Online Appendix

"Slums and Pandemics"

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A Data Sources and Definitions

In this appendix, we detail the data used in the empirical motivation discussion (Section 2) and in the model calibration (Section 4).

Population census: We use data from the 2010 Brazilian Population Census carried out by IBGE (Brazilian Bureau of Statistics) to obtain information on households and people living inside and outside slums. In the paper, we define slums as housing units in "subnormal agglomeration." According to the 2010 census, a subnormal agglomeration satisfies three conditions: (i) it consists of a group of at least 50 housing units, (ii) where land is occupied illegally and (iii) is urbanized in a disordered pattern and/or lacks basic public services such as sewage or electricity.

The 2010 census interviewed all households in the country ("universe questionnaire") and also executed more detailed interviews on a 5% random sample of households ("sample questionnaire"). We use data from both the universe and sample questionnaires, as detailed here.

From the universe questionnaire, we obtained information on the characteristics of people and households at the census tract level (*Setor censitário*). Apart from obtaining information on the total number of people and households in each census sector, we are able to identify whether or not sectors are slums (subnormal agglomeration). Using this information, we constructed the following variables for the cities of Rio de Janeiro and Sao Paulo:

- Total population
- Total number of households
- Number of people living in slums
- Number of households that are in slums
- Average population density of each census tract, where the density is number of inhabitants divided by the area of the tract in Km^2

- Average population density of slums
- Average number of people in households
- Average number of people in households located in slums

From the sample questionnaire, we collected data on the average labor income per capita as well as the average age of the population. However notice that, different from the results of the universe of the Brazilian census, the sample dataset does not identify whether the household lives in a slum. Hence, we constructed a proxy to identify whether or not each household lived in a slum. More precisely, a household is considered to live in a slum if any of the following conditions is met: it does not have a toilet; it has a lack of essential public services and utilities (sewage, electricity, garbage collection, or piped water); there are more than four people per bedroom. After classifying housing units as slums, we tabulated the aforementioned income and demographic variables.

Covid RADAR — June/2020 — (`www.covidradar.org.br`): Covid Radar is a collective of more than 40 companies and organizations that coordinate efforts to build a reliable dataset on Covid-19 in Brazil. We use this website to collect municipality (city) data on the number of private and public intensive care units (ICUs) in Brazil.

ANS — Agência Nacional de Saúde Complementar — March/2020: From the ANS (National Supplementary Health Agency)—which provides legal and administrative regulation of the private health insurance market—we obtained municipality (city) data on the number of people covered by private health insurance in Brazil.

Expenditures: IBGE's Brazilian Consumer Expenditure Survey (2008–2009) provides data on expenditure on goods. To calculate the fraction of income spent on goods consumed outside the home, we use the following items of the consumption basket: food away from home, public transportation, medical services, and entertainment.

Social distancing: Inloco (`www.inloco.com.br`), a Brazilian technology company, collects anonymized location data from 60 million mobile phones in Brazil. By tracking with 3-meter precision the device's location and movements to different places (while ensuring user privacy), the company calculates the social distancing index for cities (municipalities) in Brazil, including the municipalities of Rio de Janeiro and Sao Paulo. For each municipality, the index calculates the percentage of devices that remained within a radius of 450 meters of the location identified as home. The index is computed daily and ranges from zero to one.

The company also measures the social distancing index for nonoverlapping areas within the municipalities of Rio de Janeiro and Sao Paulo, called "hexagons." Each hexagon in Rio de Janeiro measures between 756,000 square meters and 760,000 square meters. In Sao Paulo, hexagons have between 738,000 square meters and 745,000 square meters. Rio de Janeiro has 841 hexagons and Sao Paulo 1,301. The methodology to calculate the index for hexagons is similar: the percentage of devices in each hexagon that remained within a radius of 450 meters of the location identified as home.

Census tracts to hexagons: The spatial unit of analysis in Section 2 (stylized fact 2) is the hexagon provided by Inloco. To compute the number of slum dwellers and the number of housing units in slums for each hexagon, we needed to match those hexagons' boundaries to the boundaries of the census tracts. Notice that each city has more census tracts than hexagons—9,853 and 17,990 census tracts in Rio de Janeiro and Sao Paulo, respectively. When aggregating census tracts into hexagons, we consider that the population and households are uniformly distributed within each census tract. Hence, we calculate the characteristic of the hexagon as the weighted average of the census tracts' characteristics that intersect the hexagon, weighted by the fraction of the census tract's area that intersects the hexagon area. See Figures A1 and A2 for the location of census tracts and hexagons in Rio de Janeiro and Sao Paulo, respectively. Figure A3 shows the location of the 510 hexagons with slums in Rio de Janeiro, and the 598 with slums in Sao Paulo.

Covid-19 data at the neighborhood level: We obtained the neighborhood-level number of Covid-19 cases and deaths from the following websites:

- `https://www.data.rio/`
- `https://www.prefeitura.sp.gov.br/cidade/secretarias/upload/saude/COVID19_Relatorio_SItuacional_SMS_20200529.pdf`

Mortality data at the neighborhood level: Monthly data on Covid and non-Covid deaths at the neighborhood level stem from the Brazilian Mortality Information System (SIM). Sao Paulo data was obtained in the following website: `https://www.prefeitura.sp.gov.br/cidade/secretarias/saude/tabnet/mortalidade/index.php?p=6529`. Besides, Rio de Janeiro data are available at `http://tabnet.rio.rj.gov.br/cgi-bin/dh?sim/definicoes/sim_apos2005.def`.

