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Optimally Targeting Interventions in Networks during a Pandemic: Theory and Evidence from the Networks of Nursing Homes in the United States

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Supplement to “Optimally Targeting Interventions in Networks during a Pandemic: Theory and Evidence from the Networks of Nursing Homes in the United States”

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October 16, 2021

In this supplement, we provide complementary information to the simulations and empirical analyses that we perform in the study “Optimally Targeting Interventions in Networks during a Pandemic: Theory and Evidence from the Networks of Nursing Homes in the United States.” Section 1 offers additional explanations of the simulations that we use to derive our comparative statics analyses. Section 2 provides sources and complements the selection of parameters to calibrate our N-SIRD model with the lockdown. Section 3 provides more details on our estimation approach of the tolerable infection incidence, λ . Section 5 gathers robustness check (1) for our comparative statics analyses regarding the changes in tolerable infection incidence, λ , on three network structures: lattice, random, and scale-free networks; (2) to test our N-SIRD predictions’ sensibility to COVID-19 epidemiological parameters; we replicate Figure 1 (p. 24) and Table 1 (p. 33) from the main text with COVID-19 Delta variant data; (3) of our empirical analyses by replacing eigenvector centrality with the degree centrality in Table 4 (p. 42) of our corresponding regression-based analyses in the main text.

1 Comparative Statics Analyses

Section 4 of the main text presents the comparative statics analyses of our N-SIRD model. Given the complexity and the stochastic nature of our epidemiological model, we use simulations to illustrate the behavior of our optimal lockdown and disease dynamics in networks. We perform this exercise by varying the social network structure network in several dimensions. First, we

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use different notable canonical network structures: the lattice, random, small-world, and scale-free networks. We also vary the density of the network and assess its effects on the dynamic of the pandemic. We also evaluate the impact of the tolerable COVID-19 infection incidence, λ , on lockdown, health, and wealth. For all the comparative statics experiments, around April to August 2020, the period in which the researchers from the “Protect Nursing Home Project” collected the data used in Chen et al. (2021)’s study. For robustness, we provide in Section 5 some of our simulation results with updated COVID-19 statistics worldwide and in the U.S.

Production Function. In our simulations, we use a Cobb-Douglas production function $y_i(t) = k_i(t)^{\alpha_i} h_i(t)^{1-\alpha_i}$, where we assume uniform and constant capital $k_i(t) = k_i = 1$, for each agent i , and the labor supply $h_i(t)$ as a function of lockdown, $h_i(t) = 1 - l_i(t)$. For simplicity, we also assume uniform elasticity of output with respect to the capital, $\alpha_i = \alpha = \frac{1}{3}$. Though the latter choice is for illustration purposes, the value $\alpha = \frac{1}{3}$ is in the range of values obtain for the U.S. states estimated elasticity using the data on nursing and long-term care homes (Chen et al., 2021).

Optimal Dynamics. We obtain our optimal lockdown dynamics by solving the planning problem described in Eq.(8) on page 18 in the main text. The simulation process involves solving Eqs. (9) to (13), and (16) to (19). The lockdown dynamics yield the disease and economic costs dynamics. We use the software **Matlab_2020a** and the function **ode45** to solve the system of ordinary differential equations describing our N-SIRD epidemiological model. We would deposit the codes of our simulations and other relevant information and data for replications in GitHub. The existence and uniqueness of the solution for our epidemiological model and planning problem in Propositions 1 and 4, respectively, ensure that the output from our simulations is the appropriate approximation of the N-SIRD optimal dynamics. As initial inputs in the simulations, we specify the adjacency matrix A , representing the social network structure, and randomly impose 10% of infected agents. At the initial period, there is no agent in lockdown. For each period $t \in \{1, 2, \dots, 80\}$, the simulation program optimally produces individual probabilities for each of our variables of interest. Then, we represent the average probability in the sample for each point in time t in Figures 1, 3, and 4. We can view these dynamics as representative of the population dynamics and thus useful for policy analysis and decision making.

2 Data Source and Calibration

In our study, we use data from several sources. Our primary source of external data comes from the Protect Nursing Home Project and the replication package made publicly available by Chen

et al. (2021). In our empirical section on nursing homes, we follow Chen et al. (2021) and assume that nodes are nursing homes. Table 1 describes the relevant parameters, their sources, and use in our simulations and empirical analyses.

