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The Geography of Pandemic Containment

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Abstract

How does interconnectedness affect the course of a pandemic? What are the optimal within- and between-state containment policies? We embed a spatial SIR model into a multi-sector quantitative trade model. We calibrate it to US states and the COVID-19 pandemic and find that interconnectedness increases the death toll by 146,200 lives. A local within-state containment policy minimizes welfare losses relative to a national policy or to one that reduces mobility between states. The optimal policy combines local within- and between-state restrictions and saves 289,300 lives. This optimal policy induces a peak reduction in mobility of 25.97% that saves approximately 23% more lives. Different timing of policies across states is key to minimizing losses. States like South Carolina might have imposed internal lockdowns too early but travel restrictions too late.

Topics: Coronavirus disease (COVID-19); Economic models; Regional economic developments
JEL codes: F1, H0, I1, R1

1 Introduction

Interconnectedness through trade and mobility across states is a pillar of the constitution of the United States. The COVID-19 pandemic has challenged this long-standing paradigm. Some policymakers have advocated for the limitation of mobility of individuals and goods across states as a way to mitigate the pandemic. Concerns that interconnectedness exacerbates the diffusion of the virus and dampens the effects of containment policies are rising.

In this paper, we consider interconnectedness for two reasons. First, to understand how an interconnected economy impacts the propagation of the disease and economic activity compared with a one-region economy. Second, to study containment policies that restrict the movement of people and goods across states, such as traveling restrictions or quarantines. Specifically, we analyze the extra benefit of between-state policies in saving lives and minimizing welfare losses.

In the last 20 years, the world has faced significant threats, including SARS, MERS, Ebola, avian influenza and swine flu. The likelihood of pandemics has increased over the past century due to rising global travel and integration, urbanization, changes in land use, and greater exploitation of the natural environment. Evidence suggests that the likelihood of pandemics will continue and intensify in the next decades (Jones et al., 2008; Morse, 1995). The higher vulnerability is driven not only by increased travel and tourism, but also by the increase in trade because infections also spread through insects, food and animals moving between regions.[1] Therefore, besides creating policies that mitigate the increased likelihood of future pandemics, it is also crucial to be ready to implement the right mitigation policies at the onset of a new pandemic.

Against this background, the main contribution of this paper is to provide a quantitative multi-region framework with spatial infection diffusion to study the evolution of pandemics and related economic consequences. The model is calibrated to US states using state-level data on COVID-19 cases, inter-state trade flows and mobility of people across states through mobile phone tracking. Through the lens of the model, we analyze a battery of optimal containment policies imposed at different geographical levels. In particular, we analyze and compare nation-wide, state-level and between-state policies. Although we apply this model to analyze the COVID-19 pandemic in the US, this framework is a suitable benchmark to analyze the evolution and optimal containment policies of other infectious events, such as future pandemics, or even endemic diseases and bioterrorism-related events.

The economic block of the model features two sectors: a regular consumption good and a social good sector. Each heterogeneous location produces a differentiated regular

[1] https://www.cnn.com/2017/04/03/health/pandemic-risk-virus-bacteria

consumption good that is traded across locations, generating an economic link across locations and mobility of people that varies with the level of the economic activity. For simplicity, we introduce mobility in a reduced form that positively relates mobility and economic trade flows. This assumption is motivated by empirical evidence of a positive relationship between inter-state trade and mobility. We analyze pre-pandemic US data and find a positive and strong correlation between mobility flows and trade volume between US states, even after conditioning for a large set of covariates and state fixed effects.[2] Therefore, given this empirically validated relationship presented in the model, a contraction in consumption in response to the evolution of the pandemic lowers both economic flows and mobility across regions. Exogenous restrictions on the movement of people put limits on trade and thus lead to economic losses. This modeling choice aims to capture several features of the economy. First, the movement of goods requires the movement of people. Second, tourism, working-related trips and other similar activities generate simultaneous movement of people and transference of resources across states. This modeling assumption allows for tractability and it is suitable to analyze the relationship between disease transmission, people's mobility and economic activity, which is the main goal of this paper.

The SIR block builds on Eichenbaum et al. (2020), which assumes that individuals internalize how their actions impact their own probability of getting infected, leading to an endogenous change in consumption and labor supply even in the absence of mitigation policies. We depart from them in three dimensions. First, infection transmission is sector specific. The probability of getting infected through working and consuming in the social sector is higher than in the regular good sector. Second, we distinguish between symptomatic and asymptomatic infected agents. Since asymptomatic agents are not aware of their true health status, their consumption and working behavior pose a higher threat to the spread of the virus. Third, we add a spatial component by assuming that agents in one state can be exposed to infected people in other states. The exposure across states is directly related to the size of economic flows and people's mobility between states, which are both determined endogenously in equilibrium. The greater the economic flows across regions, the greater the movement of people across states and therefore the higher the probability of the diseases spreading across states.

This framework allows us to highlight the role of interconnectedness in the spread of the disease and its impact on economic activity. Specifically, while mobility of goods and people favors economic activity, it simultaneously contributes to a faster spread of the disease,

[2] For simplicity, and given the short-term nature of the questions we are after, we assume that agents do not permanently migrate across states or change sectors. Although we could easily relax this assumption, doing so would substantially increase computational complexity. Moreover, other frameworks, such as that of Giannone et al. (2020), are more suitable to analyze these decisions in a mid- to long-term horizon.

creating a tension between economic and health outcomes. Estimating the spatial diffusion parameters is key to the quantification results of the experiment. To estimate them, we rely on data from the diffusion of COVID-19 across states as well as patterns of trade between states.

We present a set of positive and normative results. On the positive side, we find that the dynamics of the pandemic measured in terms of health and economic outcomes are more severe in a model with interconnectedness relative to one with isolated states. Without containment policies, a connected economy generates 146,200 extra deaths than an economy composed of isolated states. The peak drop in consumption is 11.4% in the model with connected states but 8.9% when we consider isolated states. These differences are substantially larger in states with lower initial infections, lower population and larger trade openness. In terms of welfare, we find that the welfare loss generated by the pandemic is 0.055 p.p. higher in the economy with connected states. Another important feature of our model is the behavioral response of agents who internalize how their actions impact their probability of getting infected. We find that a model that doesn't consider this behavioral response overestimates the total death toll by 130,000, while the consumption peak drop is 10.4 p.p. lower, which shows the importance of this feature in designing the optimal policy.

On the normative side, we study within-state optimal containment policies that resemble lockdowns. We differentiate between homogeneous (henceforth, national) and heterogeneous (henceforth, local) lockdowns across states. We also bring to the table a between-state mitigation policy that echoes traveling restrictions or quarantines. There are three main takeaways. First, local lockdown policies mitigate the pandemic more effectively than national ones. We highlight that the key factor determining the success of optimal local lockdown is *time* flexibility. The national lockdown would be imposed too early for small and low infection states like South Carolina and too late for states with high population and infections such as New York. Under both national and local optimal policies, lockdowns are almost exclusively imposed on the social sector. Second, a policy that restricts trade and mobility across states mitigates welfare losses but it doesn't reduce significantly the total death toll. This suggests that given the internal spread of the pandemic, limiting between-state mobility alone cannot mitigate the pandemic. Third, combining local lockdowns and travel restrictions is the most effective policy. This policy would save 289,300 lives, which is approximately 31,800 more lives saved under an optimal local within-state lockdown.

This paper speaks closely to the fast-growing literature of papers on COVID-19 that in the last few months have contributed to understanding the economic and health trade-off of COVID-19 and optimal policy responses (e.g. Alvarez et al., 2020; Atkeson, 2020; Atkeson et al., 2020; Eichenbaum et al., 2020; Faria-e-Castro, 2020; Jones et al., 2020; Glover et al., 2020; Guerrieri et al., 2020; Piguillem et al., 2020). A few papers in this literature have, like ours, analyzed the spatial dimension of the COVID-19 crisis, studying several economic and policy implications of the spread of the disease Among others, we highlight Antràs et al. 2020, Argente et al. 2020, Cuñat and Zymek 2020 and Fajgelbaum et al. 2020.

We contribute to the literature above in three ways. First, we develop a quantitative model of interregional trade and geographic mobility in which agents internalize the impact of their actions on their probability of getting infected. Second, through the lens of the calibrated model to US states, we study and compare optimal state-specific versus national containment policies. Third, we bring to the table the study of a between-state containment policy that could be interpreted in light of required quarantines and travel restrictions that have been put in place in recent months by several states.

2 Model

We build a two-sector quantitative trade model to study the role of interconnectedness in the transmission of a pandemic. Agents internalize how their actions impact their probability of getting infected and optimally choose consumption and labor supply. On the epidemiological side, we add an infection diffusion process across space and assume that each production sector has different infection transmission rates. The assumption that the virus diffusion also happens through trade and individuals' movement across states is a way to model trips done both for leisure and for production reasons, such as work meetings, conferences, and trade fairs. To validate this assumption, we test for the correlation between mobility and trade volume across US states. We find a strong positive relationship between trade and mobility after controlling for multiple variables and state-fixed effects. More details are reported in section 3.5.

2.1 Economic Environment

Space The economy is defined by L locations indexed by l. Every location produces a tradable differentiated regular consumption c and a non-tradable social good x. Locations differ in size, sector-specific productivities and labor force distribution.

Preferences Before the pandemic, all agents across regions are identical and maximize a similar lifetime utility function:

$$U_l = \sum_{t=0}^{\infty} \beta^t u(c_{l,t}, x_{l,t}, n_{l,t}),$$

where the flow utility function is assumed to be:

$$u(c_l, x_l, n_l) = \log\left(\left(\phi^\rho c_l^{1-\rho} + (1-\phi)^\rho x_l^{1-\rho}\right)^{\frac{1}{1-\rho}} \right) - \chi \frac{n_l^{1+\theta}}{1+\theta}.$$

$\beta \in (0,1)$ denotes the discount factor, and $c_{l,t}$, $x_{l,t}$, $n_{l,t}$ denote the regular good consumption, social good consumption and hours worked, respectively. Regular good consumption c_l is defined as a bundle of traded goods from different regions combined through the CES aggregator:

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

where $\epsilon > 0$ is the elasticity of substitution across products from different origins. $\tilde{c}_{l,j}$ denotes the consumption in region l of regular good produced in region j and $\alpha_{l,j}$ denotes the region l's measure of relative taste for the good produced in region j. This introduces economic linkages across regions. A supply disruption in one region imposes a utility cost elsewhere due to the lack of perfect sustainability across goods. Moreover, a negative income shock propagates across space due to lower demand.