Figure A1: Rio de Janeiro: Census tracts and hexagons

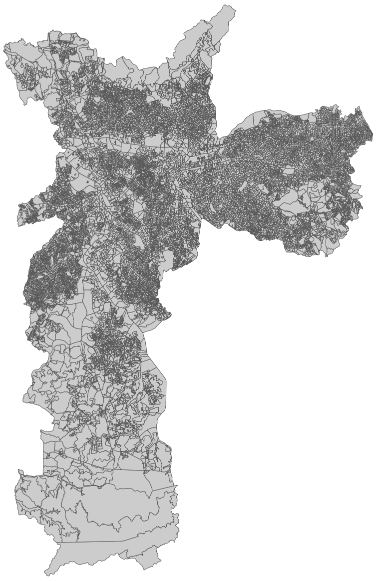
(a) 9,853 Census tracts in Rio de Janeiro

(b) 842 hexagons in Rio de Janeiro

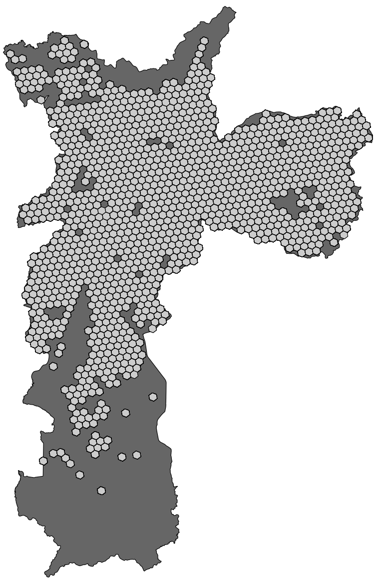
Notes. The figure shows the census tracts and the hexagons for the city of Rio de Janeiro.

Figure A2: Sao Paulo: Census Tracts and Hexagons

(a) 17,990 Census Tracts in São Paulo



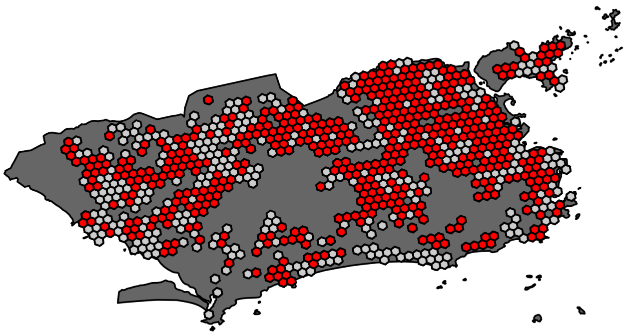
(b) 1,301 Hexagons in Sao Paulo



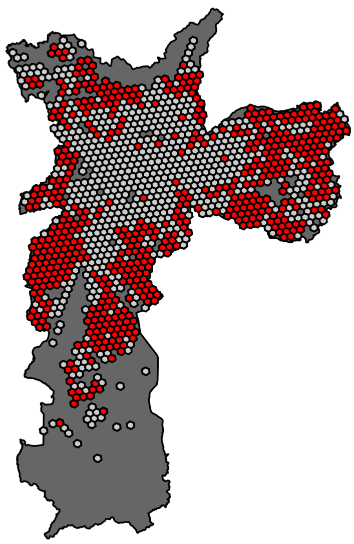
Notes. The figure shows the census tracts and the hexagons for the city of Sao Paulo.

Figure A3: Rio de Janeiro and Sao Paulo: Hexagons with slums (in red)

(a) Rio de Janeiro: Hexagons with slums (in red)



(b) Sao Paulo: Hexagons with slums (in red)

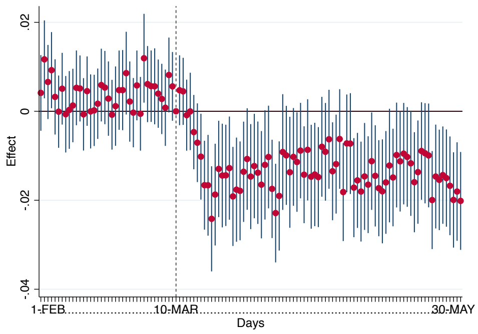


Notes. The figures show the location of the hexagons (in red) with slums. There are 510 hexagons with slums in Rio de Janeiro, and the 598 with slums in Sao Paulo.

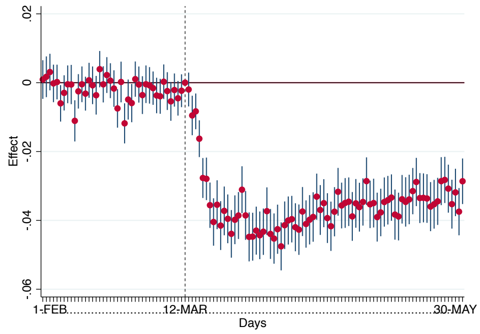
B Additional Tables and Figures

Figure B4: **Dynamic difference-in-differences analysis (results without weights): Rio de Janeiro and Sao Paulo**