For calibration, we assume that the production structure is homogeneous within a U.S. state. To estimate the production function for a nursing home i in a U.S. state, we assume a Cobb-Douglas function $y_i = k_i^{\alpha^1} h_i^{\alpha^2}$, where we consider y_i as the total number of residents who receive care (output), k_i as the total number of beds (proxy for capital), and h_i as the number of occupied beds (a proxy for the labor supply). We assume that a nursing home hires staff according to the demand for its services, and the latter is closely related to the number of occupied beds. We estimate the elasticity α^1 and α^2 by assuming a log-log specification and controlling for a series of factors, including overall rating, County SSA, CMS quality rating, urban/rural, and for-profit/not-for-profit. We use the following simple log-log econometric equation:

$$\log(y_i) = \alpha^0 + \alpha^1 \log(k_i) + \alpha^2 \log(h_i) + \beta X_i + e_i, \quad (1)$$

where $X_i(t)$ are exogenous nursing homes characteristics and $e_i(t)$ is the error term. The estimates of the parameter α^1 for each state are presented in Table 2.

Parameters or Variables	Value	Definitions and Sources	Utilization
Epidemiological			
β	$R_0/18$	The COVID-19 reproduction numbers R_0 estimated during April to July 2020, from Statista	Calibration
γ	$(1-\text{death}/\text{case})/18$	case and death per 1000 in nursing homes in each U.S. state as of Sep. 2020 from Statista	Calibration
κ	$(\text{death}/\text{case})/18$	case and death per 1000 for in nursing homes in each U.S. state as of Sep. 2020 Statista	Calibration
Death Count	80% of COVID-19 death	New York Times in each U.S. state from May 31 to August 16, 2020	Calibration
A	Network of nursing homes	Protect Nursing Home Project	Calibration
Economic			
Price	Average hourly cost of a Private Room	Senior Living Project ¹	Calibration
Wage	Average hourly wage by State	BLS Calibration	
α	Cobb-Douglass production function	Replication data from Chen et al. (2021) Estimation for each State	Calibration.
Regressions Table 4 and 5	variables	Replication data from Chen et al. (2021) and authors' calculation	Estimations
Regression Table 6	variables	Replication data from Chen et al. (2021) and authors' calculation	Estimations
Capital	Number of beds in the nursing home	Replication data from Chen et al. (2021)	Calibration

Table 1: **Description and sources of calibrated and estimated parameters for each U.S. state**

U.S. States	Wage/hour	Price/hour	Case/100000	Death/100000	R_0	α	Min degree
AL	33	9.29	365.9	59.3	0.93	0.3853637	13
AR	43	11.04	281.4	59.6	0.95	0.5218234	13
AZ	35	8.79	241.2	45.8	0.97	0.5852448	13
CA	52	15.37	274.8	51.8	0.86	0.6297461	13
CO	42	13.08	109.6	38.4	0.92	0.538735	13
CT	46	18.81	345	100	0.96	0.6257474	13
DC	42	17.07	229.9	56.3	0.92	1.002931	1
DE	52	19.30	188.3	55.3	0.97	0.7739902	1
FL	39	13.19	283	53.1	0.97	0.6614283	22
GA	38	9.64	356.1	73.7	0.84	0.4615252	22
IA	38	12.26	131.2	31	0.92	0.2876858	1
ID	40	9.44	162	22.8	0.87	0.2217902	1
IL	39	11.41	209	52.8	0.87	0.4060938	11
IN	36	9.61	159.8	59	0.88	0.2871411	11
KS	35	9.44	83.6	16	0.96	0.3383333	11
KY	34	10.67	162.4	34.9	1.01	0.331612	11
LA	34	7.85	418.6	85.5	0.89	0.2518069	11
MA	42	14.27	356.1	125.1	0.94	0.76337	11
MD	45	14.31	263.1	62.4	0.94	0.6189594	11
ME	47	18.19	48.3	9	0.96	0.7124791	1
MI	39	13.08	138.2	48.8	0.9	0.6715142	9
MN	44	16.16	100.9	33.8	0.94	0.5657483	9
MO	32	9.61	180.6	30.8	0.94	0.2763414	9
MS	36	7.73	367	74.9	1.08	0.6377482	1
MT	41	11.12	23.5	4.7	0.87	0.0505241	1
NC	38	10.66	221.9	46.1	0.92	0.5917483	NaN
ND	45	14.23	102.3	15	1.09	0.4858396	2
NE	45	15.21	94.2	26.4	0.94	0.3416526	2
NH	47	15.94	141.9	38.3	0.95	0.5850638	2
NJ	42	11.16	365.8	120.1	1.03	0.7126257	2
NM	46	17.38	138.6	50.1	0.84	0.549336	2
NV	38	10.83	209.9	26.4	0.95	0.7162963	2
NY	38	17.16	145.2	50.5	0.91	0.7638234	2
OH	38	11.04	149.2	34.9	0.88	0.5926255	2
OK	36	7.77	148.2	22.2	1.05	0.4150358	2
OR	48	15.02	74.5	13.6	0.94	0.2144981	2
PA	39	14.55	207.1	66.2	0.88	0.6404236	9
RI	46	13.74	288.8	86.6	0.92	0.9319015	9
SC	37	10.57	342.2	63.1	0.9	0.5003951	9
SD	35	10.11	78.9	14.4	0.94	0.3584688	1
TN	34	10.24	166.5	24.8	0.87	0.2476998	9
TX	38	8.59	325.7	62	0.97	0.3152237	22
UT	37	11.24	134	31.9	0.98	0.3648363	NaN
VA	41	13.86	192.3	46.2	1.05	0.6377195	NaN
VT	41	11.86	35	11.1	1.11	0.6885093	2
WA	47	14.72	152.7	38	0.97	0.6368927	9
WI	35	16.31	64	12.4	0.91	0.2780716	9
WV	41	12.67	101.7	17.8	0.87	0.2662697	9
WY	42	11.71	8.4	2.2	0.99	0.2333506	1

