16	-3.98	-4.15	-3.32	-0.467

Table A.4 reports the model-implied outcomes for the entire US economy for different parameterizations. *Cases* and *Deaths (%)* correspond to the cumulative number of cases and deaths, respectively, at the end of the pandemic as percentage of the initial population. *Deaths (mil.)* reports the cumulative number of deaths. *Cases Peak* reports the number of weeks since the beginning of the pandemic when the economy reached the peak of the number of cases. *Labor*, *Consumption* and *Openness* reports the average percentage decline in the number of hours worked, aggregate consumption and openness, respectively, in the two years after the onset of the pandemic. *Welfare* correspond to the percentage difference between welfare induced by the pandemic and welfare in absence of the pandemic. In the baseline case: $\nu^i = 0.7$, $\beta = 0.965^{1/52}$, $\pi_d = 1\%$, $\bar{\mathcal{R}}_0 = 1.57$, $\lambda = 0.3$ and $\zeta = \zeta^\tau = 0$. $\bar{\mathcal{R}}_0$ corresponds to the population weighted average of state-specific $\mathcal{R}_0$.

We now look at the share of asymptomatic among infected agents. In the baseline economy, we follow the CDC best estimate and assume that 30% of the infections are asymptomatic. In Table A.4 we analyze the two other scenarios considered by CDC: a more optimistic scenario where the asymptomatic rate is 15% and a more pessimistic case with an asymptomatic rate of 70%. As expected, health and economic outcomes are worse with a larger number of asymptomatic among infected individuals. Despite asymptomatic behaving like susceptible and therefore working and consuming more than infected individuals with symptoms, more asymptomatic people increase the risk of becoming infected. Therefore, susceptible people reduce their working hours and consumption by more. Despite these two opposite forces, the average number of hours worked and consumption tends to drop more with a higher share of asymptomatic, reflecting that in our model the second force dominates. Welfare losses increase with the share of asymptomatic.

In the baseline model, we assume that agents do not internalize their actions in the propagation of the virus. The productivity loss while infected induces fewer working hours and lower consumption by symptomatic infected than susceptible or asymptomatic, but symptomatic infected people are still able to work and consume social goods. We now consider that symptomatic people may stay home while infected. We assume that those who are forced or voluntarily stay home, receive the same income as if working but are not able to consume social goods $\left(x_{l,t}^{ih,k}=0\right)$. So, the regular good consumption of infecting individuals that stay home is given by $c_{l,t}^{ih,k}=\left(w_{l,t}^{k}\nu^{i}n_{l,t}^{i,k}\right)/p_{l,t}$, where $n_{l,t}^{i,k}$ is the number of hours worked by an infected individual in location l in sector k that does not stay home. Agents who stay home are still free to allocate their total consumption across the varieties produced in different states. We also assume that agents staying home can consume regular goods without passing the virus to others. We consider that the fraction ζ of infected people with symptoms stay home and therefore do not infect others and the fraction of ζ^{τ} of infected do not travel. Staying home impacts the probability of becoming infected as defined in equation (2). By considering staying-home behavior, we modify $h_{l,t}^{k}$ in the following manner:

$$\begin{aligned} h_{l,t}^{k}\times Pop_{l,t} = {} & \pi_{1,l}c_{l,t}^{k,s}\left(\lambda C_{l,t}^{a}+(1-\lambda)(1-\zeta)C_{l,t}^{i}\right)I_{l,t}+\pi_{2,l}x_{l,t}^{k,s}\left(\lambda X_{l,t}^{a}+(1-\lambda)(1-\zeta)X_{l,t}^{i}\right)I_{l,t} \\ & +\pi_{3,l}n_{l,t}^{k,s}\left[\left(\lambda N_{l,t}^{a,k}+(1-\lambda)(1-\zeta)N_{l,t}^{i,k}\right)I_{l,t}+\mathbb{1}_{(k=x)}\left(\lambda X_{l,t}^{a}+(1-\lambda)(1-\zeta)X_{l,t}^{i}\right)I_{l,t}\right] \\ & +\pi_{4,l}(1-\zeta^{\tau})\left[\gamma_{l,l}I_{l,t}+\sum_{j\neq l}(\gamma_{l,j}+\gamma_{j,l})\frac{\tilde{C}_{l,j,t}+\tilde{C}_{j,l,t}}{\tilde{C}_{l,j}+\tilde{C}_{j,l}}I_{j,t}\right] \end{aligned} \tag{8}$$

Note that $\zeta=\zeta^{\tau}=0$ corresponds to the baseline model. We now consider the cases where 80% and 50% of the symptomatic infected agents stay home and do not travel, respectively, $\zeta=\zeta^{\tau}=0.8$ and $\zeta=\zeta^{\tau}=0.5$. We also consider the case where agents with symptoms can work and consume social goods within their state but only 20% of symptomatic travel, $\zeta = 0$ and $\zeta^\tau = 0.2$. Results are reported in Table A.4. The ability to detect infected individuals and ensure that they minimize working and shopping activities have significant implications for health and economic outcomes. The most optimistic case, where 80% of infected people could be isolated before infecting anyone, would reduce the total death toll by approximately 470,000 lives. The average drop in labor, consumption and openness would be mitigated by approximately 3 p.p.. Restricting the movement of infected symptomatic agents across state borders without isolation within-state improves outcomes, but the gains are limited.

