Slums and Pandemics*

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Abstract

This paper studies the role of slums in shaping the economic and health dynamics of pandemics. Using data from millions of mobile phones in Brazil, an event-study analysis shows that residents of overcrowded slums engaged in less social distancing after the outbreak of Covid-19. We develop a choice-theoretic equilibrium model in which poorer agents live in high-density slums and richer individuals do not. The model is calibrated to Rio de Janeiro. Slum dwellers account for a disproportionately high number of infections and deaths. In a counterfactual scenario without slums, deaths increase in non-slum neighborhoods. Policy simulations indicate that: reallocating medical resources cuts deaths and raises output and the welfare of both groups; mild lockdowns favor slum individuals by mitigating the demand for hospital beds, whereas strict confinements mostly delay the evolution of the pandemic; and cash transfers benefit slum residents to the detriment of others, highlighting important distributional effects.

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"The issue is that everything is so close together here. One house next to the other; one on top of the other. What looks like only a small one is actually five or six in the same space. A lot of people here work outside of Paraisopolis. If the virus spreads here, it will spread all over Sao Paulo." Hebert Douglas, resident of Paraisopolis, one of the largest slums in Brazil (Folha de São Paulo 2020)

1 Introduction

Disease outbreaks can affect vulnerable people disproportionately, contributing to the increase in health and economic disparities. Since its onset, the Covid-19 pandemic has affected places where most social interactions occur, as the new coronavirus spreads mainly through close contact among people. Consequently, health authorities recommend that people avoid crowded areas and practice social distancing. Such measures can be challenging to put in practice in densely populated areas, such as overcrowded slums in developing countries.[1] Residents of these neighborhoods are also poorer individuals whose incomes are likely to be more adversely affected by lockdowns. Slums are prevalent in the majority of cities in developing countries and more than 1 billion people in the world live in them (United Nations (2020)). Despite their importance, to the best of our knowledge, no paper in the growing literature on the economics of epidemics has addressed the role of slums in shaping the economic and health dynamics of pandemics. This paper fills this gap and makes three contributions.

Our first contribution is empirical. We use daily geo-localized data from millions of mobile phones in Sao Paulo and Rio de Janeiro, the two largest cities in Brazil, one of the countries most affected by the Covid-19 pandemic.[2] Through an event-study analysis, we show that social distancing increased significantly

[1] The definition of slums varies by country, but is always associated with deprivation-related characteristics such as low-quality housing, lack of public services, overcrowding, and lack of tenure security.

[2] Inloco (`https://inloco.com.br/`), a Brazilian technology company, shared the data on social distancing. See Section 2 for details.

less in areas with slums after the adoption of non-pharmaceutical interventions (NPIs)—such as the closure of schools, restaurants and retail stores—in both of these cities. We also find that areas with slums are associated with more hospitalizations and fatalities.

The second contribution is theoretical. We build a model with heterogeneous housing tenure and behavioral choices to address how the prevalence of slums contributes to the spread of infectious diseases. Agents live in two localities: poorer agents live in high-density places (slums), while richer agents do not. Slum residents are also less likely to have access to intensive care units (ICUs) in hospitals, but they are on average younger (as in the data). People leave their houses to work or enjoy leisure outside and this can lead to infections. Individuals from different locations interact when they leave their homes. The model allows for both negative and positive externalities regarding social distancing. The risks that one group takes might spill over onto others through increased transmission (negative externality), but the point of herd immunity may be reached more quickly (positive externality).

The paper's third contribution is quantitative. We parameterize the model to be consistent with Covid-19 transmission and with key empirical moments of the city of Rio de Janeiro, one of the epicenters of the pandemic in Brazil. The model reproduces our empirical finding that, after the outbreak of the pandemic, low-income slum residents engage in less social distancing relative to individuals who live in other neighborhoods. As they are poorer, they work relatively more hours even though this means spending more time in crowded areas. This leads to worse health outcomes for this group. Although slum dwellers correspond to 22% of Rio de Janeiro's population, they account for around 30% of the Covid-19 deaths in the city. This group thus contributes more towards reaching herd immunity in society. In a counterfactual world without slums, residents in other neighborhoods end up catching the virus more and die in higher numbers, which illustrates important distributional effects.

We use the model to simulate a variety of policy experiments: the reallocation of existing medical resources, shelter-at-home policies, and cash-transfer schemes. In developing countries, most poor individuals do not have private health insurance and must rely on publicly provided health care that is often at capacity. We investigate the pooling of all intensive care units in Rio de Janeiro into one group that is offered to anyone who needs it, regardless of insurance. This alleviates the capacity constraints and decreases the death burden of the disease among both groups of the population. The total death rate is reduced by 28% relative to an environment with no policies. In our simulations, this redistributive policy positively impacts aggregate welfare and output.

Shelter-at-home policies act to delay the dynamics of the disease substantially. In our model, though these policies buy time, the long-run death rate does not change much. Interestingly, lighter policies can be more effective as they slowly increase the number of infected, and this smooths the burden on hospital resources and saves lives. On the other hand, very strict lockdowns contain the disease so much that, when lifted, the health dynamics is quite similar to a no-policy scenario, only delayed—if no improvement in health infrastructure takes place or a treatment becomes available. In addition, strict lockdowns promote a deep economic downturn in the short run. Confinement policies that shelter one particular group lead to a redistribution of deaths from the sheltered group to the other. This actually leads to the welfare of both groups decreasing: one faces more deaths and the other a restriction on their movement.

Cash transfers are particularly important for the poorer individuals who live in slums. When we implement a policy that hands over cash to the population, slum dwellers can afford to become relatively more cautious. This decreases the number of infections among this group and consequently increases this statistic among those living in other neighborhoods. Once again, the resulting outcome highlights important heterogeneous effects across groups.

This paper relates to the economics literature that adds behavioral choices to epidemiological models in the tradition of Kermack and McKendrick (1927). This effort has been mostly theoretical, e.g. Kremer (1996), Quercioli and Smith (2006), and Toxvaerd (2019). There exists some quantitative articles in the context of HIV/AIDS, such as Greenwood et al. (2017, 2019) and Chan, Hamilton, and Papageorge (2016). Our paper shares the principle of modeling infectious diseases with a special attention to behavioral choices. We contribute to this literature by studying individual choices in slums, which are an important feature in cities in the majority of developing countries.[3]

There has recently been a great incursion of the economics literature into the study of the Covid-19 pandemic. Some papers have looked at optimal confinement policies that force stricter levels of social distancing beyond what individuals endogenously choose, e.g. Farboodi, Jarosch, and Shimer (2020) and Eichenbaum, Rebelo, and Trabandt (2020). A few papers have added choices made by heterogeneous groups, like different sectors (Kaplan, Moll, and Violante (2020)) or age groups (Brotherhood et al. (2020) and Favero, Ichino, and Rustichini (2020)). Our work is mostly related to Brotherhood et al. (2020) and Alon et al. (2020). We expand the framework developed by Brotherhood et al. (2020) by adding different locations (slums and other neighborhoods), poorer and richer agents, and differential access to health care. Few quantitative papers focus on studying the Covid-19 pandemic in developing countries. One notable exception is Alon et al. (2020), but they do not model slums and the impact of high-density environments as we do.

Our work also relates to two strands of the urban economics literature. First, we connect to the papers on agglomeration economies aiming to understand the advantages and disadvantages of density in cities (Duranton and Puga (2004); Ahlfeldt et al. (2015); Henderson and Turner (2020)). Most of the papers in this field focus on the advantages of density and increased physical proximity, such as sharing ideas, fostering innovation, and faster technology adoption (Duranton and Puga (2020)). We add to some recent papers studying the costs of agglomeration (e.g., Combes, Duranton, and Gobillon (2019)) by explicitly taking into account externalities of physical proximity in the context of a pandemic. Second, we add to the strand modeling the causes and consequences of slums (e.g., Brueckner and Selod (2009); Monge-Naranjo, Ferreira, and Pereira (2018);

[3]From a historical perspective, the association between slums and pandemics goes well beyond the Covid-19 pandemic, including the cholera outbreak in the 1850s in London's slums (Smith (1964)) and the Spanish Flu outbreak in slums in Philadelphia (Crosby (2003)).

Cavalcanti, Da Mata, and Santos (2019); Henderson et al. (2020)) by taking into account the role of slums during disease outbreaks.

This paper is organized as follows. The next section presents an empirical analysis regarding how the Covid-19 pandemic evolved differently in slums and other areas in Brazil. Section 3 describes the model environment and Section 4 discusses its calibration. Section 5 presents our baseline results and Section 6 provides results for policy experiments. Section 7 concludes.

2 Empirical Motivation

Slums are densely populated areas with narrow alleys and small houses. Some informal settlements lack adequate sanitation and piped water supply. Poverty is widespread. According to the 2010 Brazilian Population Census, the population density in slums in the cities of Rio de Janeiro and Sao Paulo is approximately five times larger than in other neighborhoods. In addition, per capita income of households living in slums in these two cities is roughly one-third of the income of those living in other areas. These features of slums imply that movement restrictions are in general more costly for individuals living in slums compared with those living in other neighborhoods. We hypothesize then that it is harder to adhere to social distancing practices in slums.

To investigate how social distancing changed during the pandemic in areas with and without slums, we use a social distancing index created and developed by Inloco (`https://inloco.com.br/`), a Brazilian technology company. The company collects anonymized location data from millions of mobile phones in Brazil, tracking (with a 3-meter precision) the devices' location and movements to different places, but ensuring user privacy.[4] The company divides cities into non-overlapping "hexagons" and measures the percentage of devices in a given hexagon that remained within a radius of 450 meters of the

[4]See Peixoto et al. (2020) for more details on the Inloco data. Ajzenman, Cavalcanti, and Da Mata (2020) compare Inloco's and Google's social distancing indexes for Brazil and show a high correlation between the two measures.

location identified as home. The index is computed daily and ranges from zero to one. We obtained the social distancing index for each hexagon from February 1 to May 30, 2020 (120 days) for two cities: Rio de Janeiro and Sao Paulo. Rio de Janeiro has 841 hexagons, Sao Paulo 1,301 (see Figures A1 and A2 in Appendix A for more details on the non-overlapping hexagons).

We define slums as housing units in "subnormal agglomerations." According to the population 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. Notice that there is a connection between housing units in subnormal agglomeration and the notion of a "slum." See online Appendix A for more detail on data sources and definitions.