Production Each location produces c and x according to the following CRS technologies:

$$C_l = Z_l^c N_l^c \quad \text{and} \quad X_l = Z_l^x N_l^x$$

where N_l^c and N_l^x are the labor demands for regular-consumption and social good sectors, respectively. Labor cannot move across sectors and locations. Z_l^c and Z_l^x are the sector-location specific productivities.

Prices are region and sector specific, $\tilde{p}_{l,t}^c$ and $p_{l,t}^x$, respectively, for sector c and x. Wages and prices are fully flexible, but restrictions on labor mobility across sectors and regions induce a wage differential across sectors within region. Specifically, perfect competition implies $w_{l,t}^c = Z_l^c \tilde{p}_{l,t}^c \quad \text{and} \quad w_{l,t}^x = Z_l^x p_{l,t}^x$.

2.2 SIR with Spatial Diffusion

We augment the canonical SIR model with a spatial diffusion component similar to a long-standing tradition of spatial SIR models. We also allow for economic decisions to have an impact on the probability of becoming infected.[3] Given the heterogeneity across regions and

[3] Rowthorn et al. (2009) develop theoretical properties of spatial SIR models. Bolker and Grenfell (1995), and Rvachev and Longini Jr (1985) apply spatial SIR models to study influenza in the US. See Gatto et al. (2020) for spatial SIR work applied to COVID-19.

social contact intensity across sectors, the probability of becoming infected is region-sector specific. It depends on the region's characteristics and increases with the intensity of the economic activity, the number of infected in the region and also the number of infected agents in other regions, especially those with stronger economic links.

We assume that agents are in one of the following health states: **S**usceptible, **I**nfected (**A**symptomatic and symptomatic), **R**ecovered and **D**eceased. In a given region l, the total number of agents of sector $k \in \{c, x\}$ in these groups are given by $S^k_{l,t}$, $I^k_{l,t}$, $R^k_{l,t}$ and $D^k_{l,t}$, respectively. A fraction $\lambda \in [0, 1]$ of infected are asymptomatic while $1 - \lambda$ are symptomatic. We define the *current* number of symptomatic as $A^k_{l,t} = \lambda I^k_{l,t}$ and the *cumulative* number of asymptomatic as $\bar{A}^k_{l,t}$ that is given by $\bar{A}^k_{l,t} = \lambda \left(I^k_{l,t} + R^k_{l,t} \right)$.[4]

Susceptible agents, those who haven't contracted the disease, may become infected by interacting with infected people. Infected people, both symptomatic and asymptomatic, recover at rate π_r or die at rate π_d, which are assumed to be common across sectors and regions. We consider as asymptomatic all infected individuals who are not aware that they are infected and thus behave as susceptible.[5] The evolution of the number of individuals in each health status in a given location l and sector k is given by the following set of equations:[6]

$$\begin{aligned}
S^k_{l,t+1} &= S^k_{l,t} - H^k_{l,t} \\
I^k_{l,t+1} &= I^k_{l,t} + H^k_{l,t} - (\pi_r + \pi_d) I^k_{l,t} \\
R^k_{l,t+1} &= R^k_{l,t} + \pi_r I^k_{l,t} \\
D^k_{l,t+1} &= D^k_{l,t} + \pi_d I^k_{l,t} \\
Pop^k_{l,t+1} &= Pop^k_{l,t} - D^k_{l,t}
\end{aligned}$$

The number of newly infected, $H^k_{l,t} = h^k_{l,t} S^k_{l,t}$, is given by the number of susceptible in each

[4]Since the true health status is never revealed for the asymptomatic, they will continue behaving as susceptible even after recovering. Therefore, to compute aggregate variables, we need to keep track of the cumulative number of asymptomatic.

[5]In our framework, it is important to distinguish between individuals who know they are infected and those who, despite being infected, do not know their true health status, since individuals may behave differently once they become aware of their infection. Therefore, we consider as asymptomatic infected individuals who do not know they are infected. We define as symptomatic all individuals who are infected and have symptoms and all infected who do not have symptoms but know they are infected, for instance, non-symptomatic people who were randomly tested.

[6]The total population in a given sector-region declines with the number of the deceased.

sector times the probability of becoming effect, $h^k_{l,t}$, which is defined as follows:

$$\begin{aligned} h^k_{l,t} \times Pop_{l,t} = & \pi_{1,l} c^{k,s}_{l,t} \left(\lambda C^a_{l,t} + (1-\lambda) C^i_{l,t}\right) I_{l,t} + \pi_{2,l} x^{k,s}_{l,t} \left(\lambda X^a_{l,t} + (1-\lambda) X^i_{l,t}\right) I_{l,t} \\ & + \pi_{3,l} n^{k,s}_{l,t} \left[\left(\lambda N^{a,k}_{l,t} + (1-\lambda) N^{i,k}_{l,t}\right) I^k_{l,t} + \mathbb{1}_{(k=x)} \left(\lambda X^a_{l,t} + (1-\lambda) X^i_{l,t}\right) I_{l,t}\right] \\ & + \pi_{4,l} \left[\gamma_{l,l} I_{l,t} + \sum_{j \neq l} (\gamma_{l,j} + \gamma_{j,l}) \frac{\tilde{C}_{l,j,t} + \tilde{C}_{j,l,t}}{\tilde{C}_{l,j} + \tilde{C}_{j,l}} I_{j,t}\right] \end{aligned} \tag{2}$$

where $I_{l,t}$ is the total number of infected in location l at time t that is given by the sum of infected people working in both sectors, $I_{l,t} = I^c_{l,t} + I^x_{l,t}$.[7] Among the infected, the fraction $(1-\lambda)I_{l,t}$ have symptoms and the fraction $\lambda I_{l,t}$ are asymptomatic and behave as susceptible. $c^{k,s}_{l,t}$, $x^{k,s}_{l,t}$ and $n^{k,s}_{l,t}$ are, respectively, the consumption of regular good, consumption of social good and the number of hours worked by a currently susceptible agent who lives in location l at time t and works in sector k. $C^i_{l,t}$, $X^i_{l,t}$ are, respectively, the average consumption of regular good and the average consumption of social good of of infected (symptomatic) agents in location l at time t. $N^{k,i}_{l,t}$ is the average number of hours worked by infected people in location l and sector k. $C^a_{l,t}$, $X^a_{l,t}$ and $N^{a,k}_{l,t}$ are the equivalent allocation for asymptomatic agents. $\tilde{C}_{l,j,t}$ is the average consumption in location l of goods produced in location j and $\tilde{C}_{j,l,t}$ is the average consumption in location j of goods produced in location l at time t. $\tilde{C}_{l,j}$ and $\tilde{C}_{j,l}$ correspond to the same allocations in the pre-pandemic equilibrium.[8]

According to equation (2), susceptible people can contract the disease by meeting infected people while purchasing regular goods, consuming social goods, working or meeting infected people outside working and consumption activities. Following Eichenbaum et al. (2020), we assume that the probability of contacting people while purchasing goods is directly related to the shopping intensity and the number of both infected and susceptible people. π_1 and π_2 relate to the probability of contracting the disease per encounter during shopping for regular and social goods, respectively. Asymptomatic and symptomatic contribute differently to the number of new infected as they have distinct consumption and work behavior.

The likelihood of becoming infected while at work in the regular sector is proportional to the number of agents and hours worked by infected and susceptible. Agents in the social

[7] The total number of individuals in location l at time t in each of the health status is given by $B_{l,t} = B^c_{l,t} + B^x_{l,t}$ for $B \in \{S, I, R, D, A, \bar{A}, Pop\}$. The total population in each sector k is given by $Pop^k_{l,t} = S^k_{l,t} + I^k_{l,t} + R^k_{l,t}$.

[8] The average consumption of regular goods in location l at time t of individuals in health status B is defined as: $C^B_{l,t} = \frac{B^c_{l,t} c^{c,B}_{l,t} + B^x_{l,t} c^{x,B}_{l,t}}{B_{l,t}}$, for $B = \{S, I, R, A, \bar{A}\}$. $X^B_{l,t}$ follows the same reasoning. The average consumption of regular good is given by $C_{l,t} = \frac{(S_{l,t} + \lambda(I^k_{l,t} + R^k_{l,t}))C^S_{l,t} + (1-\lambda) I_{l,t} C^I_{l,t} + (1-\lambda) R_{l,t} C^R_{l,t}}{Pop_{l,t}}$. $X_{l,t}$, $\tilde{C}_{l,j}$ and $\tilde{C}_{j,l}$ are computed in a similar fashion. Given the lack of heterogeneity within health status, $N^{k,s}_{l,t} = n^{k,s}_{l,t}$ and $N^{k,i}_{l,t} = n^{k,i}_{l,t}$.

sector, besides interacting with co-workers, are also exposed to potentially infected clients. We then assume that the number of infections depends both on hours worked and the number of social goods consumed by infected agents, as a proxy for the total number of potential interactions with infected clients. We assume that the probability of becoming infected in the case of meeting one infected person at work, π_3, is the same in both sectors. But as workers in the social sector meet on average more people, the effective probability of contracting the virus is higher in sector x.