A.6 Policies Outcomes

Before we turn to the optimal policies, the top panel of table A.5 reports the some key outcomes for the Baseline US economy, $\zeta = \zeta^\tau = 0$, and for the economy where 50% of the symptomatic infected individuals stay home and do not travel, $\zeta = \zeta^\tau = 0.5$. For each of the two cases, we present results for the Connected economy and the Isolated economy. We also present the outcomes for all the national and local policies considered in the main text. Results were reported for the entire US economy (US) as well for New York (NY), Ohio (OH) and South Carolina (SC).

Regarding the optimal policies when 50% of the infected stay home and do not infect others, we find that, in absolute terms, optimal policies under this scenario have different impacts given that the severity of the pandemic are significantly different when no mitigation policies are in place. However, on the health side, optimal policies contribute similarly in relative terms. The combination of local within- and local between-states tax rates reduces cases and deaths by approximately 23% in both cases. However, to achieve the same proportion of saved lives, optimal policies require a relatively larger drop in economic activity when infected agents stay home relative to the scenario where no containment policies are in place.

Table A.6 compares the welfare effects of the optimal policies for the baseline US economy and for the case where symptomatic agents do not consume social goods and do not travel. Once again, in absolute terms, policies are less effective under this last scenario. But overall, policies are equally effective in relative terms. A policy that combines local within-state and between-state policies mitigates welfare losses by approximately 25% under both economies.