(a) Rio de Janeiro



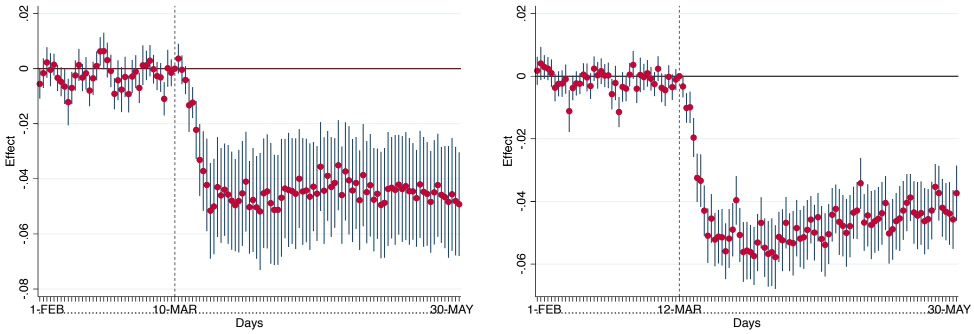
(b) Sao Paulo



Notes. The figure shows the results for coefficients estimated from Equation (1) without weighting for population. Coefficients should be interpreted as a change in percentage points relative to the base period, which corresponds to the day before each NPI. The "treated group" is composed of hexagons with at least one housing unit in a slum. We use 841 hexagons in Rio and 1,301 hexagons in Sao Paulo. Data are provided at the hexagon-day level. The dependent variable: social distancing index for hexagon h on day t. Standard errors clustered at hexagon level. Confidence intervals: 95%.

Figure B5: **Dynamic difference-in-differences analysis (results clustering at the neighborhood level): Rio de Janeiro and Sao Paulo**

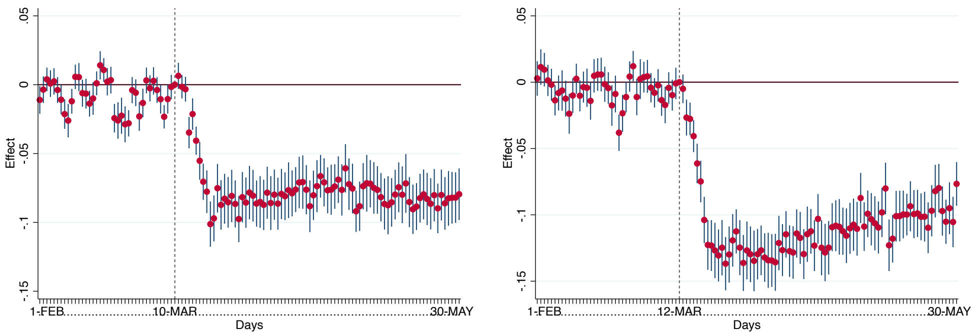
(a) Rio de Janeiro (b) Sao Paulo



Notes. The figure shows the results for coefficients estimated from Equation (1) clustering the standard errors at the neighborhood level. Each neighborhood has several hexagons. Coefficients should be interpreted as a change in percentage points relative to the base period, which corresponds to the day before each NPI. Vertical dotted lines indicate the day of the NPI in each city. The “treated group” is composed of hexagons with at least one housing unit in a slum. We use 841 hexagons in Rio and 1,301 hexagons in Sao Paulo. Data are provided at the hexagon-day level. The dependent variable: social distancing index for hexagon h on day t. Standard errors clustered at the neighborhood level. Confidence intervals: 95%.

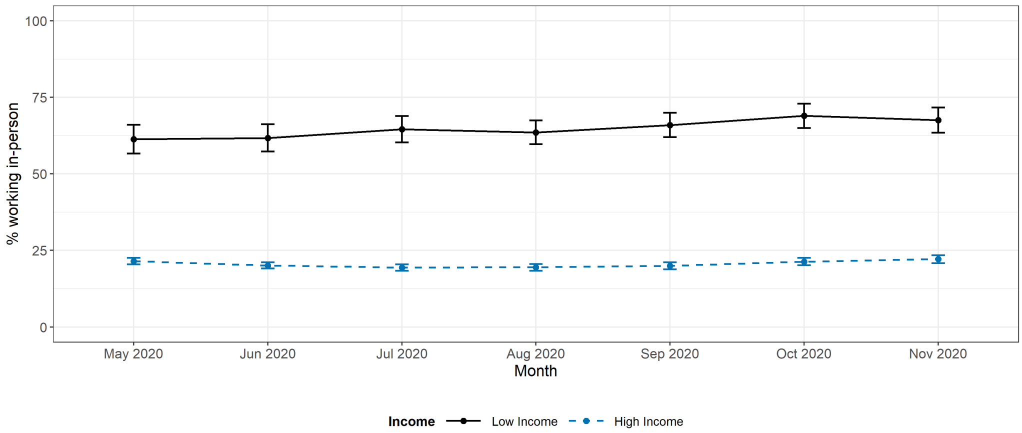
Figure B6: **Dynamic difference-in-differences analysis (share of slums as the treatment dummy): Rio de Janeiro and Sao Paulo**

(a) Rio de Janeiro (b) Sao Paulo



Notes. The figure shows the results for coefficients estimated from Equation (1). The treatment is the share of slums in each hexagon. Coefficients should be interpreted as a change in percentage points relative to the base period, which corresponds to the day before each NPI. Analysis at the hexagon-day level (841 hexagons in Rio and 1,301 hexagons in Sao Paulo). The dependent variable: social distancing index for hexagon h on day t. Standard errors clustered at hexagon level. Confidence intervals: 95%.