Table 2: **Data used for calibration for each U.S. states.** This table provides the values used to for for the calibration. The sources are described in Table 1. “NaN” means “Non Available”. For these U.S. states there was no degree centrality level for which our model could be simulated based on the epidemiological and economical parameters we have obtained.

3 Estimation of the Tolerable Infection Incidence Parameters

Our study uses the simulated minimum distance estimator to estimate the tolerable COVID-19 infection incidence value for all U.S. states in our sample. Given the lack of daily COVID-19 deaths in the nursing homes data by Chen et al. (2021), we use daily data count from New York Times in each U.S. state between May 31 and August 16, 2020. Using information from National Center for Health Statistics (2020) and Freed et al. (2020), we assume that 80% of U.S. COVID-19 deaths on average are senior (65 years and older). We use these figures as our observed outcome. Let's index a U.S. state in Chen et al. (2021)'s data set by $s \in S$, with $S = \{1, \dots, 49\}$. Let d_{ts} denote the number of COVID-19 deaths observed at time $t = 1, \dots, T$ in the U.S. state $s \in S$. For each value of the tolerable infection incidence λ , we can simulate death dynamics denoted as $\hat{d}_{ts}(\lambda)$. Since our simulations are deterministic, there is no random shock in our model. Thus, repeating the simulations with the same initial conditions produce the same results. For each U.S. state, we estimate the parameter that we denote as $\hat{\lambda}_s$ by solving the following minimization problem:

$$\hat{\lambda}_s = \underset{\lambda \in [0, 1]}{\operatorname{argmin}} \left\{ \sum_{t=1}^T (\hat{d}_{ts}(\lambda) - d_{ts})^2 \right\}, \quad (2)$$

We provide in Figure 6 (p. 40 in the main text) the estimated values of $\hat{\lambda}_s$ for 26 states. Existing literature on simulated minimum distance estimators (Gertler & Waldman, 1992; Smith Jr, 1993; Forneron & Ng, 2018) suggests that $\hat{\lambda}_s$ is a consistent estimator of the tolerable COVID-19 infection incidence level for each U.S. state.

4 Network characteristics of selected U.S. states nursing homes

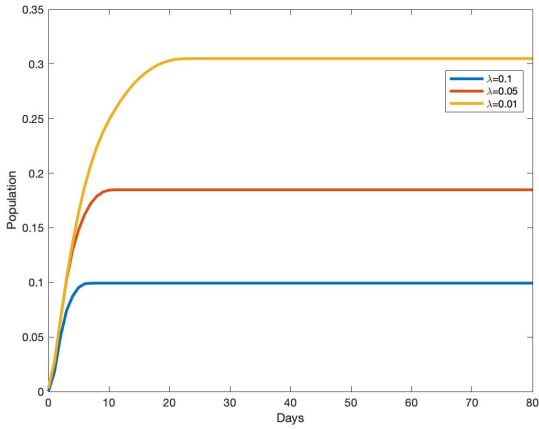
States	Number of nursing homes	COVID-19 deaths			Eigenvector	
		Max	Mean	Sd	Mean	Sd
South Dakota	103	22	0.22	2.17	0.043	0.17
Connecticut	196	67	7.31	10.46	0.13	0.21
Louisiana	259	26	2.68	5.06	0.09	0.22
Colorado	214	22	1.49	3.73	0.11	0.18
Oklahoma	257	17	0.3	1.59	0.08	0.18
Missouri	483	21	0.56	2.52	0.07	0.15

Table 3: **Network characteristics for six selected nursing homes from Chen et al. (2021)’s Replication data.** COVID-19 deaths are confirmed among residents reported to the U.S. Centers for Medicare and Medicaid Services (CMS) as of May 31, 2020. “Sd” means standard deviation.