The last component of equation 2 defines the infection spatial diffusion. As people move, susceptible people may be exposed to infected ones from different regions. We assume that the likelihood of meeting an infected person from another region is directly related to the fraction of the population that moves and the level of economic linkage between the two regions. We assume that the number of people moving across regions is proportional to the trade-flows in the period. Specifically, the gross flow of individuals moving between locations l and j is given by $(\gamma_{l,j} + \gamma_{j,l})\frac{\tilde{C}_{l,j,t}+\tilde{C}_{j,l,t}}{\tilde{C}_{l,j}+\tilde{C}_{j,l}}$, where $\tilde{C}_{l,j} + \tilde{C}_{j,l}$ are the pre-pandemic gross trade flow between these two states. Therefore, $\gamma_{l,j}$ is the average share of the population of the region j present in the region l before the beginning of the pandemic. Then, we interpret $\gamma_{l,j} + \gamma_{l,j}$ as the movement of people across regions consistent with the pre-pandemic gross trade flows. The bilateral γ's, as explained next, vary across states and are calibrated to match the movement of people across states before the pandemic. However, the flow of people varies during the pandemic as it follows the change in trade flows. When the gross flows are below the pre-pandemic values, the number of people moving across states declines as well. Symmetrically, the number of people moving across locations is higher than pre-pandemic values only if gross trade flows exceed the ones before the onset of the pandemic. Therefore, the expected number of infected people from region j that a susceptible person in region l may meet is proportional to the gross trade flows and number of infected people in region j and is given by $(\gamma_{l,j} + \gamma_{j,l})\frac{\tilde{C}_{l,j,t}+\tilde{C}_{j,l,t}}{\tilde{C}_{l,j}+\tilde{C}_{j,l}}I_{j,t}$, which decreases as trade flows fall. π_4 reflects the probability of becoming infected conditional on randomly meeting someone infected.

2.3 Optimization

Mobility frictions across locations and sectors and the absence of any insurance mechanism against the risk of infection make the budget constraint location-sector-health specific. We assume that the budget constraint of an agent in region l, sector k and health status $b \in \{s, i, r, a\}$ is:

$$(1 + \tau^c_{l,t})p_{l,t}c_{l,t} + (1 + \tau^x_{l,t})p^x_{l,t}x^{b,k}_{l,t} = w^k_{l,t}\nu^b n^{k,b}_{l,t} + T^{k,b}_{l,t} \tag{3}$$

where $(1+\tau^c_{l,t})p_{l,t}c_{l,t}$ denotes the total cost of purchasing aggregate regular good $c_{l,t}$ in location

l and that is defined as

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

ν^b determines the effective hours worked for different health states. We set $\nu = 1$ for the susceptible/asymptomatic and recovered people and $\nu < 1$ for infected (symptomatic) people. $\tau^x_{l,t}$ is the consumption tax on social good and $\tau^c_{l,j,t}$ is the tax rate in state l of goods from region j. $T^{b,k}_{l,t}$ are location-sector specific transfers. We assume that the government runs a balanced budget every period and rebates the revenues generated in each location-sector to the workers of the same location-sector. Taxes on foreign goods are rebated for both sectors in the state.[9]

Agents face a dynamic problem during the pandemic because their consumption and labor decisions impact the future probability of becoming infected.[10] In cases where they become infected, the agent faces two consequences. First, they have lower labor productivity, which translates into less effective hours of work and, therefore, income. Second, they face a positive probability of death and, therefore, forgone utility.

Susceptible/Asymptomatic People A susceptible person s in location l in sector k chooses consumption $c^{k,s}_l$ and $x^{k,s}_l$ and hours worked $n^{k,s}_l$, which solve the following optimization problem:

$$U^{k,s}_{l,t} = \max_{\{c^{k,s}_{l,t}, x^{k,s}_{l,t}, n^{k,s}_{l,t}\}} u(c^{k,s}_{l,t}, x^{k,s}_{l,t}, n^{k,s}_{l,t}) + \beta\left[\left(1-h^k_{l,t}\right)U^{k,s}_{l,t+1} + h^k_{l,t}U^{k,i}_{l,t+1}\right] \quad \text{s.t.} \quad (3) \qquad (4)$$

where, $h^k_{l,t}$, the probability of becoming infected is defined in equation (2). We assume that susceptible people take as given aggregate variables but understand how their consumption and working decisions impact their probability of becoming infected. However, they don't internalize how their decisions impact the aggregate variables, giving origin to an infection externality. An asymptomatic person has the same information set as a susceptible person and therefore, behaves as such, solving the same optimization problem. Therefore, $c^{k,a}_{l,t} = c^{k,s}_{l,t}$, $x^{k,a}_{l,t} = x^{k,s}_{l,t}$ and $n^{k,a}_{l,t} = n^{k,s}_{l,t}$.

[9] Rebating foreign taxes solely to sector c underperforms in terms of mitigating welfare losses.

[10] Although total regular consumption c, social consumption x and total hours worked n are chosen taking into consideration the dynamic component of the problem, the allocation of the consumption of c across goods produced in different locations is purely a static problem. Given the consumption aggregator defined in (1), any agent in region l at time t in sector k and health status b demands from region j: $\tilde{c}^{k,b}_{l,j,t} = \left(\frac{(1+\tau^c_{l,j,t})\tilde{p}_{j,t}}{\alpha_{l,j,t}(1+\tau^c_{l,t})p^c_{l,t}}\right)^{-\epsilon} c^{k,b}_{l,t}$. The price level for c-sector goods in city l is given by $(1+\tau^c_{l,t})p^c_{l,t} = \left[\sum_{j=1}^{L}\alpha_{l,j,t}{}^{\epsilon}\left((1+\tau^c_{l,j,t})\tilde{p}_{j,t}\right)^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}}$.

Infected (Symptomatic) People We implicitly assume that the cost of death is the foregone utility of life and that infected people do not lose utility by infecting others. Therefore, infected people that are symptomatic solve the following problem:

$$U_{l,t}^{k,i} = \max_{\{c_{l,t}^{k,i}, x_{l,t}^{k,i}, n_{l,t}^{k,i}\}} u\left(c_{l,t}^{k,i}, x_{l,t}^{k,i}, n_{l,t}^{k,i}\right) + \beta\left[(1-\pi_r-\pi_d)U_{l,t+1}^{k,i} + \pi_r U_{l,t+1}^{k,r}\right] \quad \text{s.t.} \quad (3) \qquad (5)$$

Recovered People Similarly to infected people, the decisions of recovered people are also static and satisfy the following problem:[11]

$$U_{l,t}^{k,r} = \max_{\{c_{l,t}^{k,r}, x_{l,t}^{k,r}, n_{l,t}^{k,r}\}} u\left(c_{l,t}^{k,r}, x_{l,t}^{k,r}, n_{l,t}^{k,r}\right) + \beta U_{l,t+1}^{k,r} \quad \text{s.t.} \quad (3)$$

2.4 Equilibrium Definition

Given the initial labor allocations across sectors and space, $\left\{Pop_l^k\right\}_{l=\{1,..,L\}}^{k=\{c,x\}}$, and a sequence of taxes and transfers, $\left\{\tau_{l,t}^c, \tau_{l,t}^x, T_{l,t}^c, T_{l,t}^x\right\}_{t=\{1,..,\infty\}}^{l=\{1,..,L\}}$, the equilibrium consists of a set of prices, $\{\tilde{p}_{l,t}^c, p_{l,t}^x, w_{l,t}^c, w_{l,t}^x\}_{t=1}^{\infty}$, and allocations, $\{c_{l,t}^{k,b}, x_{l,t}^{k,b}, n_{l,t}^{k,b}\}_{t=1}^{\infty}$, for each sector, $k \in \{c, x\}$, and region, $l \in \{1, ..., L\}$, and health status, $b \in \{s, i, a, r\}$, that solve the agents' maximization problems and satisfy the goods and labor markets clearing conditions defined as:

$$\begin{aligned}
\sum_{k\in\{c,x\}} \left(S_{l,t}^k + \lambda\left(I_{l,t}^k + R_{l,t}^k\right)\right) X_{l,t}^{k,s} + (1-\lambda)I_{l,t}^k X_{l,t}^{k,i} + (1-\lambda)R_{l,t}^k X_{l,t}^{k,r} &= X_{l,t} \\
\sum_{j\in\{1,...,L\}} \sum_{k\in\{c,x\}} \left(S_{l,t}^k + \lambda\left(I_{l,t}^k + R_{l,t}^k\right)\right) \tilde{C}_{j,l,t}^{k,s} + (1-\lambda)I_{l,t}^k \tilde{C}_{l,j,t}^{l,i} + (1-\lambda)R_{l,t}^k \tilde{C}_{l,j,t}^{l,r} &= C_{l,t} \\
\left(S_{l,t}^x + \lambda\left(I_{l,t}^x + R_{l,t}^x\right)\right) N_{l,t}^{x,s} + (1-\lambda)I_{l,t}^x \nu^i N_{l,t}^{x,i} + (1-\lambda)R_{l,t}^x \nu^r N_{l,t}^{x,r} &= X_{l,t}/Z_l^x \\
\left(S_{l,t}^c + \lambda\left(I_{l,t}^c + R_{l,t}^c\right)\right) N_{l,t}^{c,s} + (1-\lambda)I_{l,t}^c \nu^i N_{l,t}^{c,i} + (1-\lambda)R_{l,t}^c \nu^r N_{l,t}^{c,r} &= C_{l,t}/Z_l^c
\end{aligned}$$

3 Taking the Model to the Data

3.1 Parameter Values

We calibrate the model at a weekly frequency and to the characteristics of pre-pandemic US states. The decision to make a state-specific model is driven by the fact that most

[11]The solutions to agents' problem are contained in the Online Appendix.

containment policies, such as lockdowns and quarantines, are implemented at state level.

In the Online Appendix, section A.2, we describe in detail the full calibration. Here, we restrict most of our attention to the parameters related to the spatial and SIR components. Specifically, we set the elasticity of substitution across states, ϵ, to 5 as estimated by Ramondo et al. (2016). The relative taste for goods of different states, α's, are chosen to match the share of imported goods from each state, using shipments data between-states from the 2012 Commodity Flow Survey. To pin down the movement of people across states before the pandemic, γ, we use cell phone tracking data from 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. As stated in equation (2), the number of people moving in both directions between state j and l is given by: $(\gamma_{l,j} + \gamma_{j,l})\frac{\tilde{C}_{l,j,t}+\tilde{C}_{j,l,t}}{\tilde{C}_{l,j}+\tilde{C}_{j,l}}$, where $\tilde{C}_{l,j} + \tilde{C}_{j,l}$ corresponds to the pre-pandemic gross trade-flows. Therefore, in the pre-pandemic equilibrium, the movement of people across states collapses to $\gamma_{l,j} + \gamma_{j,l}$. So our calibration of γ's matches the pre-pandemic gross trade flow between any two states.