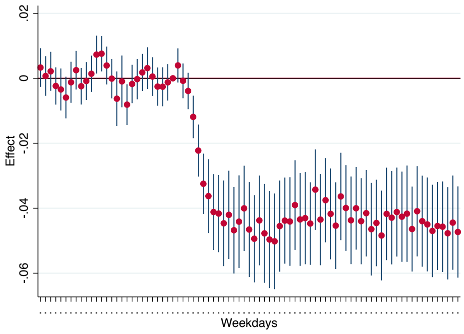
Figure B7: Working in-person and Income



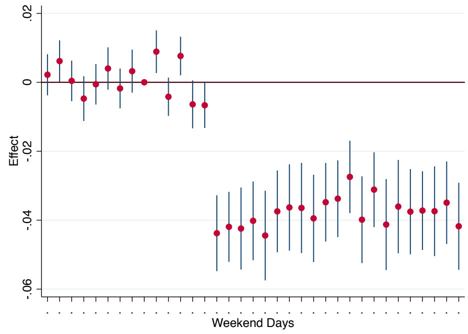
Notes. The figure shows the percentage of lower- and higher-income workers working in-person during the pandemic in Brazil. PNAD-Covid is a national household survey held by IBGE during seven months of the pandemic (from May to November 2020). The survey asks respondents about their work and health situation during the previous week, as well as socioeconomic characteristics. The survey data is used to calculate the association between income and in-person work during the pandemic. Lower-income workers are defined as those in the bottom 10% of the income distribution.

Figure B8: **Dynamic difference-in-differences analysis: heterogeneity analysis for weekdays and weekend days in Rio de Janeiro and Sao Paulo**

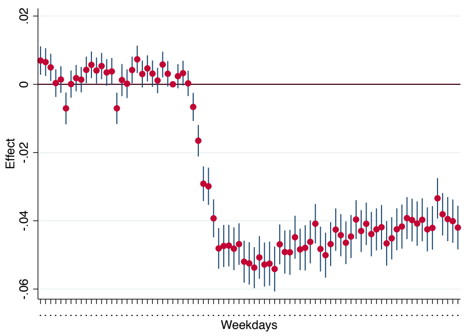
(a) Rio de Janeiro: Weekdays



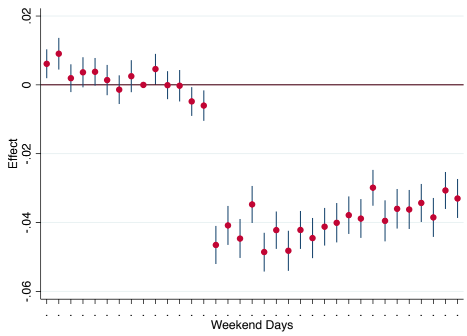
(b) Rio de Janeiro: Weekend days



(c) Sao Paulo: Weekdays



(d) Sao Paulo: Weekend Days



Notes. The figure shows the results for coefficients estimated from Equation (1) splitting the sample into weekdays (Monday to Friday) and weekend days (Saturday and Sunday). Coefficients should be interpreted as a change in percentage points relative to the base period, which corresponds to the day before each NPI. The "treated group" is composed of hexagons with at least one housing unit in a slum. We use 841 hexagons in Rio. Data are provided at the hexagon-day level. The dependent variable: social distancing index for hexagon h on day t. Standard errors clustered at the hexagon level. Confidence intervals: 95%.

Table B1: Difference-in-differences: Average impact of NPIs on social distancing

	Dependent variable: Social distancing index		
	(i)	(ii)	(iii)
Post × Slum Dummy	-0.0386***	-0.0429***	-0.0429***
	(0.0050)	(0.0021)	(0.0021)
Post × Slum Dummy × Rio Dummy			0.0043
			(0.0054)
Control group mean	0.2989	0.2820	0.2903
Hexagon FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Time FE × Rio Dummy	-	-	Yes
Observations	97,684	151,504	249,188
Number of Hexagons	841	1,301	2,142
City	Rio de Janeiro	Sao Paulo	Rio de Janeiro & Sao Paulo

Notes. Each column displays the results from a separate regression. This table presents results from the estimation of the following difference-in-difference specification: $Y_{ht} = \beta$ Post × Slum Dummy $+ \omega_h + \delta_t + \epsilon_{ht}$, where Y_{ht} is the social distancing index for hexagon h on day t, ω_h is the hexagon fixed effect, and δ_t is the time fixed effects. The unit of observation is a hexagon-day. The "treated group" is composed of hexagons with slums, while the comparison group is composed of hexagons without slums. The treated dummy "Post × Slum Dummy" equals one for hexagons with at least one housing unit in a slum for the days after implementation of the first NPI, and is zero otherwise. There are 841 hexagons in Rio de Janeiro and 1,301 hexagons in Sao Paulo. Robust standard errors (in parentheses) are clustered at the hexagon level. Observations are weighted by the hexagon population in 2010. The value for the control group mean is for the day before the implementation of the first NPI for each city. The regressions are for 120 days (from February 1 to May 30, 2020). Coefficients should be interpreted as a change in percentage points. Column (I) shows the results for the hexagons of Rio de Janeiro, while column (II) presents the results for Sao Paulo. Column (III) shows the results of a triple difference specification with all the hexagons of Rio de Janeiro and Sao Paulo (2,142 in total), where Rio Dummy equals one if the hexagon belongs to the city of Rio de Janeiro. The "Post × Slum Dummy × Rio Dummy" equals one for hexagons in Rio de Janeiro with at least one housing unit in a slum for the days after the implementation of the first NPI.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

C Laws of Motion

In the main body equation (9) describes the overall laws of motion, and equation (10) describes the sub-part that determines the transitions for the susceptible agents. The following contains the transitions for all other types.