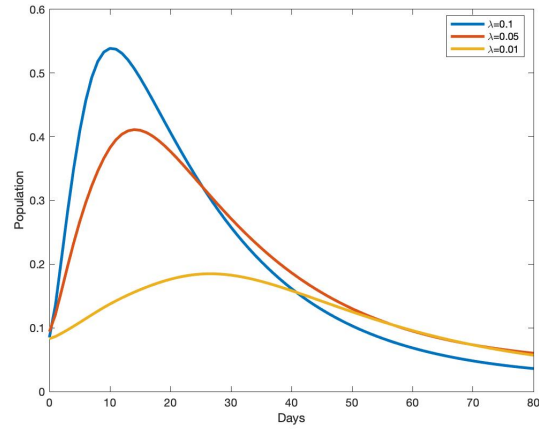
5 Robustness Checks

5.1 Replication of Figure 1 (p. 24, main text) For Scale-free, Random, and Lattice Networks

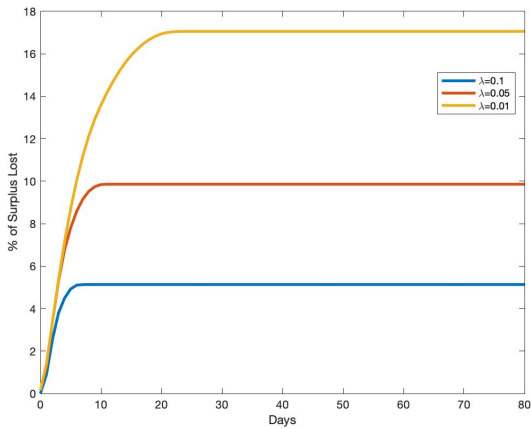
We replicate the results of the comparative statics analyses in Figure 1 (p. 24) using three different network geometries. In line with Figure 1, for each network configuration, we consider three different values of the tolerable infection incidence λ . The results in Figures 1, 2, and 3 are qualitatively consistent with the dynamics in Figure 1 (p. 24).