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 this economy work 28 per week in the pre-pandemic steady state. We estimate the state-sector productivities to match wages from 2019 QCEW. This parameterization implies an average weekly income in the economy of $\$58,000/52$. We also set the weekly 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.

Regarding the SIR parameters, we set the fraction of asymptomatic, λ, to 0.3, we match the probability of death to 1% and assume that 18 is the average number of days to recover or die. Since the model is weekly, we set $\pi_d + \pi_r = 7/18$ and $\pi_d = 7 \times 0.01/18$. These values are within the range of the estimates reported by the CDC.[12] To estimate $\pi_{1,l}, \pi_{2,l}, \pi_{3,l}$ and $\pi_{4,l}$ in equation (2), we use a similar approach to that in Eichenbaum et al. (2020). These parameters are jointly estimated to match different transmission rates across activities. Using data from the Time Use Survey, we find that 18% and 30% of the time spent on the general community is used for the purchase of "goods and services" and "eating and drinking outside," respectively. According to Ferguson et al. (2006), 33% of virus transmission is likely occur in the general community; thus, we set the average number of infections originated by consumption of c to 6% (0.33×0.18) and those originated by the consumption of x to 10% (0.33×0.3). 17%

[12]https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html

of infections occur in the workplace with the largest share occurring in the social sector, as implicitly assumed by the functional form chosen in equation (2). 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). Finally, to initialize the model, we take into consideration the heterogeneity in the evolution of the pandemic across states. Specifically, 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, 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

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

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

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

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

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. In Appendix, Table A.1 reports the main parameters of the model that are common across locations. Table A.2 reports for each state key data moments used in the calibration and calibrated parameters that vary across states, such as the calibrated initial infection rate, $\epsilon_{l,0}$, SIR parameters in equation (2) and sector-specific productivities. In section 3.3, we perform several robustness exercises in which we vary key parameters.

3.2 Understanding the Model's Mechanisms

In this section, we highlight the main mechanisms at play in our model and the role of interconnectedness.[13] Figure 1 shows the large degree of heterogeneity across states in health and economic outcomes generated by the pandemic. Panels A and B present a map of

[13] In this section, we assume no policy intervention, $\tau_{l,t}^c = \tau_{l,t}^x = 0$ for any l and t.

Figure 1: Heterogeneous Impact of Pandemic

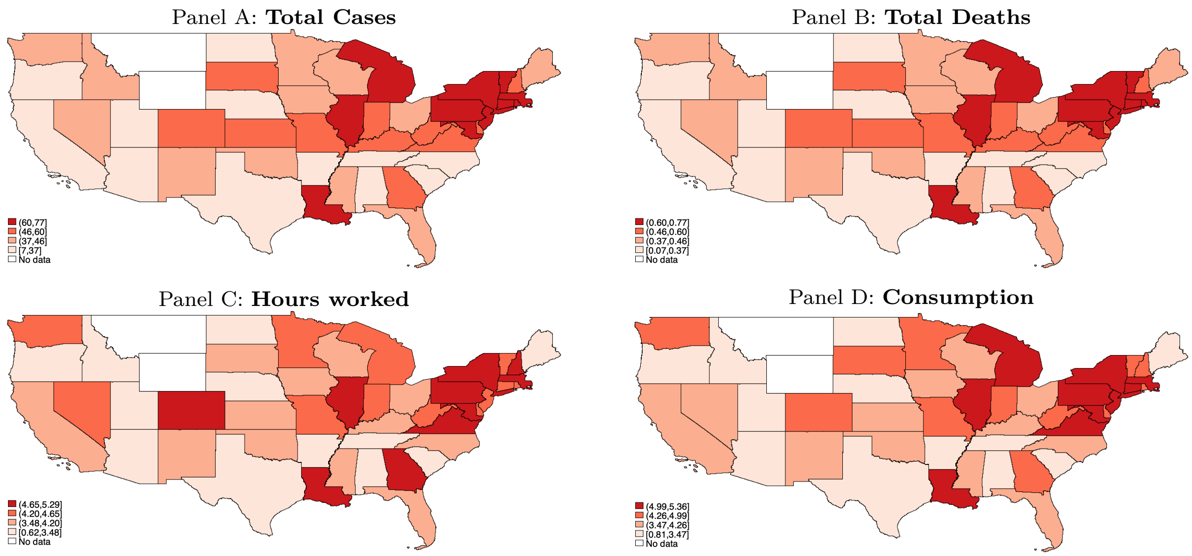


Figure 1 plots the heterogeneous impact of the pandemic across states. Panel A and Panel B plot the total number of cases and deaths at the end of pandemic as percentage of initial population, respectively. Panel C and Panel D plot the average drop in hours worked and consumption in the first two years relative to pre-pandemic steady state.

cumulative infections and deaths as percentages of initial population, respectively. We find that the most affected states are hit three times more than the least affected ones, with most affected states concentrated in the Northeast. States with a larger number of cases and deaths per capita have, on average, higher levels of population, $\mathcal{R}_0$, and openness. State openness refers both to trade and to people's mobility and it is defined as

$$(\gamma_{l,j} + \gamma_{j,l}) \frac{\tilde{c}_{l,j,t} + \tilde{c}_{j,l,t}}{\text{income}_l} \tag{6}$$

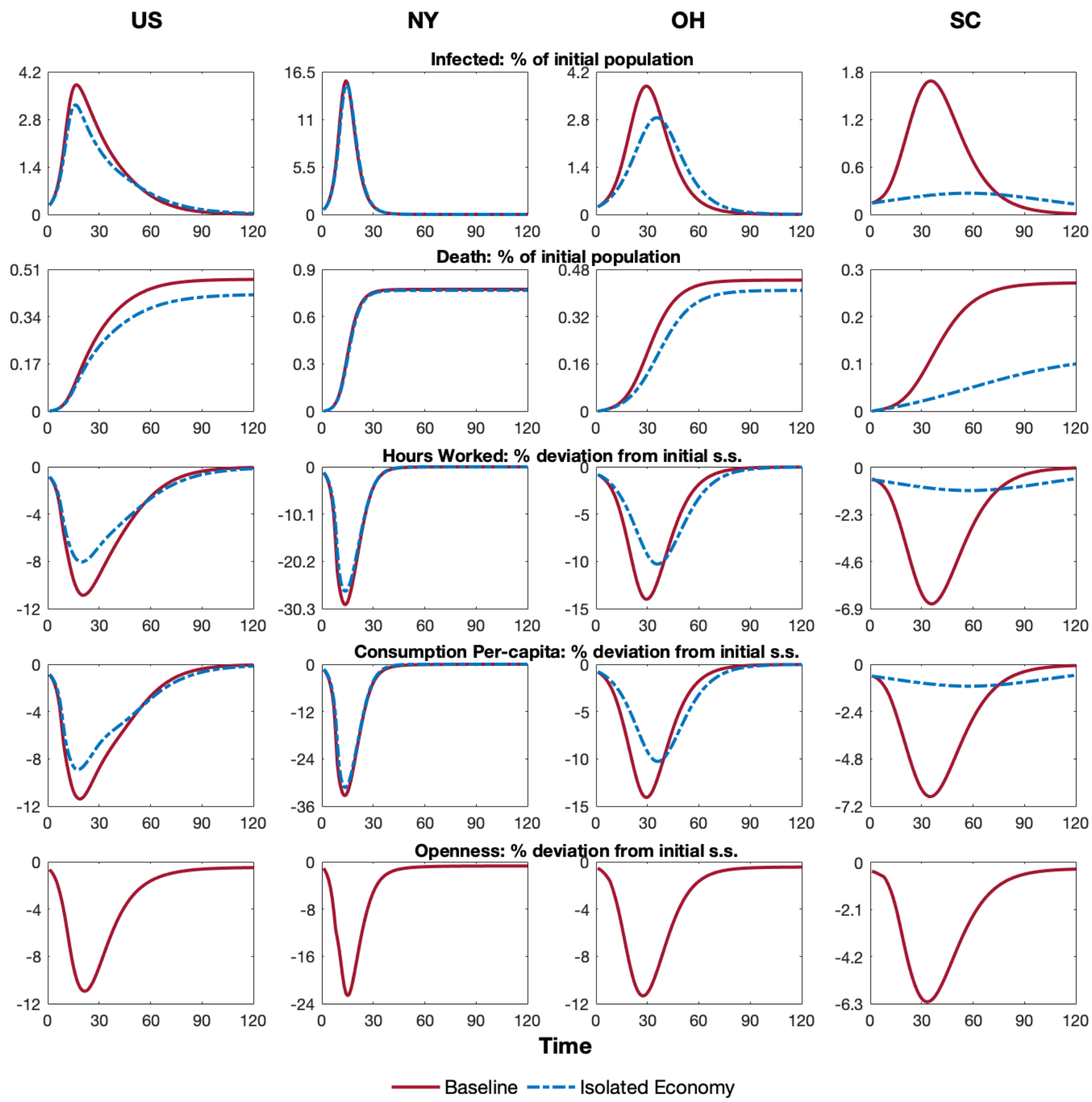
Panels C and D report the average decline in hours worked and consumption over the first two years relative to the pre-pandemic equilibrium, respectively. We find that the most affected states had a decline in labor and consumption around two times larger than the decline in the least impacted ones.[14]

States with a larger drop of labor supply and consumption have, on average, higher levels of population and $\mathcal{R}_0$ but lower openness. Finally, we find a positive relationship between health and economic outcomes. On average, states with larger number of cases also face a large drop in economic conditions. This analysis emphasizes the large degree of spatial heterogeneity in the pandemic outcomes and points in the direction of state-specific interventions.

[14]We exclude District of Columbia from this calculation since it is a strong outlier. DC has a degree of openness that is five times larger than the degree of openness in the second-most-open state.

We now analyze the dynamics of health and economic outcomes and show that interconnectedness plays an important role in shaping the evolution of the pandemic. Figure 2 shows the number of cumulative cases and deaths as a percentage of the initial population, as well as the hours worked and consumption per-capita in percentage deviation from the pre-pandemic equilibrium. We report these outcomes for the "Baseline" economy (solid red line) and an economy without trade and geographic mobility, denoted by "Isolated Economy" (dashed blue line).