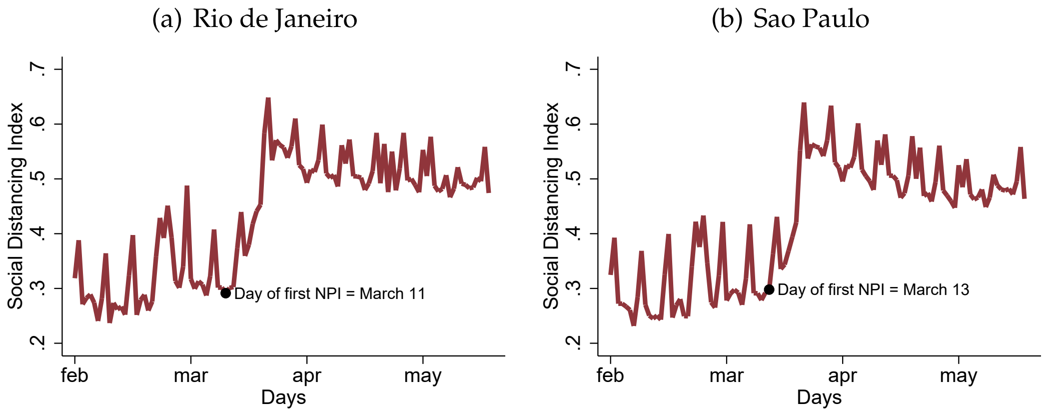
Fact 1: Social distancing increased after non-pharmaceutical Interventions (NPIs)

Figure 1 contains the daily average social distancing index for the cities of Rio de Janeiro (Figure 1(a)) and Sao Paulo (Figure 1(b)). It shows that social distancing increased in both cities after NPIs were implemented. The first NPI affecting the city of Rio de Janeiro was announced on March 11. One can observe a sharp increase in the social distancing index just a few days after this measure was implemented. A similar pattern is observed for Sao Paulo, where the first NPI was announced on March 13.

Fact 2: In slums, social distancing increased less after the adoption of NPIs

We now present reduced-form evidence showing an association between social distancing and slums. The unit of investigation is the hexagon provided by Inloco. We build a dataset of socioeconomic characteristics for each hexagon based on the census tracts of the 2010 Brazilian Population Census conducted by the country's statistical office (*Instituto Brasileiro de Geografia e Estatística*, IBGE)—see Appendix A for more details—and combine this dataset with our social distancing index. We then calculate the number of slum housing units in each hexagon. We create a dummy variable that equals one if the hexagon

Figure 1: **Social distancing index**



Notes. The figure shows the evolution of the social distancing index for the cities of Rio de Janeiro and Sao Paulo between February 1 and May 18. The first non-pharmaceutical intervention in Rio de Janeiro was put in place on March 11 and in Sao Paulo on March 13.

has any slum within its boundaries and zero otherwise. Rio de Janeiro has 510 hexagons with slums; Sao Paulo has 598 (see Figure A3 in online Appendix A for the location of those hexagons). The "treated group" is composed of hexagons with slums, while the comparison group is composed of hexagons without slums.

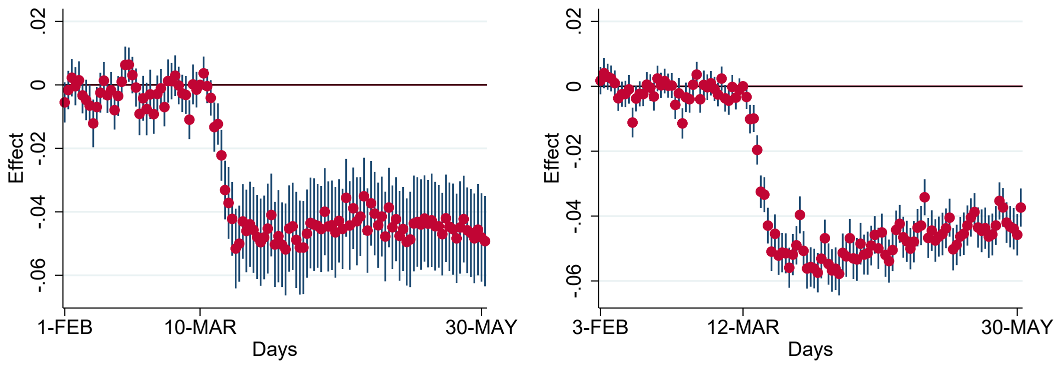
To investigate how social distancing evolved in slums compared to other areas after the implementation of NPIs, we use the following event-study specification:

$$Y_{ht} = \sum_{\tau=-K}^{L} \beta_\tau \mathbf{1}\{t_t - t^* = \tau\} + \omega_h + \delta_t + \epsilon_{ht} \ , \tag{1}$$

where Y_{ht} is the social distancing index for hexagon h on day t. The hexagon fixed effect ω_h accounts for unobserved time-invariant determinants of social distancing, while the inclusion of time fixed effects δ_t adjusts for aggregate shocks that are common to all hexagons. The indicator variable $\mathbf{1}\{t_t - t^* = \tau\}$ takes the value of one for hexagons with slums when τ periods (days) away from the day of the first NPI (t^*), and zero otherwise. The parameter β_τ is the dynamic treatment effect. We set the coefficient on β_{-1} equal to zero to use the day before the first NPI as the base date—March 10 in Rio de Janeiro and

Figure 2: **Event-study Analysis: Effect of NPIs on social distancing in areas with slums relative to those without slums**

(a) Rio de Janeiro (b) Sao Paulo



Notes. The figure shows the results for coefficients estimated from Equation (1). 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 de Janeiro and 1,301 hexagons in Sao Paulo. Data are provided at the hexagon-day level. The dependent variable is the social distancing index for hexagon h on day t. Standard errors clustered at the hexagon level. Confidence intervals: 95%.

March 12 in Sao Paulo.[5] As the social distancing index is bounded between 0 and 1, each coefficient β_τ should be interpreted as a change in percentage points relative to the day before the first NPI. We cluster the standard errors at the hexagon level and weight the observations by the hexagon population in 2010.[6] The identifying assumption is that in the period of analysis, hexagons with slums would have had similar trends in social distancing (compared to hexagons without slums) in the absence of NPIs.

Figure 2 shows the results of the event-study analysis. Hexagons with and without slums evolved similarly during the period before the NPIs in both cities. This suggests the absence of different pre-trends in social distancing and therefore yields support for the main identifying assumption. After the first NPI, a sharp decline in social distancing (of about 4–5 percentage points) fol-

[5]Since we have data for 120 days starting from February 1, there are 39 and 41 pre-treatment periods in Rio de Janeiro and Sao Paulo, respectively.

[6]Figure B4 in Appendix B shows that results are qualitatively similar when we do not use population weights, but the point regression coefficients are less precisely estimated.

lows in hexagons with slums, compared to those without slums.[7] Indeed, the results of a difference-in-difference strategy in Table B1 in online Appendix B show a (statistically significant) average reduction of the social distancing index of 3.9 and 4.3 percentage points in slum areas in Rio de Janeiro and Sao Paulo, respectively.[8]

The adherence of individuals to social distancing measures is quite different in areas with and without slums. Interestingly, the magnitude of the treatment effect is similar in both Rio de Janeiro and Sao Paulo, but the coefficients are more precisely estimated for the latter.

Fact 3: More Covid-19 deaths occurred in areas with slums than in areas without slums.

The risk of Covid-19 transmission is higher in overcrowded areas that lack access to basic sanitation and running water. Those are precisely some of the characteristics of urban slums. In addition, one might expect that health facilities would be more congested in areas near slums. People in slums usually have less access to private health providers.[9] Therefore, we would expect more Covid-related deaths in areas with slums than in other neighborhoods.

Figure 3 provides descriptive evidence suggesting that places in Rio de Janeiro and in Sao Paulo with more slums experienced more Covid-19 deaths.[10] For the city of Sao Paulo, we have geo-referenced data on hospitalizations and deaths caused by Covid-19 and other acute respiratory diseases (see Appendix A). We matched the geo-referenced data into hexagons to check the correlation between slums and hospitalizations/deaths. Due to constraints on the availability of data, we could not conduct this analysis using the event-study specification.

[7] Figure B5 in Appendix B shows the results when we change the treatment dummy for the share of slums in each hexagon. The qualitative implications are the same.

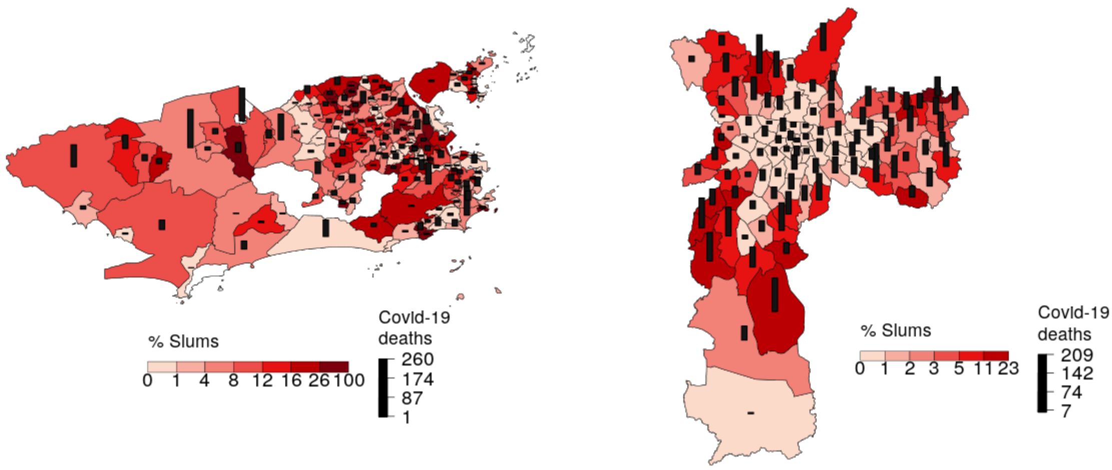
[8] In column (III) of Table B1 in Appendix B, we perform a "triple-difference" strategy and show that the reduction in social distancing index was 0.43 percentage points lower in Rio de Janeiro compared to Sao Paulo (but statistically not significant).

[9] Approximately 15% and 22% of the overall population have access to private health insurance in Rio de Janeiro and Sao Paulo, respectively.

[10] Figure 3 uses Covid-19 death data at the neighborhood level (which is a group of hexagons), as this is the most disaggregated level officially reported by both cities.