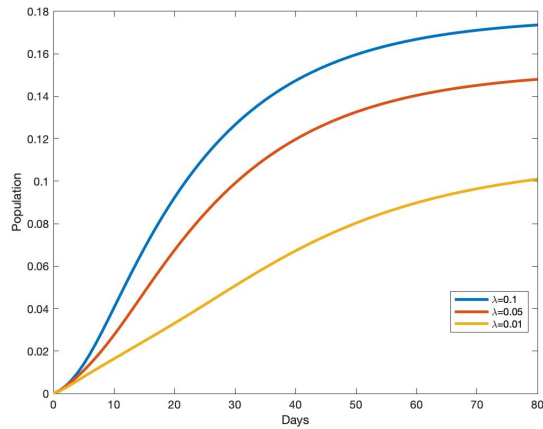
(a) Dynamics of lockdown



(b) Dynamics of infection

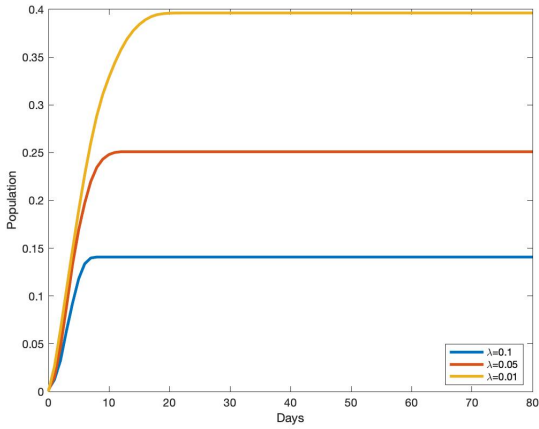


(c) Dynamics of economic Cost

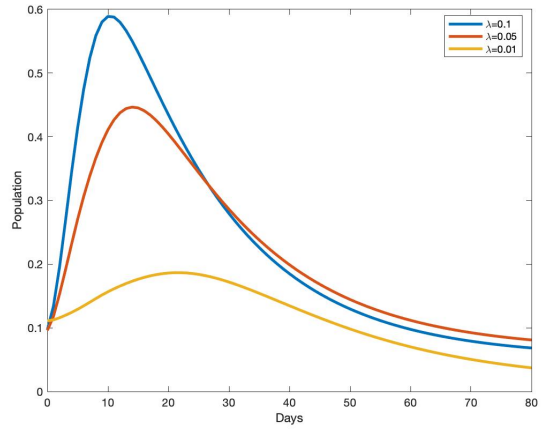


(d) Dynamics of death

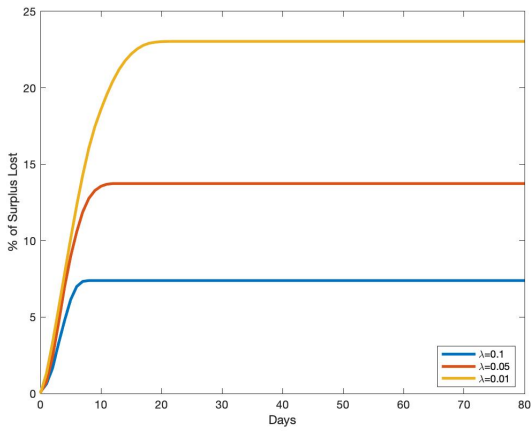
Figure 1: Health versus Wealth tradeoff in a scale-free network. We perform three sets of simulations with three different values of the tolerable infection incidence λ : 0.01, 0.05, and 0.1. The results are displayed in a two-dimensional graphic, with days in the horizontal axis, and the percentage of population affected for the variable (infection, lockdown, or death) illustrated on the vertical axis. In each period, a point in the graphic represents the average value of individual probabilities. For the economic cost, the vertical axis represents the percentage of economic (or surplus) lost relative to the economy without the pandemic. Each graph shows three curves corresponding to three dynamics for a single variable of interest for a given value of λ . All variability within each curve in each graph is a result of the stochastic nature of transmission and not variation in the network nor λ .