Figure 2: Health and Economic Outcomes of COVID-19 Crisis



The top panel reports the results for the evolution of infections at the aggregate level in column one, and for New York, Ohio and South Carolina in the second, third, fourth columns, respectively. These three states represent extreme cases of high, medium and low initial infection level and population size. In row one, we find a 0.6 p.p. difference in the peak of infection rates between the baseline economy and the isolated one. The plots for the three states separately show that the largest differences are generated in Ohio and South Carolina, while there are nearly zero differences between models for New York. Similarly, in the second row, we show the evolution of deaths over time. The baseline economy produces approximately 146,200 more deaths than the isolated one.

By analyzing the three graphs on the right, we find that the largest overall death toll occurs in New York with similar values under both economies. In contrast, we find larger differences for Ohio and South Carolina, where interconnectedness generates 0.03 and 0.15 p.p. more deaths per-capita, respectively. Overall, interconnectedness impacts relatively more states with lower $\mathcal{R}_0$ and smaller populations, as these states, like South Carolina, import relatively more infections per-capita. In large states, like New York, the propagation of the disease within state is very large, so the number of imported cases is much less relevant in relative terms.

Rows three and four of Figure 2 report the evolution of hours worked and consumption per-capita in percentage deviation from the pre-pandemic steady state, respectively. Individuals voluntarily contract consumption and labor supply as the virus spreads to mitigate the probability of becoming infected. We find that labor supply and consumption drop the most around the time of the infection peak. The peak drops in labor supply and consumption at the aggregate level are, respectively, 2.83 p.p. and 2.49 p.p. smaller in the economy where states are not connected. When we compare the average decline in hours worked and consumption over the first two years of the pandemic, we find that interconnection exacerbates the drop by 0.64 p.p. and 0.55 p.p., respectively, as reported in Table 1. At the state level, we observe that New York displays the largest drop in labor supply and consumption, followed by Ohio and South Carolina. In New York, we find almost no difference between an isolated and interconnected economy while the largest differences are displayed for South Carolina. In the connected case, the drop in labor supply and consumption in South Carolina occur earlier and at a greater extent than in an isolated economy. The endogenous decline in economic activity induced by the pandemic generates a decline in the degree of openness. The drop in demand leads to less trade between states and consequently a decline in people's mobility. For the US as a whole, openness declines at the peak by almost 10.94% and 3.58% on average during the first two years of the pandemic. The larger the state and the initial $\mathcal{R}_0$ the larger the endogenous decline in openness. At the peak of the pandemic, openness reduces 22.68%

in New York.

Table 1, besides reporting some key statistics for the baseline and isolated-states models for the US as a whole, also reports the same statistics for a model without behavioral responses. In a model without behavioral response, agents do not adjust labor and consumption when they observe the infection rate going up.[15] The lack of adjustment in labor and consumption generates significantly more cases and deaths, which suggests that taking into account the endogenous response to the health outcomes of the pandemic is crucial to analyze optimal policies. Regarding welfare losses[16], reported in the last column of Table 1, we find that the three models generate substantial welfare losses, mostly driven by lost lives. This is well illustrated in the non-behavioral economy case, in which, despite the economy remaining pretty close to the pre-pandemic equilibrium, the overall welfare drops around 51%, driven by the loss of 1.44 million lives. Although the economy contracts more in the baseline case, welfare drops by approximately 49%. Welfare losses would be smaller in an isolated economy because health and economy are less impacted.

3.3 Robustness

In this section, we perform a series of robustness exercises in which we vary some key parameters of the model. Table 1 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.

[15] For the non-behavioral economy, we assume that labor and consumption remain fixed at the pre-pandemic equilibrium for all health status during the entire pandemic.

[16] Welfare is defined as the average lifetime utility of all agents in the economy. In the pre-pandemic period, it is given by $U_{pre} = \sum_{l=1}^{l=L}\left[Pop^c_{l,pre}U^c_{l,pre} + Pop^x_{l,pre}U^x_{l,pre}\right]$. At the time $t = 0$, when the pandemic hits, welfare is given by $U_0 = \sum_{l=1}^{l=L}\left[S^c_{l,0}U^{s,c}_{l,0} + S^x_{l,0}U^{s,x}_{l,0} + \lambda I^c_{l,0}U^{a,c}_{l,0} + \lambda I^x_{l,0}U^{a,x}_{l,0} + (1-\lambda)I^c_{l,0}U^{i,c}_{l,0} + (1-\lambda)I^x_{l,0}U^{i,x}_{l,0}\right]$.

Table 1: 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 1 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 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 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 $\mathcal{R}_0$.

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 are 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 1, 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 $\mathcal{R}_0$.

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 1 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:

$$\begin{aligned}h_{l,t}^{k}\times Pop_{l,t}=&\ \pi_{1,l}c_{l,t}^{k,s}\left(\lambda C_{l,t}^{a}+(1-\lambda)(1-\zeta)C_{l,t}^{i}\right)I_{l,t}+\pi_{2,l}x_{l,t}^{k,s}\left(\lambda X_{l,t}^{a}+(1-\lambda)(1-\zeta)X_{l,t}^{i}\right)I_{l,t}\\&+\pi_{3,l}n_{l,t}^{k,s}\left[\left(\lambda N_{l,t}^{a,k}+(1-\lambda)(1-\zeta)N_{l,t}^{i,k}\right)I_{l,t}+\mathbb{1}_{(k=x)}\left(\lambda X_{l,t}^{a}+(1-\lambda)(1-\zeta)X_{l,t}^{i}\right)I_{l,t}\right]\\&+\pi_{4,l}(1-\zeta^{\tau})\left[\gamma_{l,l}I_{l,t}+\sum_{j\neq l}(\gamma_{l,j}+\gamma_{j,l})\frac{\tilde{C}_{l,j,t}+\tilde{C}_{j,l,t}}{\tilde{C}_{l,j}+\tilde{C}_{j,l}}I_{j,t}\right]\end{aligned} \tag{7}$$

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 1. The ability to detect infected individuals and ensure that they minimize working and shopping activities has 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 consumption 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.

3.4 The Geography of Optimal Containment Policies

In this section, we analyze and compare within-state and between-state containment policies. Since agents are atomistic, they don't internalize the impact of their behavior on the disease transmission. Therefore, the competitive equilibrium is not Pareto Optimal and there is room for government intervention. The social planner maximizes the social welfare in the entire country by imposing a set of tax instruments that constrain economic activity and disease dynamics. The social planner can choose a sequence of consumption tax rates that can vary across sectors and states. Specifically, for each state l, the social planner can tax consumption of social goods, $\tau^s_{l,t}$, own-state regular good, $\tau^c_{l,t}$, and regular goods imported from each of the other states, $\left\{\tilde{\tau}^c_{l,j,t}\right\}_{j\neq l}$ for T periods.[17] The aggregate social welfare, U_0, is defined as a weighted average of the lifetime utility of the different agents in each health status:[18]

$$U_0 = \sum_{l=1}^{l=L} \left[S^c_{l,0}U^{c,s}_{l,0} + S^x_{l,0}U^{x,s}_{l,0} + I^c_{l,0}U^{c,i}_{l,0} + I^x_{l,0}U^{x,i}_{l,0}\right]$$

$U^{k,s}_{l,0}$ and $U^{k,i}_{l,0}$ are the lifetime utility at time 0 (beginning of the pandemic) of susceptible and infected, respectively, in each state l and sector k. Those are the solution to the optimization problems (4) and (5) given the sequence of tax rates imposed by the government. We assume that the social planner observes the true health status of each individual.[19]

If we consider $T = 250$, it would imply a choice of 451,500 parameters, which is computationally very challenging. Therefore, we approximate the optimal time paths by a generalized logistic function of time:[20]

$$\tau(t) = \kappa_1 \frac{\kappa_2\kappa_3 e^{\kappa_3(t-\kappa_4)}}{\left[1 + e^{\kappa_3(t-\kappa_4)}\right]^{1+\kappa_2}}$$

κ_1 determines the highest level of the mitigation and κ_2 its persistence, κ_3 controls mitigation in the earlier periods and κ_4 determines the period with the highest mitigation policy.

Below we study and compare different optimal containment policies with different characteristics. We first consider policies that focus on within-state consumption behavior, denominated within-state policies. Second, we study a policy that targets trade flows across regions, called between-state policy. Finally, we look at the optimal policy that combines both within and between-state policies. We consider both the cases in which policies are equally implemented everywhere and policies that vary across states. The *local policy* consists of state-specific consumption taxes on social and regular consumption good. Regular goods are taxed equally regardless of their origin. The *national policy* imposes the same tax rate in all the states, but it can vary across sectors.[21]

[17] After period T, all rates are set to 0.

[18] Note that at the initial period, there are no deaths or recovered people.

[19] To solve this Ramsey problem, we guess a sequence of tax rates and solve for the competitive equilibrium. We then evaluate the social welfare function and iterate on this sequence until we find the optimum set of tax rates.

[20] We consider alternative functional forms, but they under performed compared to this one.

[21] To be more specific, a national policy imposes $\tau^s_{l,t} = \tau^s_{j,t} = \tau^s_t$, $\tau^c_{l,t} = \tau^c_{j,t} = \tau^c_t$ and $\tilde{\tau}^c_{l,j,t} = \tilde{\tau}^c_t$ for any states

Optimal Within-State Containment Policy In this section we analyze the impact of the optimal local and national within-state policies. These policies only impact the consumption produced within the state. Specifically, we impose $\tau^c_{l,l} \geq 0$, $\tau^x_l \geq 0$ and $\tau^c_{l,j} = 0$ if $l \neq j$. Figure 3 shows the tax path and the evolution of health and economic outcomes under national and local optimal within-state containment policies. Table A.3 in the Online Appendix reports some key health and economic results associated with these policies as well for all the other policies discussed in this section.

The top-left panel shows the optimal national tax rates for sectors x and c. The other three plots of the first row show the local tax rates for New York, Ohio and South Carolina, respectively. First, we find that taxing c is not optimal under both policies. Second, under the local policy, the maximum tax rate of the social sector varies across states and positively related with the severity of the pandemic in each state. States with a higher death toll face higher tax rates. Third, the timing of the peak of the containment policy also varies across states and closely follows the evolution of cases across states.