To account for infected people, one counts those who started the last period susceptible and get infected this period, but also those who started the last period infected who neither require hospitalization nor recover:

$$\begin{aligned} M_{t+1}(i,g) &= M_t(s,g)\pi(n_t(s,g)+\ell_t(s,g),\Pi_t(g)) \\ &\quad + M_t(i,g)(1-\phi(0,g))(1-\alpha(g)) \end{aligned} \tag{16}$$

People in hospitals include those who entered the last period infected and do not recover but instead require hospitalization, as well as those already in the hospital in the previous period who neither die nor recover:

$$\begin{aligned} M_{t+1}(h,g) &= M_t(i,g)(1-\phi(0,g))\alpha(g) \\ &\quad + M_t(h,g)(1-\delta_t(g))(1-\phi(1,g)) \end{aligned} \tag{17}$$

Recovered and therefore resistant individuals include those who were infected and recover, those in hospitals who do not die but recover, and resistant individuals from the previous period:

$$M_{t+1}(r,g) = M_t(i,a)\phi(0,g) + M_t(h,g)\phi(1,g) + M_t(r,g) \tag{18}$$

The right-hand sides of equations (16) to (18) give the map T_j for states $j = i, s, r$.

For accounting purposes, the measure of deceased agents as a result of Covid-19 is given by new Covid deaths and those who died of it in previous periods:

$$M_{t+1}(deceased,g) = M_t(deceased,g) + (1-\phi(1,g))\delta_t(g)M_t(h,g),$$

while the number of newly infected people is given by susceptible agents who get infected:

$$N_{t+1}(i,g) \quad = \quad M_t(s,g)\pi(n_t(s,g)+\ell_t(s,g),\Pi_t(g)).$$

D Details on Calibration

D.1 Basic Reproduction Number — R_0

Consider an agent who is infected with Covid-19. They may recover with probability $\phi(0)$ or develop serious symptoms with probability α. These are functions of g also, but we suppress this dependence for notational convenience. The following table gives what happens to a measure 1 of agents who are infected right now over the course of the next few weeks:

Week	Frac. recovered	Frac. still infected	Frac. w/ symptoms
1	$\phi(0)$	$(1-\phi(0))(1-\alpha)$	$(1-\phi(0))\alpha$
2	$(1-\phi(0))(1-\alpha)\phi(0)$	$[(1-\phi(0))(1-\alpha)]^2$	$(1-\phi(0))(1-\alpha)(1-\phi(0))\alpha$
3	$[(1-\phi(0))(1-\alpha)]^2\,\phi(0)$	$[(1-\phi(0))(1-\alpha)]^3$	$[(1-\phi(0))(1-\alpha)]^2\,(1-\phi(0))\alpha$
4	...	...	...

The probability that an infected agent leaves such state is therefore $\bar{\phi}(0) = \phi(0)+(1-\phi(0))\alpha$. This is the probability of recovery and the probability that the agent requires hospitalization. Hence, the expected amount of time one stays in state i is[39]

$$T_i = \frac{1}{\phi(0)+(1-\phi(0))\alpha}.$$

Similarly, the probability that a hospitalized agent leaves such state is $\phi(1)+(1-\phi(1))\delta$. This is the probability of recovery and the death-because-of-Covid probability. Hence, the expected amount of time one stays in state h is

$$T_h = \frac{1}{\phi(1)+(1-\phi(1))\delta}.$$

Now, the probability that one moves from the i state to the h state is given by:

$$P_h = \frac{(1-\phi(0))\alpha}{1-(1-\phi(0))(1-\alpha)}.$$

Note that these expressions should be functions of one's group g, but we have suppressed this for notational convenience.

[39] Let T_i be the expected amount of time one stays in state i, this is given by

$$T_i = E\left(\sum_{j=1}^{\infty} j\bar{\phi}(0)(1-\bar{\phi}(0))^{j-1}\right) = \frac{1}{\bar{\phi}(0)} = \frac{1}{\phi(0)+(1-\phi(0))\alpha}.$$

Let $\tilde{n}(g)$ denote the amount of time an infected person of group g spends outside. Let $\bar{\ell}$ be the interaction time for people in hospitals. Finally, let $\bar{n}$ be the average (across groups) amount of time people spend outside. At the outset of the disease, a measure 1 of the population is susceptible.

Then, $R_0(g)$ (i.e., for an infected person of group g) is given by

$$R_0(g) = \left[\tilde{n}(g)T_i(g) + \bar{\ell}P_h(g)T_h(g)\right]\bar{n}\Pi_0.$$

This is the average number of people someone infects (for a person of a given group). The economy's R_0 will be the weighted average across groups:

$$R_0 = \sum_a \omega(g)R_0(g),$$

where $\omega(g)$ is the weight of group g in the population.

D.2 Computing Weekly Rates

From the table of the previous subsection (Appendix D.1), one can show that the fraction of people who will require hospitalization F_h is given by

$$\begin{aligned} F_h &= (1-\phi(0))\alpha + (1-\phi(0))(1-\alpha)(1-\phi(0))\alpha + [(1-\phi(0))(1-\alpha)]^2(1-\phi(0))\alpha + ... \\ &= (1-\phi(0))\alpha\left[1 + (1-\phi(0))(1-\alpha) + [(1-\phi(0))(1-\alpha)]^2 + ...\right] \\ &= (1-\phi(0))\alpha\frac{1}{1-(1-\phi(0))(1-\alpha)}. \end{aligned}$$

Solving out for α gives

$$\alpha = \frac{B\phi(0)}{1-B(1-\phi(0))},$$

where $B = F_h/(1-\phi(0))$. With $\phi(0)$ given by the average time for recovery, one can use the preceding formula to get α. Once more, these expressions should be functions of one's group g, but we have suppressed this for convenience.