Table A.5: Policies Results

	Baseline Economy $\zeta = \zeta^{\tau} = 0$								Symptomatic Stay Home $\zeta = \zeta^{\tau} = 0.5$							
	US	NY	OH	SC	US	NY	OH	SC	US	NY	OH	SC	US	NY	OH	SC
No Containment Policies																
	Connected				Isolated				Connected				Isolated			
Infection Peak (% pop)	3.82	15.47	3.78	1.68	3.23	15.03	2.84	0.27	2.85	13.14	2.08	0.64	2.57	13.02	1.54	0.14
Total Cases (% pop)	47.39	77.27	44.32	27.14	42.11	76.61	40.87	12.02	37.58	74.07	33.75	14.40	33.82	73.90	30.99	2.95
Death (% pop)	0.47	0.77	0.44	0.27	0.42	0.77	0.41	0.12	0.38	0.74	0.34	0.14	0.34	0.74	0.31	0.03
Death (10^4)	131.33	13.98	4.21	1.09	116.71	13.86	3.88	0.48	104.14	13.40	3.20	0.58	93.72	13.37	2.94	0.12
Cons. Peak Drop (%)	11.40	33.32	14.08	6.72	8.91	31.29	10.27	1.10	7.18	26.08	6.30	2.23	5.98	24.51	4.49	0.46
Cons. Ave. Drop (%)	4.21	5.19	4.20	2.72	3.66	4.76	3.69	0.92	2.64	4.16	2.61	1.20	2.23	3.81	2.23	0.21
Labor Peak Drop (%)	10.87	29.44	14.00	6.67	8.04	26.59	10.29	1.14	6.39	22.83	6.34	2.05	5.12	20.69	4.50	0.47
Labor Ave. Drop (%)	4.06	4.69	4.20	2.69	3.42	4.25	3.75	0.96	2.53	3.77	2.59	1.11	2.07	3.40	2.25	0.21
Openness Peak Drop (%)	10.94	22.68	11.34	6.22	0.00	0.00	0.00	0.00	6.30	16.95	5.49	2.36	0.00	0.00	0.00	0.00
Openness Ave. Drop (%)	3.58	4.30	3.61	2.51	0.00	0.00	0.00	0.00	2.35	3.53	2.27	1.17	0.00	0.00	0.00	0.00
Within-State Policies																
	National				Local				National				Local			
Infection Peak (% pop)	2.57	11.43	1.80	0.71	2.64	11.40	1.84	0.74	2.05	10.20	1.01	0.29	2.09	10.16	1.04	0.30
Total Cases (% pop)	39.62	71.50	33.93	19.22	38.10	71.49	32.80	17.76	31.63	69.05	25.91	9.91	29.89	68.94	24.13	8.82
Death (% pop)	0.40	0.71	0.34	0.19	0.38	0.71	0.33	0.18	0.32	0.69	0.26	0.10	0.30	0.69	0.24	0.09
Death (10^4)	109.80	12.93	3.22	0.77	105.58	12.93	3.11	0.71	87.64	12.49	2.46	0.40	82.82	12.47	2.29	0.35
Cons. Peak Drop (%)	18.69	33.77	17.11	14.46	17.54	33.74	17.61	14.32	16.32	27.99	14.25	13.26	14.50	28.09	14.70	12.70
Cons. Ave. Drop (%)	10.26	11.25	10.46	9.33	10.56	10.97	10.88	9.81	8.98	10.17	9.19	8.25	9.79	10.24	10.19	9.17
Labor Peak Drop (%)	23.11	39.05	21.25	18.40	21.84	39.00	21.81	18.11	20.70	33.48	18.46	17.31	18.76	33.70	18.99	16.59
Labor Ave. Drop (%)	13.44	15.38	13.38	12.00	13.94	14.93	14.01	12.73	12.12	14.25	12.05	10.88	13.29	14.36	13.49	12.19
Openness Peak Drop (%)	6.38	18.70	5.25	2.54	6.63	18.71	5.43	2.62	3.59	13.47	2.50	1.00	3.70	13.39	2.56	1.00
Openness Ave. Drop (%)	2.64	3.95	2.49	1.48	2.58	3.95	2.42	1.38	1.62	3.03	1.46	0.63	1.57	3.02	1.36	0.57
Between-State Policies																
	National				Local				National				Local			
Infection Peak (% pop)	3.18	13.88	2.79	0.80	3.21	13.86	2.81	0.77	2.49	12.13	1.55	0.30	2.51	12.09	1.56	0.30
Total Cases (% pop)	43.67	75.12	40.35	20.14	43.21	75.11	40.07	18.78	34.97	72.45	30.74	10.10	34.56	72.37	30.37	9.31
Death (% pop)	0.44	0.75	0.40	0.20	0.43	0.75	0.40	0.19	0.35	0.72	0.31	0.10	0.35	0.72	0.30	0.09
Death (10^4)	121.02	13.59	3.83	0.81	119.75	13.58	3.80	0.76	96.90	13.10	2.92	0.41	95.77	13.09	2.88	0.37
Cons. Peak Drop (%)	14.52	36.02	15.52	10.57	14.13	35.70	15.89	11.23	10.87	28.98	9.18	8.50	10.16	28.73	9.80	8.21
Cons. Ave. Drop (%)	6.77	8.76	7.20	6.75	7.03	8.82	7.47	7.31	5.00	7.37	5.41	5.07	5.33	7.73	5.80	5.64
Labor Peak Drop (%)	11.44	31.70	13.37	6.68	11.66	31.89	13.53	6.92	8.06	25.40	7.44	4.34	8.08	25.64	7.68	4.51
Labor Ave. Drop (%)	5.63	7.19	5.90	4.50	5.80	7.10	6.17	4.88	4.07	6.13	4.29	3.14	4.32	6.21	4.63	3.49
Openness Peak Drop (%)	63.83	68.18	64.38	60.67	61.45	66.81	63.75	59.52	56.78	61.35	57.46	54.00	54.11	63.03	56.61	50.45
Openness Ave. Drop (%)	35.59	35.96	36.60	34.07	38.46	34.53	40.33	39.43	31.62	32.25	32.63	29.88	35.23	33.80	37.50	33.79
Within & Between State Policies																
	National				Local				National				Local			
Infection Peak (% pop)	2.33	10.68	1.48	0.51	2.34	10.40	1.46	0.51	1.88	9.65	0.82	0.20	1.87	9.27	0.80	0.22
Total Cases (% pop)	38.92	70.07	33.30	18.35	36.95	69.56	31.56	16.55	30.92	67.77	25.40	9.08	28.62	66.95	22.94	7.79
Death (% pop)	0.39	0.70	0.33	0.18	0.37	0.70	0.32	0.17	0.31	0.68	0.25	0.09	0.29	0.67	0.23	0.08
Death (10^4)	107.86	12.67	3.16	0.74	102.40	12.58	3.00	0.67	85.70	12.26	2.41	0.37	79.32	12.11	2.18	0.31
Cons. Peak Drop (%)	28.16	40.00	25.89	24.54	25.80	40.92	26.20	22.74	26.37	35.57	24.43	23.88	23.34	37.58	25.06	21.99
Cons. Ave. Drop (%)	15.85	16.69	15.99	14.99	16.80	17.50	17.07	15.58	14.68	15.78	14.82	14.06	16.61	17.56	17.15	15.33
Labor Peak Drop (%)	30.73	44.51	28.46	26.96	28.67	45.66	28.88	24.86	28.92	40.10	27.02	26.38	26.59	42.74	27.94	24.43
Labor Ave. Drop (%)	17.77	19.62	17.86	16.62	18.83	20.47	19.09	17.27	16.59	18.70	16.63	15.67	18.85	20.82	19.39	17.18
Openness Peak Drop (%)	23.28	30.74	22.42	20.14	25.97	35.05	26.13	21.95	20.93	26.84	20.33	18.94	20.51	28.38	20.58	17.37
Openness Ave. Drop (%)	14.43	15.10	14.74	13.31	15.70	16.17	16.31	14.41	13.64	14.43	13.93	12.59	14.26	15.21	14.91	12.81

Table A.6: Welfare Impact of the Pandemic

	No Policy	Optimal Policy					
		Within-state		Between-state		Overall	
		National	Local	National	Local	National	Local
Baseline	-0.49%	-0.419%	-0.404%	-0.451%	-0.446%	-0.396%	-0.371%
Symptomatic Stay Home	-0.383%	-0.333%	-0.317%	-0.355%	-0.35%	-0.311%	-0.29%