The second and third rows of Figure 3 report the evolution of infections and cumulative deaths. We find lower infection and death rates under both optimal policies than in the baseline, but a local policy can save more lives than the national one. Overall, we find that the local policy would reduce the number of overall deaths by 257,500, while a national policy would mitigate the death toll by 215,300. The largest improvement in death rates by imposing local or national policies would come from states with a smaller population and lower initial reproduction number, $\mathcal{R}_0$, as Ohio and South Carolina. In New York, even though the optimal policy reduces slightly the infection peak, the high initial $\mathcal{R}_0$ prevents policies from significantly reducing the death rate.

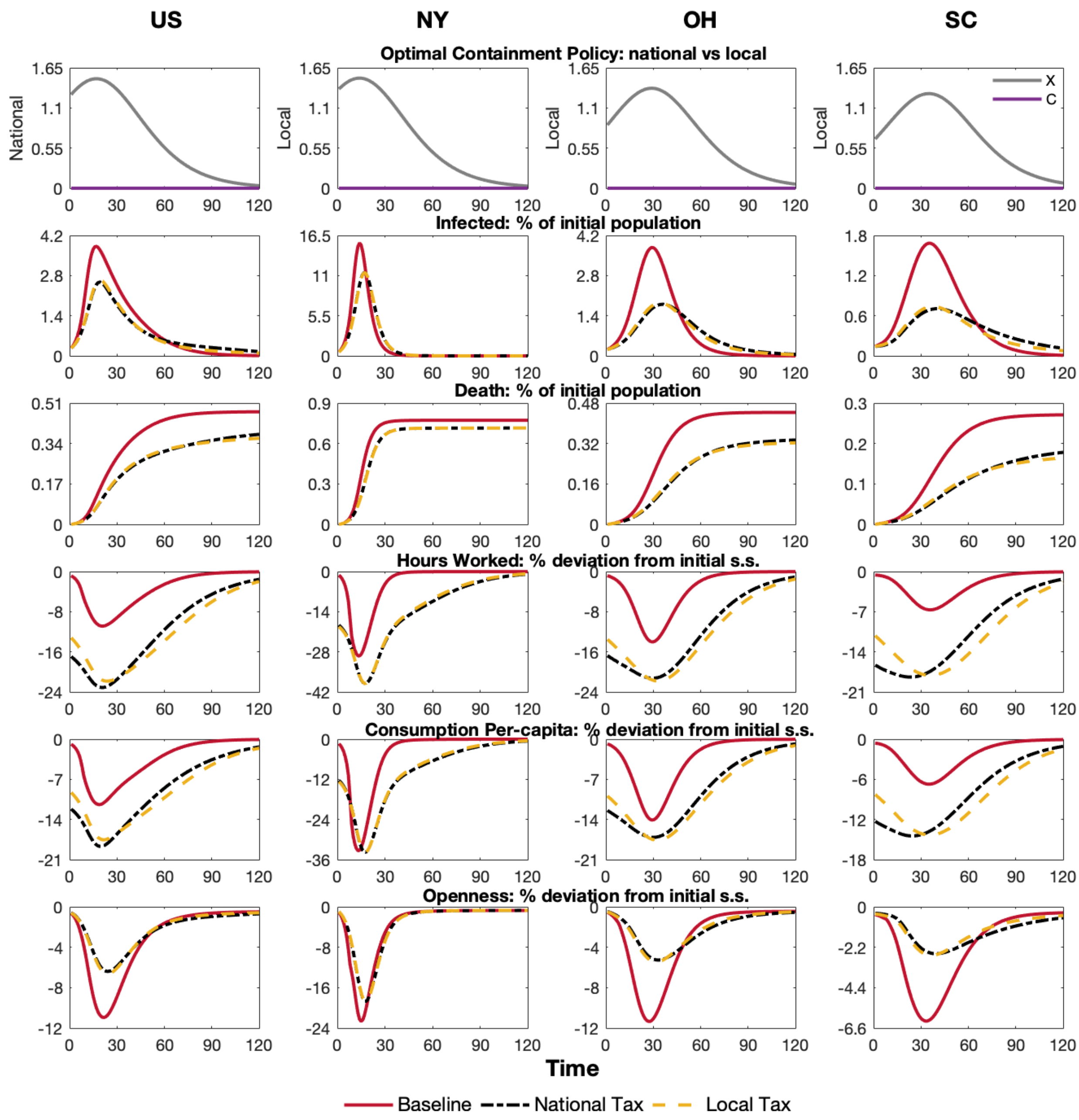
Rows four and five report the evolution of labor and consumption, respectively. Both policies generate a larger drop in hours worked and consumption than in the baseline economy. At the aggregate level, local policy amplifies the peak drop in hours worked and consumption by 10.97 p.p. and 6.14 p.p., respectively, relative to the baseline economy with no intervention. Differences are even higher when we look at average drop during the first two years of the pandemic. Since these policies do not directly target the movement of people and goods across states, the level of openness actually increases relative to an economy without containment policies, as people substitute away from social goods to regular consumption goods. This effect is quite substantial. For the overall economy, at the peak of the pandemic, openness is around 4 p.p. higher when local policies are in place. This difference is more salient in states where the pandemic hits less hard, as Ohio and South Carolina. Local policy amplifies

l and j. Regarding the local policies, the social planner maximizing the aggregate welfare of the country can choose different tax rates for different states.

the peak drop in hours worked and consumption by 1.27 p.p. and 1.15 p.p. relative to the national policies.

Figure 3: Optimal Within-State Containment Policy

Panel A: Spatial Comparison



The differential impact of within-state polices is more pronounced in states like Ohio and

South Carolina. This is mainly explained by the timing of the different optimal local policies. As previously mentioned, the maximum tax level is reached at different time across states, a key margin through which state-specific optimal policies operate. Specifically, local tax rates on x closely follow the evolution of cases in each state. While cases are low, the tax rate is low and increases as the number of cases and deaths go up. The maximum value of the optimal policy occurs when the state reaches its peak. The optimal policy slows down the course of the pandemic as the infection peak occurs weeks later than it would in a connected economy without containment policies.

Therefore, a homogeneous policy across states would impose a lockdown too late in some states and too early in others. This result stresses that a premature lockdown can be economically very costly with little benefits in reducing the death toll.

Optimal Between-State Containment Policy We now study the optimal containment policy that restricts the movement of goods and people across states. This policy consists of taxing goods from other states, which translates into lower trade flows, lower mobility of individuals and lower spatial infection diffusion. The blue line in Figure 4 reports the evolution of health and economic outcomes under this between-state tax alone. Specifically, we impose $\tau^c_{l,l} = \tau^x_l = 0$ and $\tau^c_{l,j} \geq 0$ if $l \neq j$. The red line reports the baseline economy and the yellow line the outcomes under the optimal local within-state tax policy previously analyzed.[22]

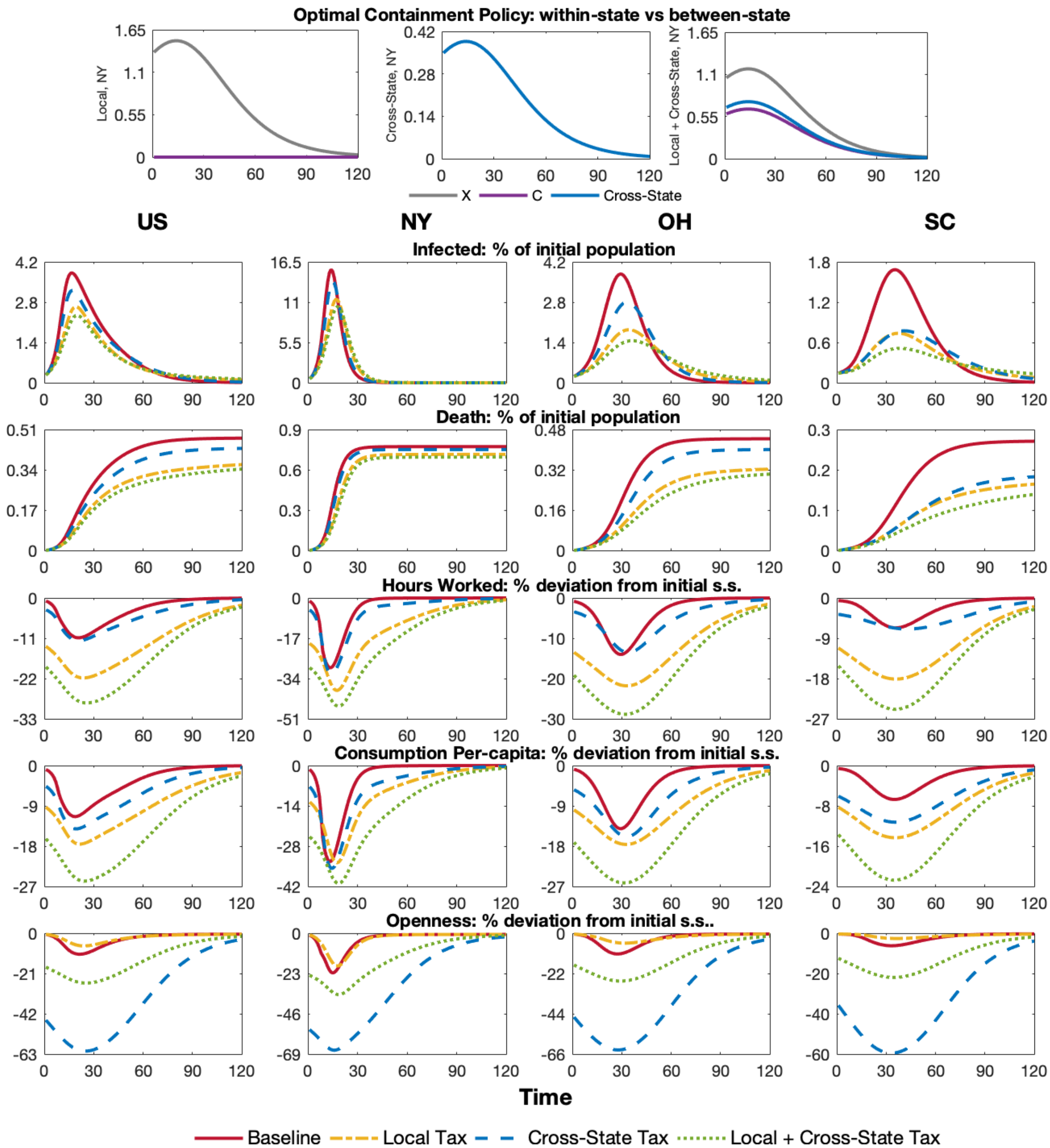
The middle graph of the first row plots the optimal between-state containment policy. The social planner finds optimal to tax foreign goods but at a much lower rate than social goods under the within-state policy. As the optimal local tax on service goods closely follows the infection cases at state level, this local between-state policy does the same. The right graph displays an optimal policy that takes into account a local and a between state (or foreign tax) instrument, a case that we will discuss later.