We can do similarly for hospitalized agents to figure out at what rate they die. Here is the table:

Week	Frac. recovered	Frac. still w symptoms	Frac. dead
1	$\phi(1)$	$(1-\phi(1))(1-\delta)$	$(1-\phi(1))\delta$
2	$(1-\phi(1))(1-\delta)\phi(1)$	$[(1-\phi(1))(1-\delta)]^2$	$(1-\phi(1))(1-\delta)(1-\phi(1))\delta$
3	$[(1-\phi(1))(1-\delta)]^2\phi(1)$	$[(1-\phi(1))(1-\delta)]^3$	$[(1-\phi(1))(1-\delta)]^2(1-\phi(1))\delta$
4	...	...	...

Using the same steps as earlier and denoting the fraction who die by F_d, we get

$$\delta = \frac{A\phi(1)}{1 - A(1 - \phi(1))},$$

where $A = F_d/(1 - \phi(1))$.

D.3 Implementing Lockdowns in the Model

In Section 6.2, we implement a variety of shelter-at-home policies. We achieve the desired lockdown by setting the policy parameter $\lambda(j, g)$ to the value necessary to induce the agent to comply with the policy. The next table reports the calibrated values of $\lambda(j, g)$ for each policy:

Lockdown	λ_p	
intensity	Noninfected	Infected
25%	1.88	0
50%	6.45	4.46
75%	33.4	31.45

E Sensitivity Analysis

Table E2 provides results of sensitivity analysis in which we perturb each parameter by 1%. The results for the modified benchmark and the counterfactual with no slums are quite similar to the ones obtained in our baseline (Table 3).

Our benchmark calibration sets $\zeta = 0.334$; that is, around 1/3 of the time an individuals spend outside is within members of their own group. Table E3 performs robustness analyses on this parameter. In particular, we increase it to 1/2 and 2/3. So, individuals spend more time within their group. The higher the parameter ζ is (the higher the degree of sorting in the economy), the more disperse the health dynamics between groups become. With more sorting, rich non-slum residents that protect themselves more interact more with one another. Hence, this group faces a less infectious environment and get infected and die less. The opposite happens to slum residents. The aggregate effect is quantitatively similar. In a one-group world (the No slums scenario), this parameter does not affect the results.

Table E2: Sensitivity analysis

	ζ		Π_0		$\phi(0,o)$		$\phi(0,f)$		$\phi(1,o),\phi(1,f)$	
	Bench.	No slum	Bench.	No slum	Bench.	No slum	Bench.	No slum	Bench.	No slum
Wks to peak srsly ill (slum)	10.00	–	10.00	–	10.00	–	10.00	–	10.00	–
Wks to peak srsly ill (other)	11.00	14.00	11.00	14.00	11.00	15.00	11.00	14.00	11.00	14.00
Dead p/ 1,000 LR (slum)	10.13	–	10.18	–	9.77	–	5.67	–	10.06	–
Dead p/ 1,000 LR (other)	6.56	7.47	6.65	7.58	4.68	5.00	6.15	7.47	6.53	7.43
Dead p/ 1,000 LR (all)	7.35	7.47	7.43	7.58	5.81	5.00	6.05	7.47	7.31	7.43
Immune in LR (slum), %	74.46	–	74.75	–	72.97	–	77.56	–	74.34	–
Immune in LR (other), %	39.63	46.01	40.16	46.54	42.20	46.87	38.05	46.01	39.71	46.03
Immune in LR (all), %	47.35	46.01	47.82	46.54	49.01	46.87	46.80	46.01	47.38	46.03
GDP 1year - rel to BM	1.00	1.17	1.00	1.17	1.00	1.18	1.00	1.16	1.00	1.17

	$\tilde{\delta}_1(o)$		$\tilde{\delta}_1(f)$		$\bar{\ell}$		ψ		Z_{pub}	
	Bench.	No slum	Bench.	No slum	Bench.	No slum	Bench.	No slum	Bench.	No slum
Wks to peak srsly ill (slum)	10.00	–	10.00	–	10.00	–	10.00	–	10.00	–
Wks to peak srsly ill (other)	11.00	14.00	11.00	14.00	11.00	14.00	11.00	14.00	11.00	14.00
Dead p/ 1,000 LR (slum)	10.10	–	10.11	–	10.11	–	10.11	–	10.10	–
Dead p/ 1,000 LR (other)	6.57	7.48	6.57	7.47	6.57	7.48	6.56	7.47	6.56	7.46
Dead p/ 1,000 LR (all)	7.35	7.48	7.35	7.47	7.35	7.48	7.35	7.47	7.34	7.46
Immune in LR (slum), %	74.33	–	74.33	–	74.34	–	74.33	–	74.34	–
Immune in LR (other), %	39.68	46.00	39.69	46.01	39.71	46.03	39.69	46.01	39.70	46.02
Immune in LR (all), %	47.36	46.00	47.36	46.01	47.38	46.03	47.37	46.01	47.38	46.02
GDP 1year - rel to BM	1.00	1.17	1.00	1.17	1.00	1.17	1.00	1.17	1.00	1.17