Figure 3: **Slums and Covid-19 deaths**

(a) Rio de Janeiro (b) Sao Paulo



Notes. The figure shows Covid-19 deaths for the cities of Rio de Janeiro on June 14 and Sao Paulo on May 25. The percentage of slums in each area is from the 2010 census.

We then used the following cross-sectional specification:

$$Y_h = \alpha + \gamma I_h + \epsilon_h,$$

where Y_h is the outcome variable (hospitalizations or deaths) for each hexagon h and I_h equals one for hexagons with slums and zero otherwise. The results reveal statistically significant and positive correlations: hexagons with slums have 11% more hospitalizations and 10% more deaths by Covid-19—and 36% more hospitalizations and 7% more deaths by other respiratory diseases (see Table B2 in Appendix B).[11]

[11]Serological tests in Brazilian slums support the claim that Covid-19 infections are higher in slums and exceed official data (Prefeitura Rio de Janeiro (2020)). Due to data restrictions, excess mortality data cannot be analyzed at the intra-city level in Brazil.

3 Model

In this section, we present the model to study the role of slums in shaping the economic and health dynamics of the Covid-19 pandemic. Assume a model economy that evolves in discrete time.[12] Suppose there are two groups of agents in this economy: those who live in slums (or *favelas*), $g = f$, and others who do not, $g = o$. Agents work, enjoy leisure outside their home, and home hours. Home hours can also be seen as a proxy for home production. In the presence of the new coronavirus, denote the agent's status by j. A healthy agent is denoted by $j = h$. By spending time outside the house, the agent may catch Covid-19. If the agent becomes infected, he is denoted by $j = i$. Conditional on being infected, the agent may either recover (with probability $\phi(0, g)$) or develop more serious symptoms (with probability $\alpha(g)$). Denote an agent with serious symptoms by $j = s$. Someone with serious symptoms may either recover (with probability $\phi(1, g)$) or die (with probability $\delta_t(g)$). The death probability is time varying as it may depend on the usage of scarce hospital resources. Such resources may also be different across the two groups. Moreover, we assume that the average slum resident is younger (as in the data). This reflects different recovery and death probabilities across groups. If an individual recovers ($j = r$), he is assumed to be immune to the disease forever. Agents discount the future with factor $\beta \in (0, 1)$.

An individual is endowed with one unit of time per period that may be used for work n, leisure outside the house ℓ, and hours at home d (''domestic" hours). The time constraint thus reads:

$$n + \ell + d = 1. \tag{2}$$

An individual derives utility from consumption c, a composite leisure good when he leaves home a, and domestic hours d. The good a is produced using hours ℓ and buying "intermediate" goods x according to the function $a =$

[12] Our model builds on the framework developed by Brotherhood et al. (2020).

$a(x, \ell)$. We normalize the utility after death to zero and capture the bliss from being alive through a parameter b. The utility function is given by:

$$u(c, a, d; j, g, p) \quad = \quad \ln c + \gamma \ln a + [\lambda_d + \lambda(j) + \lambda_p(j, g)] \ln(d) + b.$$

The term $\lambda(j)$ expresses an additional preference for staying at home when infected and is supposed to capture some partial altruism. This variable can take two levels: $\lambda(s) = \lambda(i) = \lambda_a$ and $\lambda(r) = \lambda(h) = 0$, so that individuals who can transmit the virus are partially altruistic and the others have no need for that; $\lambda_p(j, g)$ has a similar role, but from the point of view of the government.[13] This captures simple policies that confine all groups to staying at home ($\lambda_p(j, g) = \bar{\lambda}_p$) but can also capture group-specific confinements ($\lambda_p(j, g) = \bar{\lambda}_p(g)$) and even condition on infection status.

An individual's income consists of two terms. The first is labor income $w(g)n$. Note that the wage per unit of time can vary by group. The second term corresponds to government transfers and can be time dependent. Denote it by $w_p(g)$. The budget constraint of the agent is given by:

$$c + x = w_p(g) + w(g)n. \tag{3}$$

A healthy individual ($j = h$) may become infected when he strays from home. The longer one spends outside, the more likely it is that an infection takes place. For each hour spent outside the house, the transmission risk is given by $\Pi_t(g)$. Note that this is time varying as it depends on two aggregate variables: (i) the fraction of infected people in the economy and (ii) the time infected people spend outside their houses. It can also be group specific as individuals from different groups may be more exposed to one group versus the other, due to differences in the density in their neighborhoods, for instance. This will be elaborated on later. The probability of catching the virus in a given period t is given by

$$\pi(n + \ell, \Pi_t(g)) = (n + \ell)\Pi_t(g). \tag{4}$$

[13] The subscript p denotes that $\lambda_p(j, g)$ is a policy instrument.

We turn now to decision making. The problem of a healthy individual is described by the following maximization problem:

$$\begin{aligned} V_t(h,g) = & \max_{c,x,n,\ell,d} u(c,a(x,\ell),d;h,g,p_t)+ \\ & \beta\{[1-\pi(n+\ell,\Pi_t(g))]V_{t+1}(h,g)+\pi(n+\ell,\Pi_t(g))V_{t+1}(i,g)\} \\ & \text{subject to (2) and (3).} \end{aligned} \tag{5}$$

The first line in this problem corresponds to the instantaneous utility from consumption and leisure. The second line spells out the continuation value. The first term in curly brackets represents the situation in which the individual does not get infected this period and continues life as a healthy person in the next period. The second term denotes the case in which the agent gets infected today and continues life as an infected individual in the next period.

The value function for an infected person who has not developed severe symptoms of the disease is given by

$$\begin{aligned} V_t(i,g) = & \max_{c,x,n,\ell,d} u(c,a(x,\ell),d;i,g,p_t)+\beta\phi(0,g)V_{t+1}(r,g)+ \\ & \beta(1-\phi(0,g))[\alpha(g)V_{t+1}(s,g)+(1-\alpha(g))V_{t+1}(i,g)] \\ & \text{subject to (2) and (3).} \end{aligned} \tag{6}$$

The first line captures the instantaneous utility from consumption and leisure and the situation in which the agent recovers from the disease. The second line is the continuation value in which the agent either develops serious symptoms (first term in square brackets) or continues life as an infected person (second term).

Set the flow utility for an individual with serious symptoms ($j = s$) to the same as death (i.e., zero). These individuals may still recover and enjoy utility from consumption, leisure, and bliss of life later. These agents do not work, but we assume they interact with people in the hospital and may thus infect others. Set an exogenous amount of time they interact with their carers to $\ell = \bar{\ell}_s$. Their value function thus reads as follows:

$$V_t(s,g) = \beta\left[\phi(1,g)V_{t+1}(r,g) + (1-\phi(1,g))(1-\delta_t(g))V_{t+1}(s,g)\right] \tag{7}$$

This value function consists of two scenarios: the first term corresponds to the patient recovering from his symptoms and the second term represents the case in which he continues life in the hospital. With the remaining probability, he dies and his utility is normalized to zero.

Finally, an agent who has already recovered and is resistant to the virus enjoys utility:

$$V_t(r,g) = \max_{c,x,n,\ell,h} u(c, a(x,\ell), d; r, g, p_t) + \beta V_{t+1}(r,g) \tag{8}$$

subject to (2) and (3).

It is important to keep track of the number of agents who find themselves in each of the situations described earlier. Denote the measure of agents of each type j of group g in period t by $M_t(j,g)$. Let $\mathcal{M}_t$ be the set of these for all js and gs. Moreover, let $n_t(j,g)$ and $\ell_t(j,g)$ denote the policy function for hours worked and outside leisure, respectively, for each agent. Let the equilibrium time allocations in period t across all j and g be summarized in $\mathcal{N}_t$. The law of motion from one period to the next is represented by the mapping T:

$$\mathcal{M}_{t+1} = T(\mathcal{M}_t, \mathcal{N}_t, \Pi_t(o), \Pi_t(f)). \tag{9}$$

The law of motion for healthy people of a group g reads as follows:

$$M_{t+1}(h,g) = M_t(h,g)\left[1 - \pi(n_t(h,g) + \ell_t(h,g), \Pi_t(g))\right]. \tag{10}$$

That is, the measure of healthy people next period consists of those who are healthy today and did not catch the virus. The right-hand side of (10) thus describes the mapping T_h for healthy individuals. The corresponding equations for the other groups are provided in Appendix C. The aggregate mapping in (9) is given by the collection of all T_j.

Aggregate output in this economy is given by all the work supplied by agents of the different groups and infection statuses multiplied by their wages:

$$Q_t = \sum_{j,g} w(g) n_t(j,g) M_t(j,g). \tag{11}$$

Turn now to the calculation of the probability of getting infected per unit of time spent outside. First, let Π_0 represent an exogenous transmission rate from infected to susceptible. Now, assume that, when outside their homes, both groups (those who live or do not live in *favelas*) spend a fraction $1-\zeta$ of their time in a common space shared by everyone. The remaining ζ fraction of their time is spent only among members of the same group (f or o). These group-specific activities are undertaken within separate areas for each group. Denote by ξ_g the fraction of the space that is assigned to group g. This is supposed to represent the fact that slums have a much higher density than the rest of a city. Slum dwellers thus have to interact in much more confined spaces, and this contributes to a faster spread of the virus. We then have the following:

$$\begin{aligned} \hat{\Pi}_t(g) &= (1-\zeta)\Pi_0 \sum_{\tilde{g}, j \in \{i,s\}} \left(n_t(j,\tilde{g}) + \ell_t(j,\tilde{g})\right) M_t(j,\tilde{g}) \\ &\quad + \zeta \Pi_0 \sum_{j \in \{i,s\}} \frac{1}{\xi_g} \left(n_t(j,g) + \ell_t(j,g)\right) M_t(j,g). \end{aligned} \tag{12}$$

Note that when $\zeta = 0$, this expression reduces to a pure random-mixing situation.

The parameter Π_0 is usually calibrated to match a basic reproduction number (R_0) at the outbreak of the epidemic. This number can be high enough such that it drives equation (12) to more than 1 because we do not control for the possibility of multiple infections in a given period. To avoid this, we take a continuous-time approximation that yields:

$$\Pi_t(g) = 1 - e^{-\hat{\Pi}_t(g)}. \tag{13}$$

If $\hat{\Pi}_t(g)$ is small, then $\Pi_t(g) \approx \hat{\Pi}_t(g)$.