As reported in row three, the optimal between-state tax rate alone induces a higher death toll than the local within-state policy. A between-state tax alone reduces the overall death toll as percentage of initial population by about 0.4 p.p., while the local within-state policy reduces it by 0.45 p.p. This policy brings relatively larger gains to South Carolina, the most affected state by interconnectedness among these three. This occurs because between-state tax directly impacts the degree of openness of the state, as this tax reduces foreign demand, trade-flows and consequently movement of people and infection diffusion across space. Specifically, it induces an extra reduction in cross-state mobility of 50.51 p.p. at the peak and 34.88 p.p. on average during the first two years of pandemic compared with an economy without

[22]The green line reports the optimal policy combining local within- and between-state containment rules. This policy is discussed later.

containment policies. Not surprisingly, this policy generates a larger decrease in mobility compared with the baseline case in states that import relatively more infected cases, such as South Carolina.

Figure 4: Optimal Between-State and Overall Policy



This optimal between-state policy generates fewer economic losses per life saved as hours worked and consumption decline substantially less than under the within-state policy. However, this policy alone does not have the capacity to save as many lives as other policies. This policy targets movement of goods and people across regions, but disease spreads within states even if borders are completely closed. Although reduction in trade flows attenuates infection diffusion internally, a policy that does not consider the social good sector faces limitations in the number of deaths that it can avoid. When analyzing the health dynamics of the policy, we find that the optimal overall policy would reduce infection peak by 1.48 p.p. compared with the baseline with gains happening across states.

Optimal Within- & Between-State Containment Policy We now analyze the case where the social planner can jointly choose the optimal combination of local within- and local between-states consumption tax rates. The optimal tax paths for New York are reported in the third graph of the first row of Figure 4. We find that all tax rates follow very similar patterns. When analyzing the health dynamics of the policy, we find that the optimal overall policy would reduce infection peak by 1.48 p.p. compared with the baseline with gains happening across states. Similarly, the death toll would decrease by 289,300 lives compared with the baseline and 31,800 lives compared with the local within-state policy. These saved lives are followed by a stronger economic drop. The optimal policy would lead to a peak drop in hours worked and consumption of 28.67% and 25.80%, respectively. Over the first two years of the pandemic, the optimal policy would amplify the drop in hours worked and consumption relative to an economy with no intervention in 14.77 and 12.59 p.p., respectively. Mobility and trade flows would drop approximately 25.97% at the peak and 15.70% on average over the first two years of the pandemic.

These results suggest that despite some substitutability between within- and between-state policies, they mainly tackle different issues. While between-state policies can attenuate the pandemic by limiting the number of cases imported, it alone is not able to substantially mitigate the pandemic. Once cases are already within the state, only within-state policies can be effective.

In appendix, Table A.3 summarizes the main outcomes of the different policies analyzed. The same table also reports the policy implications when we consider the case in which symptomatic people are forced or voluntarily stay home while infected. Specifically, we analyze the optimal policies when 80% of the infected stay home and do not infect others, $\zeta = \zeta^{\tau} = 0.8$. 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 by 23% in both cases. However, to achieve the same proportion of saved lives, optimal policies requires a relative larger drop in economic activity when infected agents stay home relative to the scenario where no containment policies are in place.

Welfare Comparisons Table 2 reports the welfare losses attributable to the pandemic comparing different models and mitigation policies. Regarding within-state policies, we find that the optimal national within-state containment policy would ameliorate welfare losses by 0.071 p.p. while the optimal local level one would improve it by 0.086 p.p.. These results highlight that a policy that resembles a state-specific lockdown works better than a national lockdown. The key dimension through which this happens is time flexibility. We, then, report the welfare effect of a between-state tax on consumption that is either homogeneously (nationally) or heterogeneously (locally) applied across states. The welfare improvement is more modest, approximately 0.039 and 0.044 p.p., for both national and local policies, respectively, showing that the best between-state optimal policy alone would not have the same welfare effects as a local within-state consumption tax. Moreover, a national within-state lockdown is better than a simple local between-state policy. Finally, when the planner is allowed choose the optimal combination of within and between-state policy instruments, welfare gains increase relative to the optimal within-state policy. We find that this policy applied at national and local levels would mitigate the welfare losses by 0.094 p.p. and 0.119 p.p., respectively. We conclude that the optimal policy is a combination of local within-state and between-state policies.

When we analyze the case where symptomatic agents do not consume social goods and do not travel, we find similar results. Once again, in absolute terms, policies are less effective under this scenario. Overall, policies are equally effective in relative terms. A policy that combines local within-state and between-state policies mitigates welfare losses in approximately 25% under both economies.

Table 2: Welfare Impact of the Pandemic

Model	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%
Stay-Home	-0.383%	-0.333%	-0.317%	-0.355%	-0.35%	-0.311%	-0.29%

3.5 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 prior to the pandemic. Specifically, we run the following regression:

$$Trade_{l,j} = \beta_0 + \beta_1(\gamma_{l,j} + \gamma_{j,l}) + \beta_2 X_l + \theta_l + \theta_j + u_{l,j} \tag{8}$$

The dependent variable $Trade_{l,j}$ corresponds either to bilateral trade flows or to 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 3.1. 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.

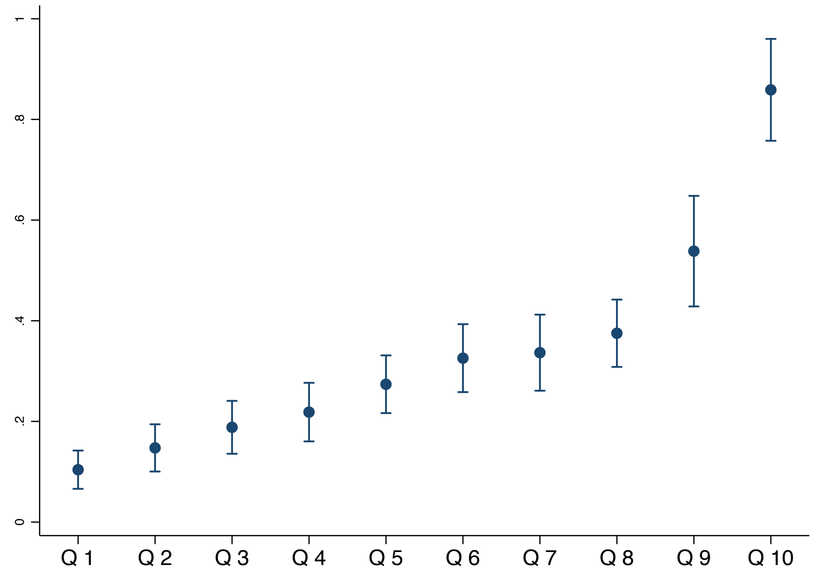
Table 3: Trade Volume and Mobility

	(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 3 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 3 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 when we run the correlations with LEX index standardized in deviation from the mean where the correlation

Figure 5: Share of Trade and Mobility (LEX Index)



Note: The graph above reports the estimated coefficients of a quantile regression where the 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.

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 5 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.

4 Conclusions

We highlight how interconnectedness amplifies the severity of pandemics. We find that if the US was constituted of isolated states, there would be approximately 146,200 fewer deaths and the peak of consumption drop would be attenuated by approximately 2.5 p.p. Therefore, we stress that the optimal containment policy must take into account interconnectedness and consider policies that temporarily limit the movement of people and goods across US states. We find that the optimal policy combines within and between-states restrictions and it saves approximately 289,300 lives. Our results also show that state-level policies rather than national ones are more effective in reducing the death toll with lower economic costs. Our quantitative framework constitutes a benchmark that can be adapted and extended to analyze future infectious events. A promising application of this framework consists of the study of the optimal traveling restriction policies among countries in mitigating the spread of pandemics. Finally, understanding whether pandemics have consequences on globalization by reducing trade and movement of people for long periods of time is a long-term goal of this research agenda.

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A Online Appendix

A.1 Optimization Problems

This section describes and solves the optimization problems faced by the agents of this 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:

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

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

where $h_{l,t}^k$, 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:

$$u_1\left(c_{l,t}^{k,s}, x_{l,t}^{k,s}, n_{l,t}^{k,s}\right)) = \lambda_{l,t}^{k,s}(1+\tau_l^c)p_{l,t}^c + \beta\left(U_{l,t+1}^{k,s} - U_{l,t+1}^{k,i}\right)\pi_1\left(\lambda C_{l,t}^a + (1-\lambda)C_{l,t}^i\right) I_{l,t}/Pop_{l,t}$$

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

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

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

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:

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

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

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:

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

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

$$\chi \left(n^i_{l,t}\right)^\theta = \lambda^{k,i}_{l,t} \nu^i w^k_{l,t}$$

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

$$U^{k,r}_{l,t} = \max_{\left\{c^{k,r}_{l,t}, x^{k,r}_{l,t}, n^{k,r}_{l,t}\right\}} u\left(c^{k,r}_{l,t}, x^{k,r}_{l,t}, n^{k,r}_{l,t}\right) + \beta U^{k,r}_{l,t+1}$$

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

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

A.2 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). We set the weekly discount factor β to be $0.965^{1/52}$. This discount factor implies a value of a life of 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 $\nu^i = 0.7$.