	Z_{priv}		ρ		θ		γ		b	
	Bench.	No slum	Bench.	No slum	Bench.	No slum	Bench.	No slum	Bench.	No slum
Wks to peak srsly ill (slum)	10.00	–	10.00	–	10.00	–	10.00	–	10.00	–
Wks to peak srsly ill (other)	11.00	14.00	11.00	14.00	11.00	14.00	11.00	14.00	11.00	14.00
Dead p/ 1,000 LR (slum)	10.11	–	10.11	–	10.11	–	10.18	–	10.05	–
Dead p/ 1,000 LR (other)	6.57	7.47	6.57	7.47	6.57	7.47	6.63	7.56	6.56	7.44
Dead p/ 1,000 LR (all)	7.35	7.47	7.35	7.47	7.35	7.47	7.41	7.56	7.33	7.44
Immune in LR (slum), %	74.33	–	74.34	–	74.34	–	74.67	–	74.14	–
Immune in LR (other), %	39.69	46.01	39.68	46.01	39.68	46.01	39.96	46.36	39.75	45.98
Immune in LR (all), %	47.36	46.01	47.36	46.01	47.36	46.01	47.65	46.36	47.37	45.98
GDP 1year - rel to BM	1.00	1.17	1.00	1.17	1.00	1.17	1.00	1.17	1.00	1.17

	λ_a		λ_d		$w(o)$		ξ_f		$\sum_j M_0(j,f)$	
	Bench.	No slum	Bench.	No slum	Bench.	No slum	Bench.	No slum	Bench.	No slum
Wks to peak srsly ill (slum)	10.00	–	10.00	–	10.00	–	10.00	–	10.00	–
Wks to peak srsly ill (other)	11.00	14.00	11.00	14.00	11.00	14.00	11.00	14.00	11.00	14.00
Dead p/ 1,000 LR (slum)	10.07	–	10.08	–	10.11	–	10.07	–	10.13	–
Dead p/ 1,000 LR (other)	6.52	7.42	6.54	7.44	6.56	7.47	6.57	7.47	6.55	7.47
Dead p/ 1,000 LR (all)	7.31	7.42	7.33	7.44	7.35	7.47	7.35	7.47	7.35	7.47
Immune in LR (slum), %	74.12	–	74.20	–	74.34	–	74.15	–	74.48	–
Immune in LR (other), %	39.42	45.72	39.55	45.85	39.67	46.01	39.73	46.01	39.59	46.01
Immune in LR (all), %	47.11	45.72	47.23	45.85	47.35	46.01	47.35	46.01	47.40	46.01
GDP 1year - rel to BM	1.00	1.17	1.00	1.17	1.00	1.17	1.00	1.17	1.00	1.17

Table E3: Robustness: alternative zetas (mixing between slum residents and others)

	$\zeta = 1/2$		$\zeta = 2/3$	
	Benchmark	No slums	Benchmark	No slums
Wks to peak srsly ill (slum)	9.00	–	8.00	–
Wks to peak srsly ill (other)	10.00	14.00	10.00	14.00
Srsly ill p/ 1,000 @ peak (slum)	2.61	–	3.30	–
Srsly ill p/ 1,000 @ peak (other)	0.76	0.65	0.70	0.65
Dead p/ 1,000 1year (slum)	10.92	–	11.47	–
Dead p/ 1,000 1year (other)	5.91	6.87	5.55	6.87
Dead p/ 1,000 1year (all)	7.02	6.87	6.86	6.87
Dead p/ 1,000 LR (slum)	10.97	–	11.51	–
Dead p/ 1,000 LR (other)	6.12	7.47	5.78	7.47
Dead p/ 1,000 LR (all)	7.19	7.47	7.05	7.47
Immune in LR (slum), %	79.20	–	82.10	–
Immune in LR (other), %	37.47	46.01	36.08	46.01
Immune in LR (all), %	46.71	46.01	46.27	46.01
Hrs @ home (slum) - peak	84.82	–	86.53	–
Hrs @ home (other) - peak	86.61	78.00	84.24	78.00
Hrs @ home (slum) - 6m	65.44	–	64.96	–
Hrs @ home (other) - 6m	67.99	72.42	67.32	72.42
Value - susceptible (slum)	1966.00	–	1964.70	–
Value - susceptible (other)	4319.70	4315.00	4321.80	4315.00
Value - susceptible (all)	3798.30	4315.00	3799.70	4315.00

F Results for Extensions

Table F4 provides results for the benchmark and no-slum scenarios when a vaccine arrives after 18 months.

Table F5 reports results for the same scenarios when individuals that recover from Covid-19 have a possibility of becoming susceptible again.

Recall from Section 7.3 that the productivity of teleworking v varies with the amount of teleworking performed according to the function $\tau(v) = \tau_0 - \tau_1 v$. As more work is moved to the home, the less productive it becomes. We must then set values for the two parameters τ_0 and τ_1. We target two values. First, at the peak of the disease, 60% of working hours for the richer non-slum residents consist of teleworking hours. This is consistent with data showing that only around 20% of richer individuals were working in person (but most certainly were not working fully from home—See Appendix Figure B7). Moreover, we assume that, at the peak of the disease, their income falls by 40%, which is consistent with the fall in credit card activity reported in Figure 9. This yields $\tau_0 = 0.8$ and $\tau_1 = 1.4$. The main results are reported in Table F6.