We now define the probability that an agent with serious symptoms ($j = s$) dies, $\delta_t(g)$. This is time varying, as it depends on the supply of scarce hospital resources (e.g., ICU beds) and the demand by sick patients. Suppose there are two networks of medical services: a public one to which everyone has access and a private one. Only individuals with health insurance can access the private network. Let Z_{pub} and Z_{priv} be the number of beds in the public and private hospitals, respectively. Assume also that no slum dweller (f) has access to health insurance and therefore to private hospitals. For the others (o), a fraction ψ has health insurance.

Let U_{pub} and U_{priv} be the number of users in the public and private networks, respectively. These are given by

$$\begin{aligned} U_{pub} &= M_t(s,f) + (1-\psi) M_t(s,o), \\ U_{priv} &= \psi M_t(s,o), \end{aligned} \tag{14}$$

where $M_t(s,g)$ is the number of type-g agents who have serious symptoms.

Assume that an individual with serious symptoms who has access to a hospital bed dies with probability $\tilde{\delta}_1(g)$. Those without access to a hospital bed die with probability $\tilde{\delta}_2(g)$.[14] The death probability for individuals living or not living in slums is given by the following two equations:

$$\begin{aligned} \delta(f) &= \tilde{\delta}_1(f) \min\left\{\frac{Z_{pub}}{U_{pub}}, 1\right\} + \tilde{\delta}_2(f) \max\left\{\frac{U_{pub} - Z_{pub}}{U_{pub}}, 0\right\}, \\ \delta(o) &= \psi \left[\tilde{\delta}_1(o) \min\left\{\frac{Z_{priv}}{U_{priv}}, 1\right\} + \tilde{\delta}_2(o) \max\left\{\frac{U_{priv} - Z_{priv}}{U_{priv}}, 0\right\}\right] \\ &\quad + (1-\psi) \left[\tilde{\delta}_1(o) \min\left\{\frac{Z_{pub}}{U_{pub}}, 1\right\} + \tilde{\delta}_2(o) \max\left\{\frac{U_{pub} - Z_{pub}}{U_{pub}}, 0\right\}\right]. \end{aligned} \tag{15}$$

The first line spells out the probability of death for a slum dweller with serious symptoms. This only depends on the excess demand for hospital beds in the

[14] We assume the death probabilities to be group specific to reflect different age structures across the two neighborhoods. See Section 4 for details.

public network. The second and third lines show the same for other agents. Now, with probability ψ, they have access to the private network through their health insurance. With complementary probability, they use the public hospital network.

A rational-expectations equilibrium in this economy with initial number of agents $M_0(j, g)$ consists of a sequence of infection and death rates $\{\Pi_t(g), \delta_t(g)\}_{t=0}^{\infty}$ and equilibrium time allocations $\{n_t(j, g), \ell_t(j, g)\}_{t=0}^{\infty}$ such that these time allocations are part of the solutions to the individual optimization problems (5) to (8), and the resulting law of motion (9), and their aggregation in (13) and (15) indeed gives rise to the sequence $\{\Pi_t(g), \delta_t(g)\}_{t=0}^{\infty}$.

4 Fitting the Model to the Data

To analyze the role of slums in the Covid-19 pandemic, we must assign values to the model parameters. There are 30 parameters to be set. Some (24 parameters) are externally calibrated and others (6 parameters) are chosen such that certain model moments match their empirical counterparts. We focus our analysis on the city of Rio de Janeiro. Given that this is a framework to understand social behavior during a pandemic, we set the model period to one week.

City parameters: According to the 2010 Brazilian census, 22% of Rio de Janeiro's population live in slums (or *favelas*). We normalize the area of the model city to one. Then, given the share of the population living in slums (22%) and the population density in areas with slums relative to those without slums (4.05), we have the fraction of space assigned to slums as $\xi_f = 0.065$.[15]

The proportion of time individuals spend with members of their same group is given by ζ. We set $\zeta = 0.334$. This corresponds to the fraction of time spent outside that is not work related. The implicit assumption is that work-related

[15]The population density in areas with and without slums in the city of Rio de Janeiro is from the 2010 census data. Population density in Rio de Janeiro's slums is about 25,701.18 individuals per square kilometer and in areas without slums it is 6,344.46. The difference is a factor of four.

activities take place across all groups whereas leisure outside is separate for each group.

We normalize the wage rate of individuals who do not live in slums to one, that is, $w(o) = 1$. We then set the wage rate of agents who live in slums to $w(f) = 0.277$. Therefore, the relative hourly wage per capita of individuals who live in slums to those who do not is 27.7%, which is the number observed in the 2010 census data for Rio de Janeiro.

Panel A of Table 1 reports the values of the parameters related to Rio de Janeiro. The third column ("Interpretation") contains a comment on how each parameter was set.

Disease transmission and development: We now turn to parameters that control the transmission and disease development of Covid-19. To discipline how infectious the disease is, we target the basic reproduction number, R_0. Appendix D.1 describes how we can compute this statistic in the model. The parameter Π_0 determines the per-period transmission rate in the model and is intimately related to R_0. We thus pick Π_0 to target a value of 2.5 for the basic reproduction number. This lies within the range used by Atkeson (2020). Ferguson et al. (2020) use $R_0 = 2.4$ while Zhang et al. (2020) estimate it to be 2.28. Remuzzi and Remuzzi (2020) report values between 2.76 and 3.25. This yields $\Pi_0 = 11.43$.

We set $\alpha(g) = 1$ for both groups. This implies that an individual who is infected with Covid-19 spends one week with mild symptoms and then either recovers or becomes critically ill. To determine the probabilities of recovery, we turn to medical data. CDC (2020) reports age-specific transition rates between infection and ICU care, and from ICU to death. We aggregate these using Rio de Janeiro's population pyramids for both slums and other areas, which come from the 2010 Brazilian census. This yields a 2.1% chance that someone in a slum who is infected ends up with serious symptoms; the counterpart for other areas is 2.9%. Moreover, the probability of death conditional on being critically ill is 15.5% for slum residents and 22.9% for other individuals. The lower probabilities for hospitalization and death for slum residents is a consequence of a

Table 1: Calibration and estimation of model parameters: City of Rio de Janeiro

Parameter	Value	Interpretation
Panel A: City parameters (6 parameters)		
$\sum_j M_0(j,f)$	0.222	Fraction of people living in slums (calibrated)
$w(o)$	1	Wage rate of non-slum agents (calibrated)
$w(f)$	0.277	Wage rate of slum agents (calibrated)
ξ_f	0.065	Frac. of space assigned to slums (calibrated)
ξ_o	0.934	Frac. of space assigned to areas wo slums (calibrated)
ζ	0.334	Prop. of time spent within group (calibrated)
Panel B: Disease parameters (15 parameters)		
Π_0	11.43	Infectiousness of Covid-19 (internatlly estimated)
$\alpha(o)$, $\alpha(f)$	1	Prob. (serious symptoms | no recovery from mild) (calibrated)
$\phi(0,o)$	0.971	Prob. of recovery from mild Covid-19, other (calibrated)
$\phi(0,f)$	0.979	Prob. of recovery from mild Covid-19, slum (calibrated)
$\phi(1,o)$, $\phi(1,f)$	0.284	Prob. of recovery from serious Covid-19 (calibrated)
$\tilde{\delta}_1(o)$	0.118	Wkly death rate, other; critically ill with ICU (calibrated)
$\tilde{\delta}_1(f)$	0.073	Wkly death rate, slum; critically ill with ICU (calibrated)
$\tilde{\delta}_2(o)$, $\tilde{\delta}_2(f)$	1.0	Wkly death rate; critically ill wo ICU (calibrated)
$\bar{\ell}$	0.158	Infections through the health care system (calibrated)
ψ	0.152	Prop. non-slum agents with priv. insurance (calibrated)
Z_{pub}	8.12e-5	Measure of beds in public system (calibrated)
Z_{priv}	4.9e-4	Measure of beds in private system (calibrated)
Panel C: Preference parameters (7 parameters)		
ρ	-1.72	Elast. of subst. bw leisure time and goods (calibrated)
θ	0.108	Production of leisure goods (internally estimated)
γ	1.089	Rel. utility weight–leisure goods (internally estimated)
λ_d	2.453	Rel. utility weight–leisure at home (internally estimated)
λ_a	1.995	Rel. utility weight–leisure at home; infected (calibrated)
β	$0.96^{1/52}$	Discount factor (calibrated)
b	8.575	Value of being alive (internally estimated)

younger population living in these neighborhoods. We turn these probabilities into weekly rates to conform with our chosen model period.[16] Moreover, Verity et al. (2020) report that a critically ill patient is discharged from the ICU after around 24.7 days, or 3.52 weeks. We assume the same length of treatment for both groups. This yields weekly probabilities of recovery from mild symptoms of $\phi(0,f) = 0.979$ and $\phi(0,o) = 0.971$, weekly probabilities of recovering from the ICU of $\phi(1,g) = 0.284$ for all g, and weekly death probabilities conditional

[16] See Appendix D.2.

on being in the ICU of $\tilde{\delta}_1(f) = 0.073$ and $\tilde{\delta}_1(o) = 0.118$. We assume the death probability of a patient with serious symptoms who does not have access to an ICU bed to be $\tilde{\delta}_2(g) = 1$ for all g.

Note that we assumed that a patient who is being treated in the ICU does not work or enjoy leisure but still interacts with others and may infect them. The amount of time in the model during which this interaction takes place is given by $\bar{\ell}$. Butler et al. (2018) estimate ICU patients interact with doctors, nurses, and other people around 7.6 hours a day. Since this is a controlled environment, we use half this number to determine infections. This yields $\bar{\ell} = 0.158$.

Panel B of Table 1 summarizes the calibrated values of the parameters related to the Covid-19 pandemic.

Preference parameters: We assume that the composite leisure good a is produced according to the following function: $a = [\theta x^\rho + (1-\theta)\ell^\rho]^{1/\rho}$. Following Kopecky (2011), we set $\rho = -1.72$. This yields an elasticity of substitution between leisure and goods of 0.368, which means they are complements.

We set the preference parameters θ, γ, and λ_d to target three data moments related to time use and expenditures in Brazil. First, we target the fraction of income spent on goods consumed outside the home.[17] According to the Brazilian expenditure survey (POF), individuals in Rio de Janeiro spend on average 27.82% of their income on goods outside the home.[18] Second, we target the average weekly hours at work. According to the 2019 national household survey (PNAD-C), Rio de Janeiro residents spend 34.2 hours per week at work.[19] Assuming an endowment of 112 non-sleeping weekly hours, this yields the fraction 0.306 for their time spent at work. Third, we target the leisure time outside. In Brazil, the average person spends around 17.2 hours a week outside, which

[17] As do Brotherhood et al. (2020), we classify the following items of the consumption basket as goods consumed outside: food away from home, public transportation, medical services, and entertainment.