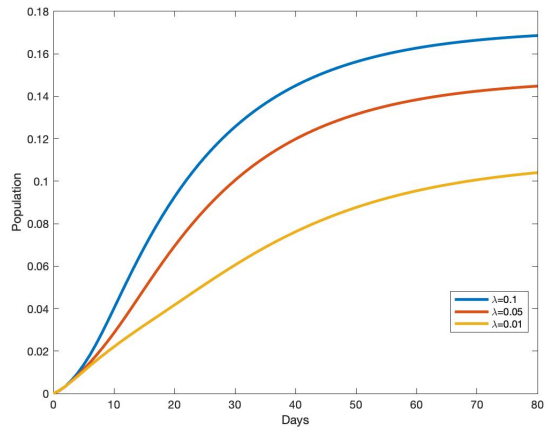
(a) Dynamics of lockdown



(b) Dynamics of infection

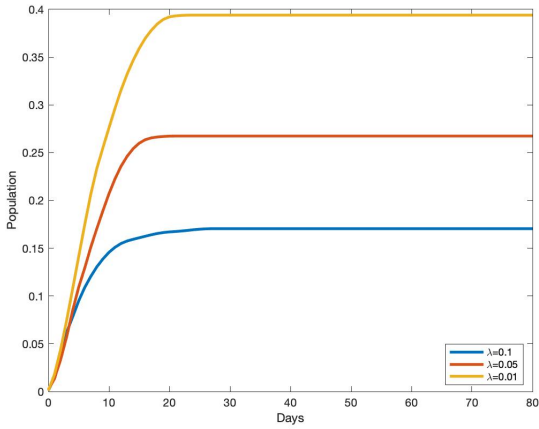


(c) Dynamics of economic Cost

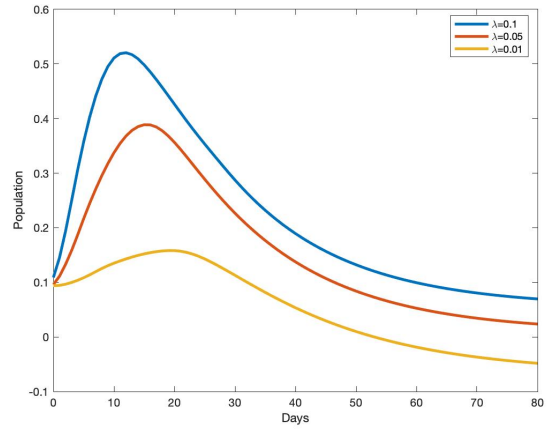


(d) Dynamics of death

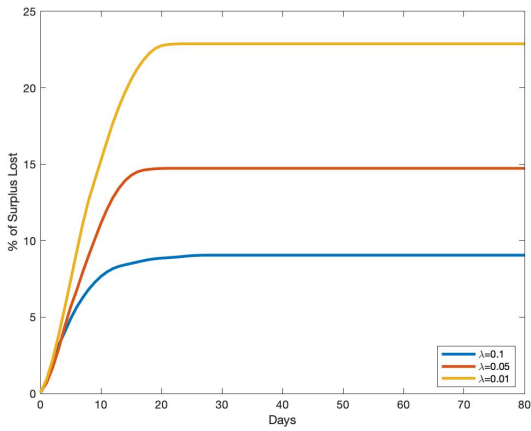
Figure 2: Health versus Wealth tradeoff in a random network. We perform three sets of simulations with three different values of the tolerable infection incidence λ : 0.01, 0.05, and 0.1. The results are displayed in a two-dimensional graphic, with days in the horizontal axis, and the percentage of population affected for the variable (infection, lockdown, or death) illustrated on the vertical axis. In each period, a point in the graphic represents the average value of individual probabilities. For the economic cost, the vertical axis represents the percentage of economic (or surplus) lost relative to the economy without the pandemic. Each graph shows three curves corresponding to three dynamics for a single variable of interest for a given value of λ . All variability within each curve in each graph is a result of the stochastic nature of transmission and not variation in the network nor λ .



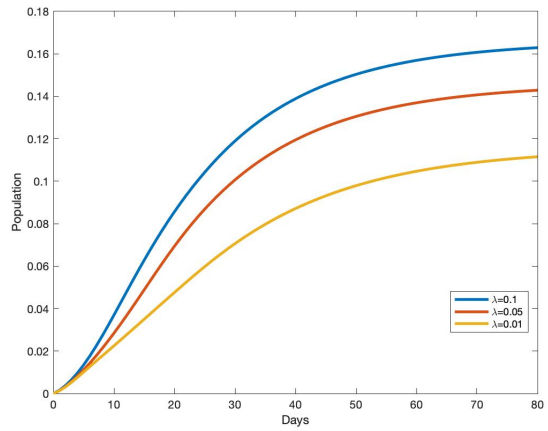
(a) Dynamics of lockdown



(b) Dynamics of Infection



(c) Dynamics of Economic Cost



(d) Dynamics of Death

Figure 3: Health versus Wealth Tradeoff In a Lattice Network. We perform three sets of simulations with three different values of the tolerable infection incidence λ : 0.01, 0.05, and 0.1. The results are displayed in a two-dimensional graphic, with days in the horizontal axis, and the percentage of population affected for the variable (infection, lockdown, or death) illustrated on the vertical axis. In each period, a point in the graphic represents the average value of individual probabilities. For the economic cost, the vertical axis represents the percentage of economic (or surplus) lost relative to the economy without the pandemic. Each graph shows three curves corresponding to three dynamics for a single variable of interest for a given value of λ . All variability within each curve in each graph is a result of the stochastic nature of transmission and not variation in the network nor λ .

5.2 Replication of Table 1 (p. 33) for Lattice, Random, and Scale-free Networks

We replicate the simulation results of network centrality measures and the lockdown dynamics of our N-SIRD model with three different network structures: lattice, random, and scale-free networks. The results in Table 4 suggest that the scale-free network maintains all the predictions that we obtain using a small-world network. Contrary to small-world and scale-free networks, the random network does not replicate the relationship between the tolerable infection incidence and the lockdown probabilities of more central individuals. Given the homogeneous level of degree centrality of agents in the lattice network, we could not compute the correlation between the degree centrality and the optimal lockdown dynamics.

		$\lambda = 0.1$			$\lambda = 0.05$			$\lambda = 0.01$		
		Lattice	Random	Scale Free	Lattice	Random	Scale Free	Lattice	Random	Scale Free
Eigenvalue	corr	-2.09E-16	0.1988	0.2733	-1.39E-15	0.2049	0.0203	-1.15E-15	0.2045	0.015
	<i>p</i> -value	1	2.26E-10	1.35E-18	1	6.17E-11	0.5223	1	6.70E-11	0.6362
Degree	corr	NaN	0.2339	0.4105	NaN	0.2389	0.1239	NaN	0.2731	0.1302
	<i>p</i> -value	NaN	6.81E-14	6.23E-42	NaN	1.91E-14	8.55E-05	NaN	1.47E-18	3.62E-05
Betweenness	corr	0.0034	0.2167	0.2647	6.31E-04	0.2116	0.0437	0.0015	0.2348	0.0434
	<i>p</i> -value	0.915	4.32E-12	1.72E-17	0.9841	1.37E-11	0.1675	0.9617	5.39E-14	0.1701
Closeness	corr	2.03E-16	0.2202	0.4006	1.39E-15	0.2426	0.0954	1.15E-15	0.2509	0.0591
	<i>p</i> -value	1	1.91E-12	7.83E-40	1	7.35E-15	0.0025	1	7.99E-16	0.0618