Table F7 reports the parameters that were changed for the Sao Paulo calibra-

Table F4: Vaccine arrives 1.5 years after the pandemic outbreak

	Benchmark	No slums
Wks to peak srsly ill (slum)	10.00	–
Wks to peak srsly ill (other)	11.00	14.00
Srsly ill p/ 1,000 @ peak (slum)	1.88	–
Srsly ill p/ 1,000 @ peak (other)	0.77	0.65
Dead p/ 1,000 1year (slum)	10.03	–
Dead p/ 1,000 1year (other)	6.34	6.84
Dead p/ 1,000 1year (all)	7.16	6.84
Dead p/ 1,000 LR (slum)	10.09	–
Dead p/ 1,000 LR (other)	6.53	7.35
Dead p/ 1,000 LR (all)	7.32	7.35
Immune in LR (slum), %	74.06	–
Immune in LR (other), %	39.24	44.36
Immune in LR (all), %	46.96	44.36
Hrs @ home (slum) - peak	80.97	–
Hrs @ home (other) - peak	86.29	78.03
Hrs @ home (slum) - 6m	66.05	–
Hrs @ home (other) - 6m	69.42	72.48
Value - susceptible (slum)	1968.20	–
Value - susceptible (other)	4317.50	4315.50
Value - susceptible (all)	3797.20	4315.50

Table F5: Individuals who recover from Covid-19 have a 50% probability of not acquiring immunity

	Benchmark	No slums
Wks to peak srsly ill (slum)	11.00	–
Wks to peak srsly ill (other)	12.00	15.00
Srsly ill p/ 1,000 @ peak (slum)	2.10	–
Srsly ill p/ 1,000 @ peak (other)	0.82	0.70
Dead p/ 1,000 1year (slum)	18.02	–
Dead p/ 1,000 1year (other)	10.31	10.04
Dead p/ 1,000 1year (all)	12.02	10.04
Dead p/ 1,000 LR (slum)	19.32	–
Dead p/ 1,000 LR (other)	12.57	14.23
Dead p/ 1,000 LR (all)	14.07	14.23
Immune in LR (slum), %	71.19	–
Immune in LR (other), %	37.85	43.57
Immune in LR (all), %	45.23	43.57
Hrs @ home (slum) - peak	80.01	–
Hrs @ home (other) - peak	87.06	78.72
Hrs @ home (slum) - 6m	72.07	–
Hrs @ home (other) - 6m	76.50	76.00
Value - susceptible (slum)	1948.20	–
Value - susceptible (other)	4287.60	4283.30
Value - susceptible (all)	3769.50	4283.30

Table F6: Simulations with teleworking

	Benchmark	No slums
Wks to peak srsly ill (slum)	10.00	–
Wks to peak srsly ill (other)	10.00	13.00
Srsly ill p/ 1,000 @ peak (slum)	1.91	–
Srsly ill p/ 1,000 @ peak (other)	0.50	0.51
Dead p/ 1,000 1year (slum)	10.13	–
Dead p/ 1,000 1year (other)	5.61	6.16
Dead p/ 1,000 1year (all)	6.61	6.16
Dead p/ 1,000 LR (slum)	10.26	–
Dead p/ 1,000 LR (other)	6.05	7.25
Dead p/ 1,000 LR (all)	6.98	7.25
Immune in LR (slum), %	76.19	–
Immune in LR (other), %	38.40	46.00
Immune in LR (all), %	46.77	46.00
Hrs @ home (slum) - peak	78.78	–
Hrs @ home (other) - peak	92.38	79.45
Hrs @ home (slum) - 6m	65.79	–
Hrs @ home (other) - 6m	71.69	74.22
Value - susceptible (slum)	1968.10	–
Value - susceptible (other)	4318.80	4315.60
Value - susceptible (all)	3798.10	4315.60

tion. Table F8 reports the baseline results for this calibration.

Table F7: Parameters that were changed for the Sao Paulo calibration

Parameter	Value	Interpretation	Source
Panel A: City parameters (6 parameters)			
$\sum_j M_0(j,f)$	0.114	Fraction of people living in slums	Census
$w(f)$	0.290	Wage rate of slum agents	Census
ξ_f	0.030	Frac. of space assigned to slums	Census
ξ_o	0.970	Frac. of space assigned to areas wo slums	Census
Panel B: Disease parameters (15 parameters)			
ψ	0.213	Prop. non-slum agents with priv. insurance	ANS
Z_{pub}	1.10e-4	ICU beds (per capita) in public system	Covid Radar
Z_{priv}	3.06e-4	ICU beds (per capita) in private system	Covid Radar
Panel C: Preference parameters (7 parameters)			
θ	0.135	Production of leisure goods	Internally estimated
γ	1.086	Rel. utility weight–leisure goods	Internally estimated
λ_d	2.449	Rel. utility weight–leisure at home	Internally estimated
λ_a	4.441	Rel. utility weight–leisure at home; infected	Internally estimated
b	8.656	Value of being alive	Internally estimated

Table F8: Calibration for Sao Paulo

	Benchmark	No slums
Wks to peak srsly ill (slum)	10.00	–
Wks to peak srsly ill (other)	12.00	14.00
Srsly ill p/ 1,000 @ peak (slum)	2.13	–
Srsly ill p/ 1,000 @ peak (other)	0.78	0.71
Dead p/ 1,000 1year (slum)	9.97	–
Dead p/ 1,000 1year (other)	6.19	6.42
Dead p/ 1,000 1year (all)	6.62	6.42
Dead p/ 1,000 LR (slum)	10.05	–
Dead p/ 1,000 LR (other)	6.50	6.93
Dead p/ 1,000 LR (all)	6.90	6.93
Immune in LR (slum), %	77.66	–
Immune in LR (other), %	43.03	46.50
Immune in LR (all), %	46.98	46.50
Hrs @ home (slum) - peak	81.80	–
Hrs @ home (other) - peak	83.31	78.11
Hrs @ home (slum) - 6m	66.97	–
Hrs @ home (other) - 6m	70.18	72.31
Value - susceptible (slum)	2199.30	–
Value - susceptible (other)	4498.50	4497.40
Value - susceptible (all)	4236.20	4497.40