[18] The expenditure survey POF is the *Pesquisa de Orçamento Familiar* for 2008–09.

[19] The national household survey PNAD-C is the *Pesquisa Nacional por Amostra de Domicílios Contínua*. We get the average hours worked per week and multiply by the share of people who have a job or are self-employed.

corresponds to the fraction 0.154 of their endowment of non-sleeping hours.[20]

The parameter λ_a denotes the increase in the marginal utility of staying at home for agents who are infected with Covid. This parameter is related to the extra amount of time an individual spends at home *without any influence from the government*. To identify this parameter, we turn to how agents behave when they contract influenza. Akazawa, Sindelar, and Paltiel (2003) report that the average American worker takes 1.3 days of sick leave when infected with influenza. Given a 40-hour workweek, this implies an average of 10.4 hours. We assume that the same would happen with Covid. As the disease lasts an average of one week (absent development of serious symptoms), this implies a 26% decline in work time. We assume the same number for Brazilian workers. Suppose that leisure outside declines by the same amount. We then choose λ_a to match an increase in time spent at home by 26% compared with a world without Covid-19.

For the preference discount factor, we assume that agents discount the future at roughly 4% per year and set $\beta = 0.96^{1/52}$. The average real interest rate in Brazil was approximately 4.9% from 2005.1 to 2020.5 and 3.5% from 2009.1 to 2020.5.[21]

Finally, we must set a value for b, the per-period value of being alive. Note that a higher value for this parameter implies that an individual will engage in more cautious behavior to avoid death. We thus pick b to generate an increase in time at home as the one observed at the outbreak of the Covid-19 pandemic. The issue is that most countries adopted lockdowns at the same time. We thus look at Sweden, a country that did not implement severe restrictions. Brotherhood et al. (2020) report an increase of 15.7% in time at home in Sweden in week 8 of the epidemic. As slums are not an important factor in Sweden, we use this 15.7% hike as the target of a version of our model without slums. This yields a

[20] The total hours of leisure outside are computed adding time spent commuting (Pereira and Schwanen 2013) and activities related to socializing and cultural and sport activities. These data come from the 2009 PNAD-C and the test pilot time-use survey.

[21] This is the monthly Over/Selic interest rate (Brazilian Central Bank rate) minus the inflation rate measured by the IGP-DI (general price index from Vargas Foundation). We annualized the monthly average real interest rate and inflation. These two variables can be downloaded from `www.ipeadata.gov.br`.

Table 2: Moments – model vs. data

Moment	Model	Data (ranges)
Share of individuals living in slums	22%	22%
Pop. density in slums/Pop. density in non-slum areas	4.5	4.5
Relative hourly labor income of individuals in slums	27.7%	27.7%
R_0, Covid-19	2.5	1.6-4
% of infected in critical care	3.6	3.6
Weeks in critical care	3.5	3-6
% in critical care who die	20.24	10.6-31.8
Hours/day interacting while in ICU	3.8	7.6 (controlled)
Hours of work per week	34.2	34.2
Hours of outside activities per week	17.2	17.2
% of income on goods outside	27.28	27.28
% ↑ in time @ home – mild symptoms	26	26 (Influenza)
% ↑ in time @ home – outset of Covid-19	15.7	15.7
% of non-slum agents with priv. insurance	15.21	15.21

value of $b = 8.575$.

Panel C of Table 1 contains the calibrated preference parameters. Table 2 summarizes some targeted moments of the model and their data counterpart. The model matches the moments of Rio de Janeiro quite well.

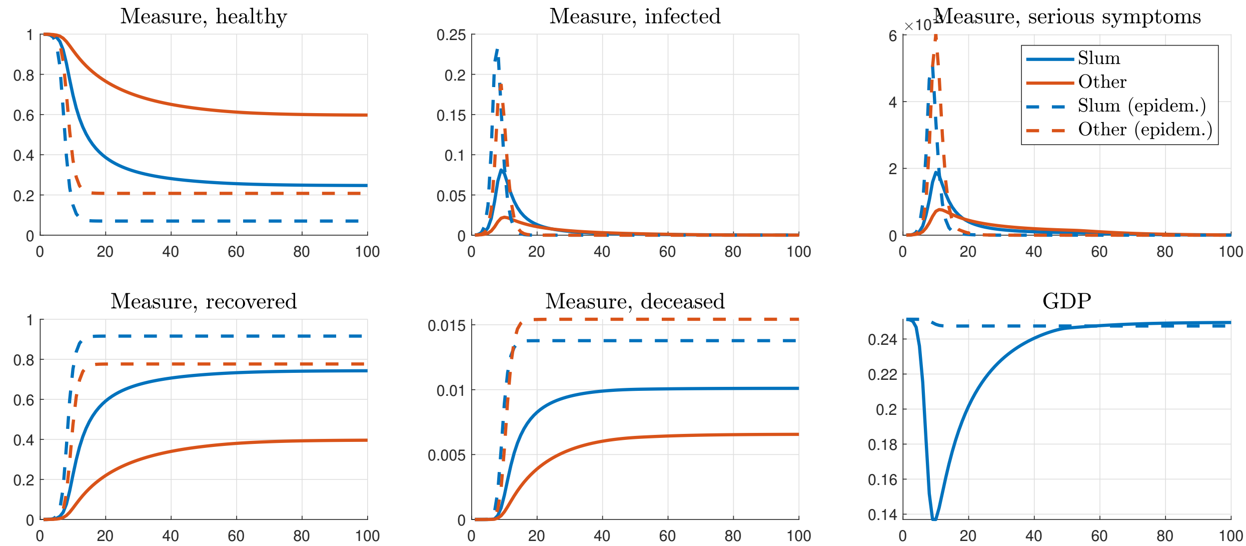
5 Baseline Results

This section presents our baseline results. Our main focus is to understand the role of slums in the pandemic. We first describe the path of our baseline economy when there is an outbreak of Covid-19 and there is no policy intervention. Different policies are investigated in the next section.

Figure 4 shows the masses of individuals in different health states: healthy, infected, with serious symptoms, recovered and deceased. The blue lines describe the dynamics of individuals who live in slums while the orange lines represent those who are not slum dwellers.[22] The solid lines display our economic model

[22]In our calibration 22% of individuals live in slums. So any change in the figure is relative

Figure 4: Aggregate variables, Baseline



with equilibrium social distancing, and the dashed lines show, for comparison, the counterfactual epidemiological model, in which behavior is unchanged relative to a world without the pandemic. The last graph in this figure displays aggregate output. Along with this figure, Table 3 summarizes key moments of the pandemic in our baseline model (first column) and in a typical epidemiological model (second column), where behavior is kept constant by assumption.

The total duration of the unchecked epidemic is about a year (when herd immunity becomes strong enough to essentially prevent further contagion) and the peak in terms of seriously ill individuals is reached in about 11 weeks. As the virus spreads, social distancing endogenously rises as evidenced by the hike in hours at home by both groups. The number of infected people is thus reduced relative to the typical epidemiological model. This also translates in a lower death toll in the benchmark. Notice that GDP at the peak is substantially higher in the epidemiological model relative to the baseline. With the rising risk of getting infected and possibly dying, agents cut time spent outside their home and sharply reduce their working hours.

to this initial mass. Non-slum dwellers thus correspond to 78% of all individuals.

Table 3: Baseline results

	Benchmark	Epidem.	No slum	Homog. densities	Homog. wage rates	Homog. age struct.
Wks to peak srsly ill (slum)	10.00	9.00	–	15.00	10.00	10.00
Wks to peak srsly ill (other)	11.00	10.00	14.00	14.00	11.00	11.00
Srsly ill p/ 1,000 @ peak (slum)	1.88	5.09	–	0.66	1.19	2.18
Srsly ill p/ 1,000 @ peak (other)	0.77	6.02	0.65	0.68	0.74	0.75
Dead p/ 1,000 1year (slum)	10.04	13.78	–	6.32	8.87	13.49
Dead p/ 1,000 1year (other)	6.35	15.43	6.87	6.86	6.78	6.57
Dead p/ 1,000 1year (all)	7.16	15.06	6.87	6.74	7.25	8.11
Dead p/ 1,000 LR (slum)	10.11	13.78	–	6.53	9.07	13.68
Dead p/ 1,000 LR (other)	6.57	15.43	7.47	7.30	7.13	6.83
Dead p/ 1,000 LR (all)	7.35	15.06	7.47	7.13	7.56	8.34
Immune in LR (slum), %	74.33	91.60	–	51.78	70.11	72.37
Immune in LR (other), %	39.69	77.66	46.01	44.72	43.03	40.76
Immune in LR (all), %	47.36	80.75	46.01	46.28	49.03	47.76
GDP at peak - rel to BM	1.00	1.82	1.48	1.23	1.29	1.03
GDP 1year - rel to BM	1.00	1.14	1.17	1.00	1.17	0.99
Hrs @ home (slum) - peak	80.95	60.48	–	69.19	86.38	83.22
Hrs @ home (other) - peak	86.28	60.48	78.00	80.00	82.26	84.90
Hrs @ home (slum) - 6m	66.03	60.48	–	65.35	74.38	68.93
Hrs @ home (other) - 6m	69.40	60.48	72.42	72.82	70.79	70.12
Value - healthy (slum)	1968.10	1962.10	–	1976.60	4305.90	1960.20
Value - healthy (other)	4317.40	4283.10	4315.00	4315.30	4315.60	4316.50
Value - healthy (all)	3797.00	3769.00	4315.00	3797.20	4313.50	3794.50

Turn now to the role of slums in shaping health and economic dynamics. Table 3 shows that the benchmark economy features a much higher death toll in slums relative to other areas. The total death rate is 7.35 per 1,000 individuals, but in slums it is roughly 10 per 1,000 residents. Though slum dwellers represent only 22% of the city's population, they account for 30% of the overall deaths. This can be explained by the higher density in slums and therefore more contagion, as well as more congestion of intensive care units—more on these issues below—but also by differences in the individual choices of slum and non-slum residents.