Table A.1: 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.2*
z^c	Productivity in c	Y	*see Table A.2*
ν^i	Symptomatic Productivity Adjustment	Y	0.7
SIR			
π_r	Probability of recovery	N	7×0.99/18
π_d	Probability of dying	N	7×0.01/18
λ	Asymptomatic Share	N	0.3
$\pi_{1,l}$	Infection Probability by X	Y	*see Table A.2*
$\pi_{2,l}$	Infection Probability by C	Y	*see Table A.2*
$\pi_{3,l}$	Infection Probability by Working	Y	*see Table A.2*
$\pi_{4,l}$	Infection Probability by General contact	Y	*see Table A.2*

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.

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 7×0.01/18, 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 7×0.99/18. 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.

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).

We also follow Eichenbaum et al. (2020) and assume that 17% of infections occur in the work place. 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. To calibrate how likely we are to meet a person from the home-state versus a different state, we use data from Couture et al. (2020). This data set uses cell phone data to measure the movement across regions. Specifically, among the smartphones that pinged in a given state in a certain day, the data report the share of those devices that pinged in each of the other 50 state 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. As stated in equation (2), the number of people moving in both directions between state j and l is given by: $(\gamma_{l,j} + \gamma_{j,l})\frac{\tilde{C}_{l,j,t}+\tilde{C}_{j,l,t}}{\tilde{C}_{l,j}+\tilde{C}_{j,l}}$, where $\tilde{C}_{l,j} + \tilde{C}_{j,l}$ corresponds to the pre-pandemic gross trade-flows. Therefore, in the pre-pandemic equilibrium, the movement of people across states collapses to $\gamma_{l,j} + \gamma_{j,l}$. As a result, our calibration of γ's matches the pre-pandemic gross trade flow between any two states.

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).[23] 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

[23] 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.

Table A.2: Key Data Moments and Steady-State Values

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 (%)
	Data					Model							
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).

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

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

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

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

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

where

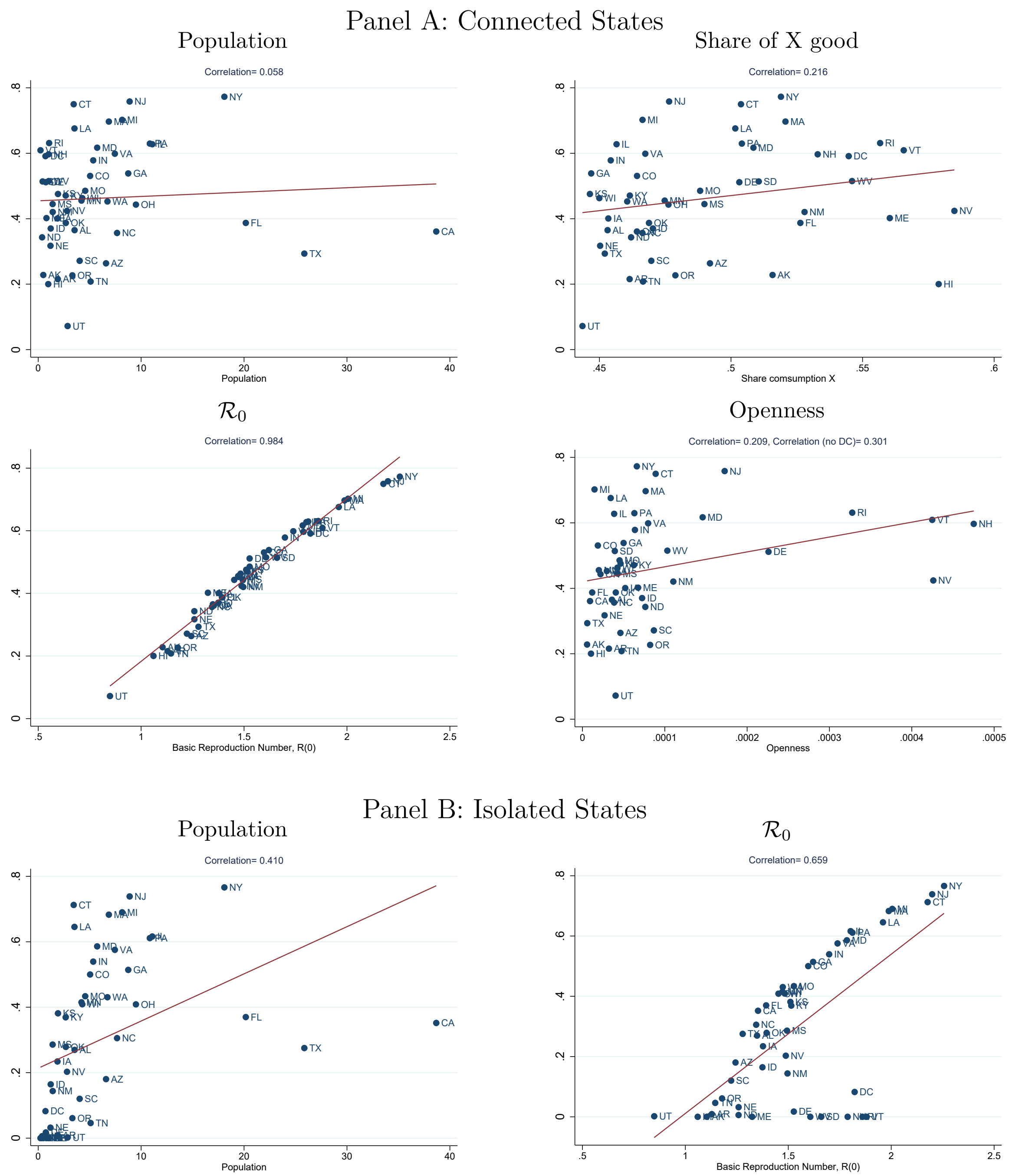
$$H_l = \pi_{1,l} X_l^2 + \pi_{2,l} C_l^2 + \pi_{3,l} \left(\left(\frac{Pop_l^c}{Pop_l}\right)(N_l^c)^2 + \left(\frac{Pop_l^x}{Pop_l}\right)\left[(N_l^x)^2 + N_l^x X_l\right]\right) + \pi_{4,l}\left(\gamma_{l,l} + \sum_{j \neq l} (\gamma_{l,j} + \gamma_{j,l}) \frac{I_{j,0}}{I_{l,0}}\right)$$

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

All allocations and population refer to the pre-pandemic equilibrium. Parameters are summarized in Table A.1, and state-level parameters and moments can be found in Table A.2.

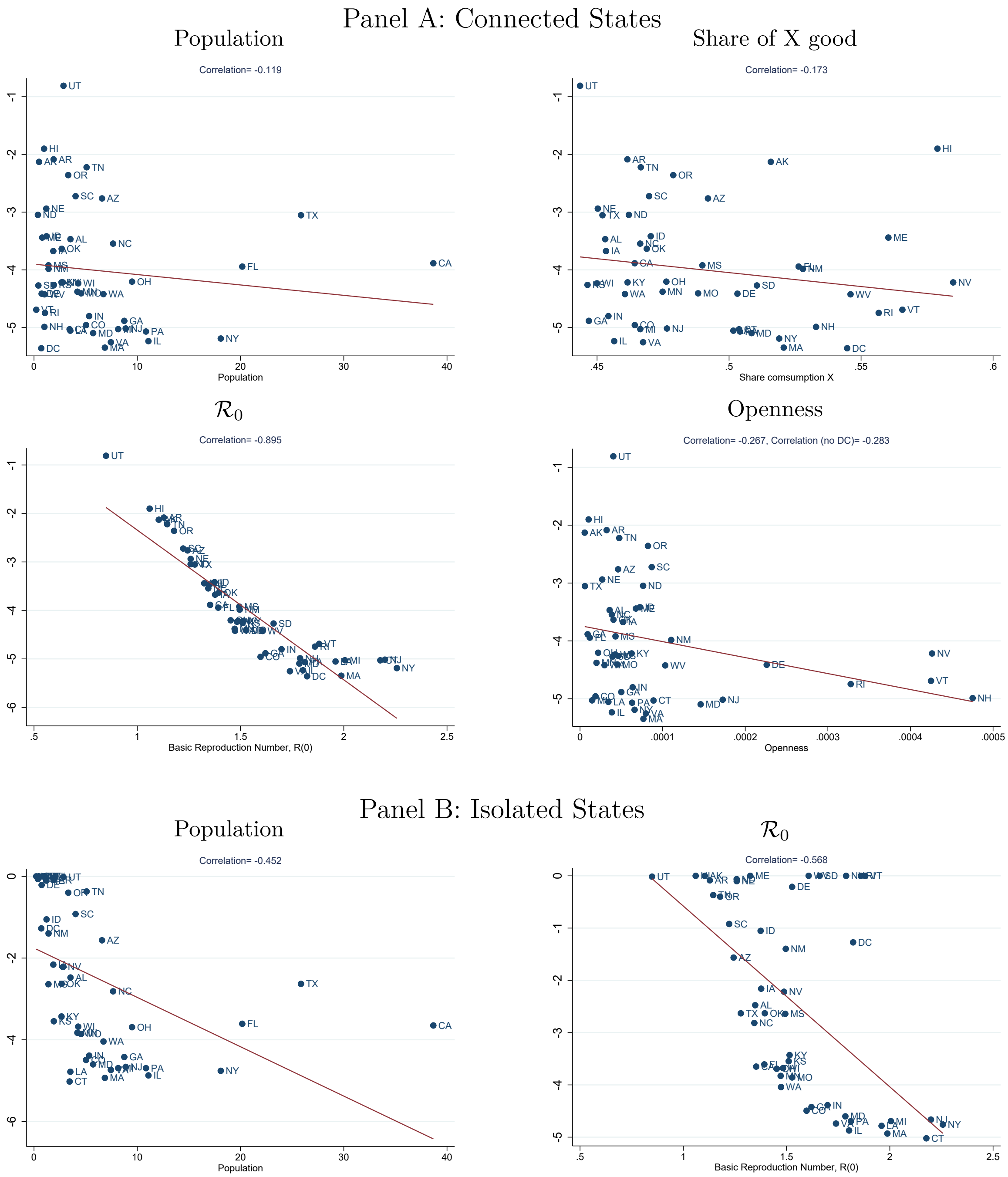
A.3 Pandemic and State Characteristics

Figure A.1: 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.2: 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.4 Policies Results

Table A.3: 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