Table 4: Correlation between measures of centrality and average optimal lockdown probability for three network configurations. The *p*-value for each centrality measure is for the test of the hypothesis $H_0 \rho = 0$ vs $H_1 \rho \neq 0$. Not all correlations are significant. The label "NaN" means "Non available." In the lattice network, all individuals have the same degree. Thus, we can't compute the correlation between the degree centrality and optimal lockdown probabilities. For the random network, we observe a strong correlation between centrality measures and the optimal lockdown probabilities. However, there is no relationship between the tolerable infection incidence and the centrality lockdown nexus. The lockdown dynamics and correlations in the scale-free and small-world networks move in the same direction.

5.3 Replication of Figure 1 (p. 24), and Table 1 (p. 33) all in main text with COVID-19 Delta variant

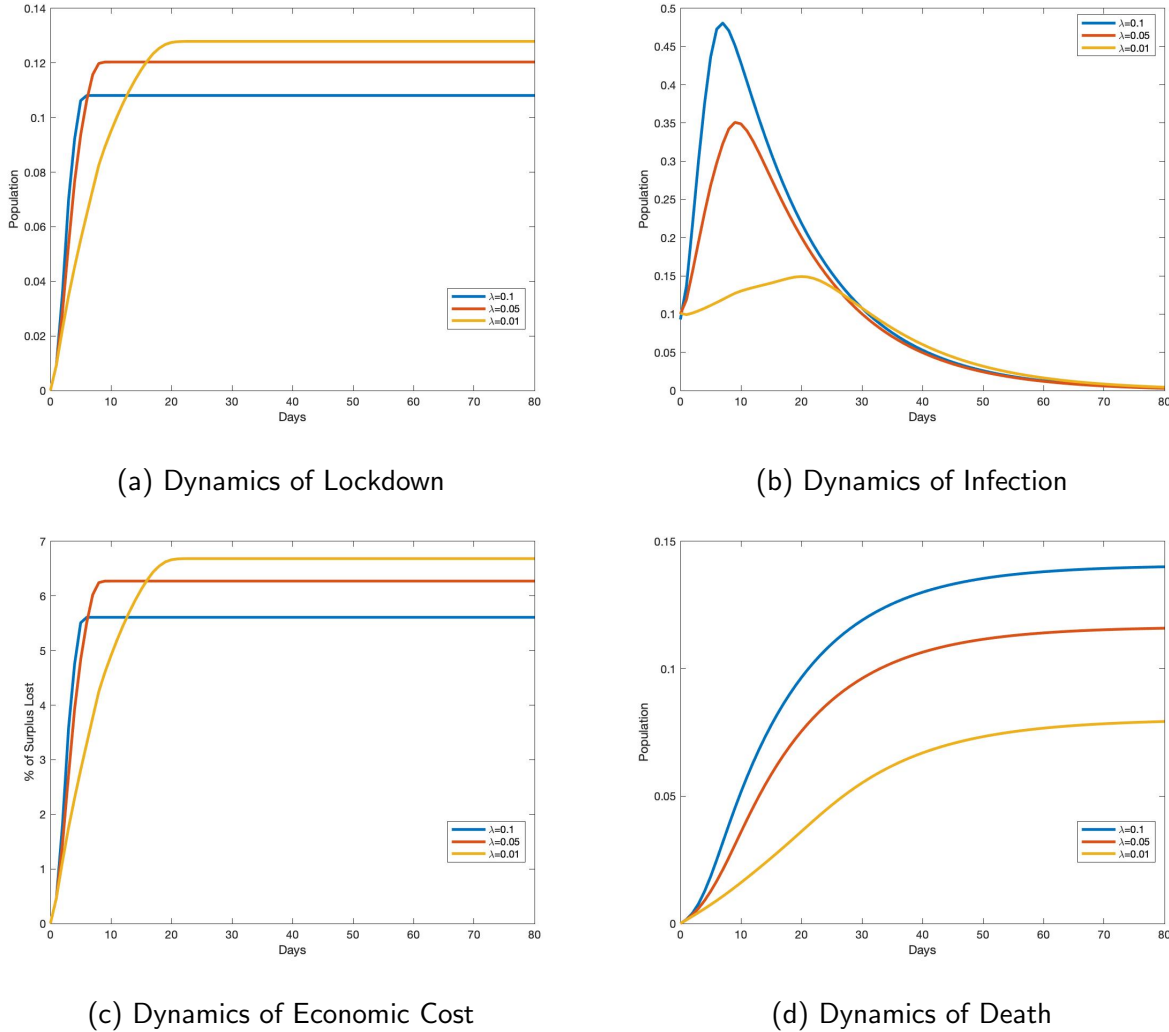


Figure 4: **Health versus Wealth tradeoff with COVID-19 Delta variant parameters in a small-world network.** We perform three sets of simulations with three different values of the tolerable infection incidence λ : 0.01, 0.05, and 0.1. The epidemiological parameters are set to match the transmissibility of the COVID-19 Delta variant ($R_0 = 5.08$; see Liu & Rocklöv (2021) and references therein). The infectious period is set to 14 days and recovery and death rate are left unchanged. The results are displayed in a two-dimensional graphic, with days in the horizontal axis, and the percentage of population affected for the variable (infection, lockdown, or death) illustrated on the vertical axis. In each period, a point in the graphic represents the average value of individual probabilities. For the economic cost, the vertical axis represents the percentage of economic (or surplus) lost relative to the economy without the pandemic. Each graph shows three curves corresponding to three dynamics for a single variable of interest for a given value of λ . All variability within each curve in each graph is a result of the stochastic nature of transmission and not variation in the network nor λ .