Figure 5 displays the time spent at home, at work and with leisure outside. Social distancing (the increase in time at home relative to an epidemiological model with no behavioral change) is lower for slum dwellers than for other individuals. Since they are poorer, slum residents decrease the number of hours

Figure 5: Choices of healthy agents

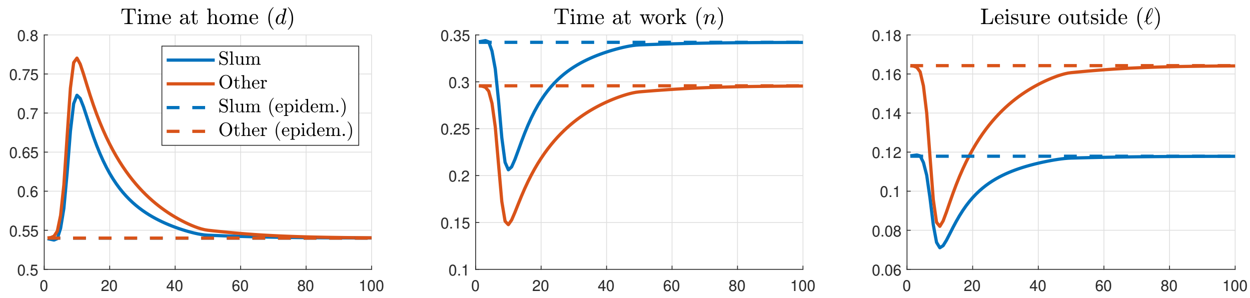
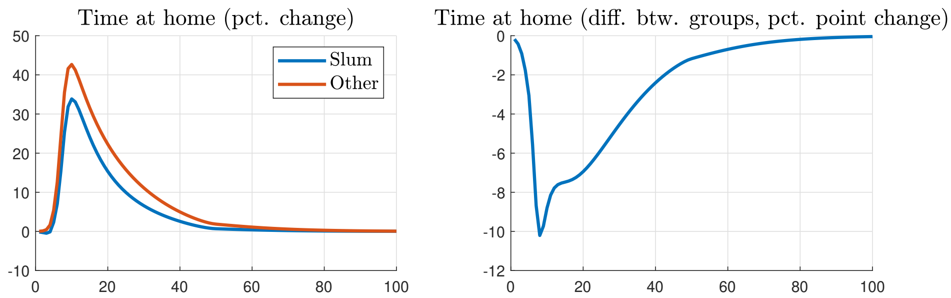


Figure 6: Difference in protection behavior between slum and non-slum agents



worked by less than non-slum individuals despite the fact they have a higher chance of catching the virus. Figure 6 shows the difference in social distancing between the two groups at the outbreak of the pandemic. At the peak of the disease, social distancing is about 10 percentage points lower for slum residents compared to others. This is qualitatively consistent with our event-study analysis using mobile phones in Rio de Janeiro, displayed in Figure 2. Quantitatively, the unchecked epidemic generates a larger effect on the difference in social distancing between slum and non-slum individuals.[23] Recall that in our model this is an unchecked epidemic, while in the data there are NPIs. We will discuss the effects of NPIs in our model in the next section.

In order to further assess the role of slums in the pandemic, we run a counter-

[23]We should interpret the comparison of our theoretical social distancing measure with the empirical index based on mobile phones with caution. The theoretical measure is an intensive margin proxy for social distancing while the index constructed by Inloco is an extensive margin measure. If we interpret in the model the home time as the fraction of households who stay at home, then the model and the empirical counterpart would be equivalent.

factual in which we set the measure of slum individuals to zero and keep all other parameters at their baseline values. See the third column of Table 3. For the non-slum residents (the only ones in this hypothetical world), the death rate is now *higher* than the baseline: 7.47 per 1,000 in the counterfactual versus 7.35 in the benchmark. There are two reasons for this. First, in the baseline, close to 75% of slum residents are immune in the long run. That is, they contribute a lot to reach herd immunity. In the benchmark, only 40% of non-slum individuals are infected throughout the pandemic. Without slums, this number rises to 46%. The second reason is that, with a safer environment in the non-slum world, other individuals are less cautious. For instance, at the peak, they spend about eight fewer hours at home. In the end, residents from other areas end up with a lower welfare in this scenario without slums.

In our model environment, slum dwellers are different in four important characteristics: they live in denser areas, their wage rate is lower, they are on average younger and it is harder for them to be admitted to an ICU. We now investigate the role of the first three factors in shaping the dynamics of the pandemic. Easier access to ICU beds will be assessed in our policy section.

The fourth column of Table 3 contains statistics for a counterfactual in which $\xi_f = 0.22$, which implies that the population density in slums is the same as what is observed in other areas. All other parameters are kept at their baseline values. The pandemic lasts longer now since the spread of the virus is reduced and it takes more time to reach herd immunity. Relative to the baseline, the death rate of slum dwellers is reduced from 10.11 to 6.53 per 1,000 individuals—a 35% reduction. The death rate of other individuals rise from 6.57 to 7.30—a rise of about 11%. That is, living in a neighborhood with higher density is crucial to generate more deaths among slum residents. With less contagion due to a lower population density in slums, individuals expose themselves more by spending less time at home, offsetting in part the direct effect of a lower population density in slums.

In the fifth column of Table 3, we increase the wage of slum dwellers and equate it to the wage of other agents; i.e. $w_f = 1$. All other parameters remain at their baseline values. Relative to the benchmark, since they are now richer, individuals who live in slums spend more time at home. As these agents are now more cautious, their death rate is reduced from 10.11 to 9.07, a reduction of 10%. Given that a lower number of slum dwellers are infected now, the economy can only reach herd immunity with a higher fraction of non-slum residents being infected. This also translates into a higher death toll among the latter group; an increase from 6.57 to 7.13 per 1,000. As non-slum residents account for a larger fraction of the population, the overall death rate slightly increases.

Recall that slum dwellers are on average younger and this translates in lower hospitalization and death rates for members of this group. The last column in Table 3 reports the results of a counterfactual in which we equate these rates across the two groups. To be more precise, the thought experiment is that slum residents now face the same (worse) recovery and death probabilities as individuals from other areas. Note that, even though the infection rates are similar to the benchmark, death numbers are about 13% higher in this scenario. Therefore, ignoring the fact that individuals living in slums are younger can lead to misleading conclusions about the number of fatalities in these communities. As life is now riskier in slums, this group becomes more cautious and spends more time at home. With a lower supply of labor, GDP goes down even further compared to the baseline.

In sum, in our unchecked pandemic calibrated to Rio de Janeiro, slums have a non-trivial role in shaping the effects of Covid-19. First of all, the death rate in slums is higher than in other areas. Slum dwellers' share in total deaths is much higher than their fraction in the overall population of the city. In addition, the very high population density in slums compared to other parts of the city seems to be a key feature in explaining the high death rate observed in slums. Interestingly, the presence of slums decreases significantly the time to reach herd immunity and protects individuals who live in other neighborhoods, generating important distributional effects. Policies that aim to curb the Covid-19 pandemic in societies with a high fraction of their population living in slums must then take this fact into account. The next section explores the effects of a variety of such policies.

6 Policy Experiments

In this section, we assess the impact of NPIs to control the health and economic impact of the pandemic in our model economy. We evaluate three different policies: the government requisition of private hospital intensive care units to increase capacity in order to meet the demand for Covid-19 related treatment; lockdown interventions to increase social distancing (shelter-at-home orders); and financial aid policies to help people stay at home.

6.1 Public Hospital Beds

In Rio de Janeiro approximately 15% of the individuals have private health insurance and therefore access to private hospital beds. There are 510 and 3,079 beds in intensive care units in public and private hospitals, respectively (in a city of about 6.3 million people).

In our calibration, we assume that slum dwellers have no health insurance and approximately 19% of the individuals who do not live in slums have private insurance. We should expect that congestion of health services is therefore greater in slum areas. In this policy intervention, we investigate the impact of a counterfactual experiment in which the ICUs in private hospitals could be used to treat all individuals in need for critical care.[24]

Table 4 shows that the total death rate is reduced by approximately 28% with this policy. Although slum dwellers are the ones who benefit the most from this policy, individuals who live in non-slum areas are also positively affected since only a small fraction of them have private health insurance. Observe that most of the agents decrease social distancing with this intervention as time at

[24] We abstract from any financial and political economy barrier to implement such a policy.

Table 4: All hospital beds used by the public system

	Benchmark	All beds public
Wks to peak srsly ill (slum)	10.00	10.00
Wks to peak srsly ill (other)	11.00	11.00
Srsly ill p/ 1,000 @ peak (slum)	1.88	2.84
Srsly ill p/ 1,000 @ peak (other)	0.77	1.07
Dead p/ 1,000 1year (slum)	10.04	6.84
Dead p/ 1,000 1year (other)	6.35	4.82
Dead p/ 1,000 1year (all)	7.16	5.27
Dead p/ 1,000 LR (slum)	10.11	6.85
Dead p/ 1,000 LR (other)	6.57	4.86
Dead p/ 1,000 LR (all)	7.35	5.30
Immune in LR (slum), %	74.33	77.03
Immune in LR (other), %	39.69	42.89
Immune in LR (all), %	47.36	50.46
GDP at peak - rel to BM	1.00	1.02
GDP 1year - rel to BM	1.00	1.04
Hrs @ home (slum) - peak	80.95	80.26
Hrs @ home (other) - peak	86.28	85.01
Hrs @ home (slum) - 6m	66.03	62.61
Hrs @ home (other) - 6m	69.40	65.91
Value - healthy (slum)	1968.10	1974.90
Value - healthy (other)	4317.40	4325.80
Value - healthy (all)	3797.00	3805.10

home decreases. But the difference is not quantitatively so different from the unchecked epidemic. The decrease in the death rate is mainly explained by the direct effect of reducing congestion in access to public hospital care units rather than by indirect effects of changing behavior. In the long run, more individuals of both groups survive and become immune to the disease. Note also that this policy increases GDP and the welfare for both groups.

6.2 Shelter-at-home Policies

We now investigate stay-at-home orders that can be implemented with the closing of non-essential businesses and schools, among other interventions. Results for different lockdown restrictions are displayed in Table 5.

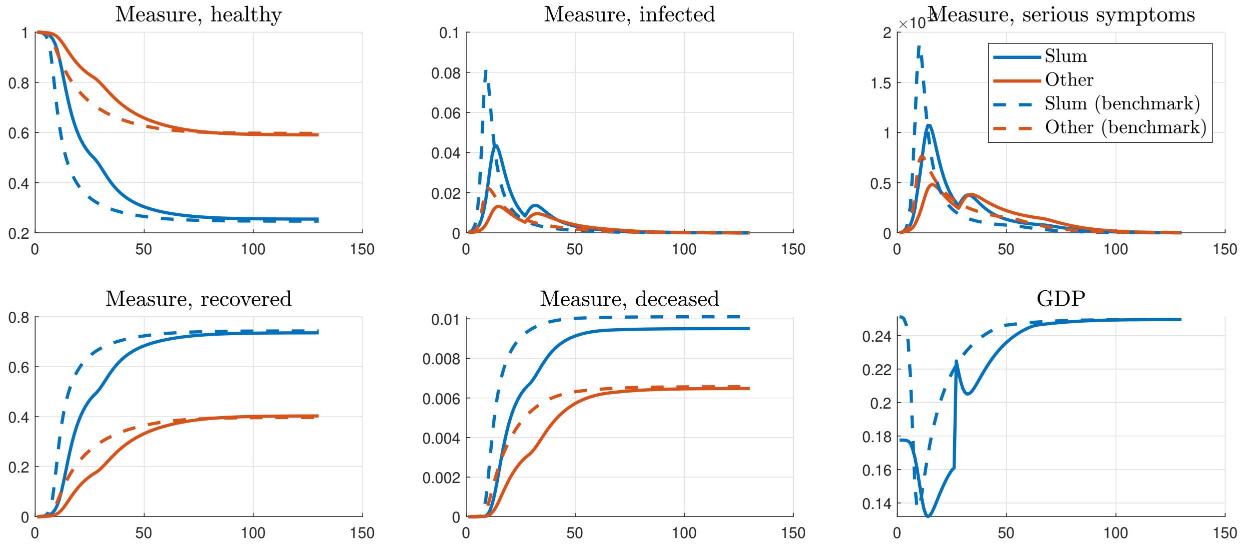
Table 5: Shelter-at-home policies

		Immediate lockdown				6-week late lockdown
	Benchmark	25%, all 26 weeks	25%, slums 26 weeks	25%, non-slum 26 weeks	75%, all 35 weeks	25%, all 26 weeks
Wks to peak srsly ill (slum)	10.00	14.00	13.00	11.00	66.00	11.00
Wks to peak srsly ill (other)	11.00	16.00	14.00	12.00	67.00	12.00
Srsly ill p/ 1,000 @ peak (slum)	1.88	1.07	1.11	1.86	1.88	1.10
Srsly ill p/ 1,000 @ peak (other)	0.77	0.48	0.71	0.57	0.77	0.48
Dead p/ 1,000 1year (slum)	10.04	9.21	9.13	10.00	0.00	8.68
Dead p/ 1,000 1year (other)	6.35	5.84	6.92	5.28	0.00	5.26
Dead p/ 1,000 1year (all)	7.16	6.58	7.41	6.33	0.00	6.02
Dead p/ 1,000 LR (slum)	10.11	9.51	9.29	10.19	10.10	9.29
Dead p/ 1,000 LR (other)	6.57	6.48	7.22	5.91	6.56	6.34
Dead p/ 1,000 LR (all)	7.35	7.15	7.68	6.86	7.35	7.00
Immune in LR (slum), %	74.33	73.58	70.96	76.68	74.36	73.29
Immune in LR (other), %	39.69	40.32	42.96	38.18	39.67	40.57
Immune in LR (all), %	47.36	47.69	49.16	46.71	47.35	47.82
GDP at peak - rel to BM	1.00	0.96	1.12	0.86	0.99	0.95
GDP 1year - rel to BM	1.00	0.87	0.98	0.89	0.47	0.87
Hrs @ home (slum) - peak	80.95	83.18	84.40	79.79	80.19	83.76
Hrs @ home (other) - peak	86.28	85.87	81.83	89.56	85.95	86.16
Hrs @ home (slum) - 6m	66.03	78.32	79.22	63.80	105.84	77.22
Hrs @ home (other) - 6m	69.40	79.79	70.83	78.39	105.84	78.36
Value - healthy (slum)	1968.10	1964.40	1964.20	1968.20	1863.20	1964.40
Value - healthy (other)	4317.40	4312.90	4315.30	4314.80	4213.00	4313.30
Value - healthy (all)	3797.00	3792.70	3794.50	3795.00	3692.50	3793.10

The first column in Table 5 reports moments related to the baseline unchecked pandemic for comparison. The second column shows the same statistics for a scenario in which there is a shelter-at-home policy that covers 26 weeks from the start of the health crisis. During the duration of this policy, individuals are required to increase their time at home by 25% relative to an environment without the pandemic.[25] As we can also see in Figure 7, the lockdown (solid lines) flattens out the infected and critically-ill curves relative to the unchecked pandemic (dashed lines). The total death rate decreases, mainly among slum dwellers. There is less congestion of public beds with the lockdown, which is a more binding issue for individuals living in slums. The total death rate among slum dwellers decreases by approximately 6% while the overall death rate is

[25]We implement this by increasing $\lambda_p(j, g)$ to the necessary value to induce agents to follow the lockdown policy. Appendix D.3 reports the calibrated values for all counterfactuals in this section.

Figure 7: Aggregate variables (lockdown, 25% increase in time at home, all groups, 26 weeks)



reduced by 3%.

Notice that GDP during the first year of the pandemic decreases by 13% relative to the no-policy baseline. The strong impact on the economy comes from a reduction in the time spent at work. Figure 8 reports the choice of the agents with a 26-week shelter-at-home policy (solid lines), as well as the benchmark (dashed lines). Individuals stay longer at home with this lockdown policy than in the baseline, reducing the peak of infection but delaying the duration of the health crisis.

Notice that the time spent at home increases by about 20 percentage points relative to the baseline before the outset of the disease (left panel of Figure 8). This is approximately the average percentage point change in the social distancing index observed in the city of Rio de Janeiro (recall Figure 1 in Section 2). In addition, the model implies a difference in social distancing between slum and non-slum dwellers of around five percentage points (Figure 9). This is similar to those reported in our event-study analysis in Figure 2 of Section 2.

In order to understand the role of slums in shaping the dynamics of the pan-

Figure 8: Choices of healthy agents (lockdown, 25% increase in time at home, all groups, 26 weeks)

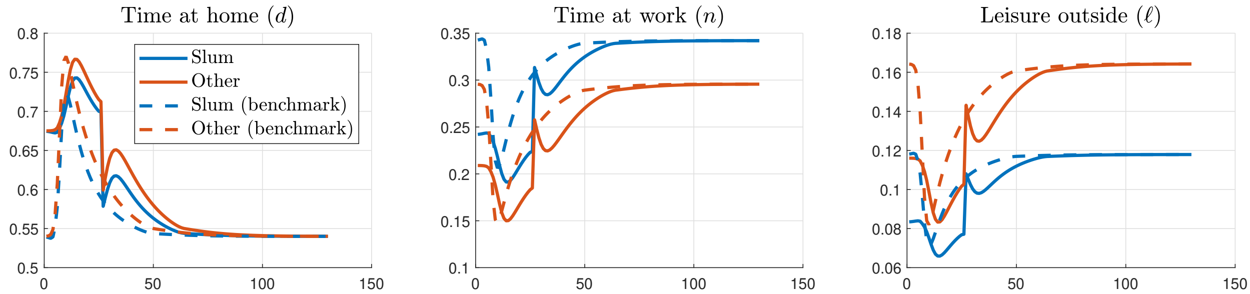
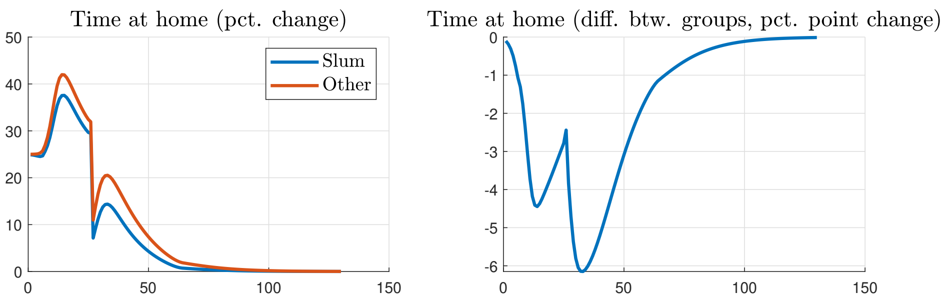


Figure 9: Difference in protection behavior between slum and non-slum agents (lockdown, 25% increase in time at home, all groups, 26 weeks)



demic under a lockdown, we also investigate the effects of targeted shelter-at-home orders: a policy of increased social distancing applied only to individuals living in slums (third column of Table 5) and one applied only to those who live in other areas (fourth column of Table 5). Interestingly, the shelter-at-home policy in slums only increases the long-run death rate for non-slum individuals. This is due to the fact that the fraction of non-slum dwellers necessary to reach herd immunity would need to rise to compensate for the lower transmission in slums. As the non-slum group is larger, this translates into a higher overall death rate. This policy ends up lowering the welfare of both groups: slum residents are worse off because they are sheltered (even though deaths among this group decrease) and the others suffer a worse health shock.

We also implement a more extreme lockdown policy (fifth column of Table 5) in which we target a rise in 75% in the time spent at home relative to the baseline. This policy lasts for 35 weeks or approximately 8 months. There are almost no deaths in the first year of the pandemic, which now lasts much longer. Therefore, a stricter lockdown is an effective strategy to delay the peak and to control temporarily the number of infected individuals and deaths. This might be an important policy while waiting to build public infrastructure (e.g. hospital beds) and/or define a future plan of action to control the virus, including waiting for a possible treatment or vaccine. Without improvements in infrastructure, treatment or a vaccine, however, the total number of deaths with or without an extreme lockdown are roughly the same. The reason is that, when the extreme lockdown is relaxed, the numbers of infections and seriously ill patients rise sharply leading to similar deaths compared to the case without the policy. The extreme shelter-at-home policy clearly causes a deep economic downturn.

Our shelter-at-home policies so far were implemented in the beginning of the pandemic, when congestion of public goods is not necessarily binding. In the last column of Table 5 we implement a lockdown policy similar to the one in column two, but that is imposed in week 6 of the pandemic, instead of week 1. This later lockdown is more effective in saving lives. The total death rate is reduced by 5% instead of 3%, as in the lockdown that is implemented in week 1. The economic effects of both shelter-at-home policies are similar.