λ	Eigenvalue		Degree		Betweenes		Closeness	
	corr	p-value	corr	p-value	corr	p-value	corr	p-value
0.1	0.2121	1.24E-11	0.2769	4.67E-19	0.231	1.39E-13	0.2277	3.17E-13
0.05	0.2055	5.38E-11	0.2696	4.04E-18	0.2296	2.00E-13	0.2386	2.09E-14
0.01	0.1012	0.0014	0.1829	5.66E-09	0.1334	2.30E-05	0.1513	1.53E-06

Table 5: **Correlation between measures of centrality and average optimal lockdown probability in a small-world network with Delta variant parameters.** The p -value for each centrality measure is for the test of the hypothesis $H_0 \rho = 0$ vs $H_1 \rho \neq 0$.

5.4 Replication of Table 4 (p. 42, main text) with the degree centrality

	(1)	(2)	(3)	(4)	(5)
λ	0.197 (0.57)	1.129** (3.02)	1.700** (2.58)	-0.451 (-0.89)	1.601** (2.19)
Degree Centrality	0.0616*** (6.34)	0.0900*** (6.79)	0.0622*** (6.41)	0.0612*** (6.29)	0.0903*** (6.75)
County_ssa	-0.000773 (-1.09)	-0.000824 (-1.17)	-0.000501 (-0.70)	-0.000786 (-1.11)	-0.000598 (-0.84)
D_Profit	0.208* (1.76)	0.211* (1.79)	0.210* (1.78)	0.0772 (0.56)	0.0358 (0.26)
$\lambda \times$ Degree Centrality		-0.169*** (-3.12)			-0.170*** (-3.07)
$\lambda \times$ County_ssa			-0.00475*** (-2.64)		-0.00424** (-2.39)
$\lambda \times$ D_Profit				0.980 (1.57)	1.327** (2.03)
Overall_rating	-0.188*** (-4.70)	-0.182*** (-4.52)	-0.188*** (-4.68)	-0.191*** (-4.75)	-0.185*** (-4.58)
County FE	Yes	Yes	Yes	Yes	Yes
Observations	6478	6478	6478	6478	6478
R^2	0.078	0.079	0.079	0.078	0.080

Table 6: **Estimation of the “laissez-faire” Effect: the Dependant variable is the Total Number of COVID-19 Deaths in the Nursing Home.** t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust to heteroscedasticity of unknown form.

	Mean	Standard Deviation	Minimum	Maximum
GDP Growth, %	-3.46	1.47	-7.00	-0.10
Democrat Governor	0.47	0.50	0.00	1.00
Female Governor	0.18	0.39	0.00	1.00

Table 7: **Descriptive statistics of GDP and U.S. state governorship political affiliation and gender in 2020.**

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