6.3 Financial Aid

We now turn to study the effects of an emergency measure designed to compensate individuals for income losses due to a rise in social distancing. Table 6 contains such counterfactual experiments. Again for comparison, the first column of this table contains the moments of the unchecked pandemic. The second column displays the same statistics for the case in which the government transfers 300 Brazilian Reais (R$) per month for all individuals in the first 26 weeks of the pandemic.[26] This corresponds to 44% and 12% of the monthly income of slum and non-slum dwellers, respectively.

Figure 10 shows that this policy flattens out the infection curves. This effect is more pronounced in slums. The income effect is stronger for slum dwellers than for those individuals who live in other areas (time at home at the peak is essentially the same across the two groups). This implies that individuals living in slums increase social distancing much more than in the benchmark. The total death rate among individuals living in slums is reduced by 8% relative to the baseline. Given that the threshold for herd immunity rises for non-slum dwellers, this ends up increasing their total death rate by 5% during the pandemic. The overall death rate rises since the measure of individuals not living in slums is large. Notice that this composition effect on death rates becomes more pronounced when only slum dwellers receive the financial aid—third column of Table 6—or when the financial aid is more generous (600 R$ for 26 weeks instead of 300 R$)—fourth column of Table 6.

We now combine cash transfers lasting 26 weeks with stay-at-home orders that cover the same period (we target a rise in 25% in the time spent at home relative to the baseline by rising λ_p, see Appendix D.3). Such combination of policies

[26]This amount is approximately 60 US dollars in July, 2020.

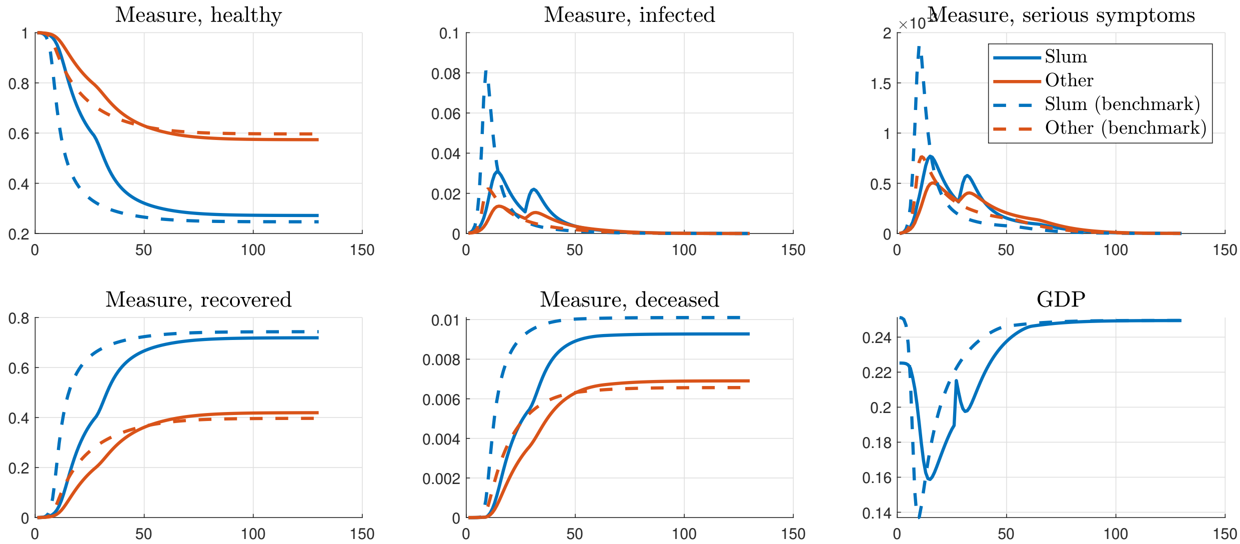
Table 6: Financial aid policies

		Only financial aid			Aid and 25% lockdown for all		
	Benchmark	300R$, all 26 weeks	300R$, slums 26 weeks	600R$, slums 26 weeks	300R$, all 26 weeks	300R$, slums 26 weeks	600R$, slums 26 weeks
Wks to peak srsly ill (slum)	10.00	15.00	14.00	32.00	32.00	32.00	32.00
Wks to peak srsly ill (other)	11.00	16.00	15.00	19.00	33.00	33.00	33.00
Srsly ill p/ 1,000 @ peak (slum)	1.88	0.77	0.80	1.16	1.51	1.23	1.61
Srsly ill p/ 1,000 @ peak (other)	0.77	0.50	0.63	0.52	0.67	0.58	0.63
Dead p/ 1,000 1year (slum)	10.04	8.99	8.94	8.81	9.01	8.96	9.07
Dead p/ 1,000 1year (other)	6.35	6.40	6.94	6.89	5.49	5.98	5.88
Dead p/ 1,000 1year (all)	7.16	6.97	7.39	7.31	6.27	6.64	6.59
Dead p/ 1,000 LR (slum)	10.11	9.28	9.16	9.15	9.54	9.40	9.58
Dead p/ 1,000 LR (other)	6.57	6.91	7.30	7.36	6.48	6.72	6.70
Dead p/ 1,000 LR (all)	7.35	7.43	7.71	7.76	7.15	7.32	7.34
Immune in LR (slum), %	74.33	71.90	70.69	70.33	73.58	72.44	72.27
Immune in LR (other), %	39.69	41.95	43.41	43.96	40.35	41.39	41.55
Immune in LR (all), %	47.36	48.58	49.45	49.80	47.71	48.27	48.36
GDP at peak - rel to BM	1.00	1.16	1.24	1.30	1.10	1.20	1.12
GDP 1year - rel to BM	1.00	0.94	0.99	0.98	0.84	0.89	0.91
Hrs @ home (slum) - peak	80.95	78.61	80.46	77.55	78.85	77.99	80.36
Hrs @ home (other) - peak	86.28	77.74	77.99	80.32	83.88	82.00	84.49
Hrs @ home (slum) - 6m	66.03	73.96	74.77	80.16	82.24	83.64	87.05
Hrs @ home (other) - 6m	69.40	71.91	70.83	70.03	77.57	77.49	72.87
Value - healthy (slum)	1968.10	1985.60	1985.70	1998.80	1982.40	1982.60	1996.70
Value - healthy (other)	4317.40	4322.20	4315.70	4315.60	4320.70	4315.10	4316.70
Value - healthy (all)	3797.00	3804.60	3799.60	3802.40	3802.80	3798.50	3802.80

was implemented in several countries including Brazil.[27] Start with a transfer of 300 R$. The combined policy extends the duration of the pandemic; much longer than when each of the policies is implemented separately. When the policy is relaxed, infections rise rapidly and the overall death rate is only 3% below the baseline. Notice, however, that the death rate among slum dwellers is higher than in the case of only cash transfers or only the lockdown. Welfare with transfers and lockdown is of course higher than in the case with only lockdown. Targeting the transfer to slum dwellers exacerbates the differences across groups, as it decreases infections and deaths in slums and increases these statistics in other areas.

[27] In 2020, Brazilian informal workers received 600 R$ per month for three months during the pandemic ("Emergency Assistance") as a compensation for their confinement. There were several issues related to the timing of the policy and to the bureaucracy to receive this cash transfer.

Figure 10: Aggregate variables (300R$ financial aid for 26 weeks, all groups)



7 Conclusions

Over one billion people in the world live in slums. These are usually crowded neighborhoods where social distancing is hard to be followed. Infectious diseases can thus spread rapidly in such areas. This paper studies the role of slums in shaping the health and economic dynamics of pandemics. Using rich data gathered from millions of mobile phones in Brazil, we show that social distancing increased less in slums at the outset of the Covid-19 pandemic.

We build and calibrate a model where poor agents live in high-density slums and richer individuals live in other areas. The former have a harder time accessing health care due to capacity constraints in public hospitals, but they are on average younger. We fit our model to match key moments of Rio de Janeiro, where 22% of individuals live in slums. Our simulations suggest that a disproportionately high number of deaths occur in slums. In a counterfactual scenario without slums, a higher fraction of residents from other areas catch the disease as the burden to achieve herd immunity falls only on this group, illustrating important distributional effects.

Using the model to explore a variety of policy experiments highlights the importance of taking this heterogeneity into account. Reallocating private ICUs into a single pool helps all groups, decreasing the death toll significantly. Very stringent shelter-at-home orders buy time but only delay deaths if no other policy is put in place. If lockdowns shelter a particular group, the other group suffers worse health outcomes, and the welfare of both groups declines. Cash transfers have a disproportional impact on slum residents and, as they can now afford to cut their labor supply, infections fall more heavily on the other group. In sum, policies can have contrasting effects across different groups in society.

Though our framework has considerable heterogeneity that allows for an array of policy experiments, we have abstracted from potentially important margins. For instance, individuals in our model are assigned a place of residence and cannot move. Perhaps long-lasting pandemics may lead them to relocate and health considerations may then affect the very structure of the city. Additionally, temporary cuts in labor supply may have enduring effects on job prospects. Being more likely to have informal jobs, slum dwellers may suffer more from such displacements. These and other issues are left for future research.

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Online Appendix

A Data Sources and Definitions

In this appendix, we detail the data used in the empirical motivation (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 Population 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 Population Census interviews all households in the country ("universe questionnaire") and also executes more detailed interviews on a 5% random sample of households ("sample questionnaire"). We use data from both the universe and sample questionnaires, as detailed below.

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 sectors are slums ("subnormal agglomeration") or not. 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 slum
- 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, differently from the results of the universe of the Brazilian census, the sample dataset does not identify whether the household lives in slums. Hence, we constructed a proxy to identify whether each household lived in a slum. More precisely, a household is considered to live in a slum if any of the following conditions are 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 - Jun/2020 - (https://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) level data on the number of private and public intensive care units (ICU) in Brazil.

ANS - Agência Nacional de Saúde Complementar - Mar/2020: From the ANS (National Supplementary Health Agency)—which provides legal and administrative regulation of the private health insurance market—we obtained municipality (city) level 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(`https://inloco.com.br`), a Brazilian technology company, collects anonymized location data from 60 million mobile phones in Brazil. By tracking with a 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. There are 841 hexagons in Rio de Janeiro and 1,301 hexagons in Sao Paulo. 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 then to match those hexagons' boundaries to the boundaries of the census tracts. Notice that are more census tracks than hexagons in each city—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 tracks' characteristics that intersect the hexagon, weighted by the fraction of the census track's area that intersects the hexagon area. See Figures A1 and A2 for the location of census tracks 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.

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.

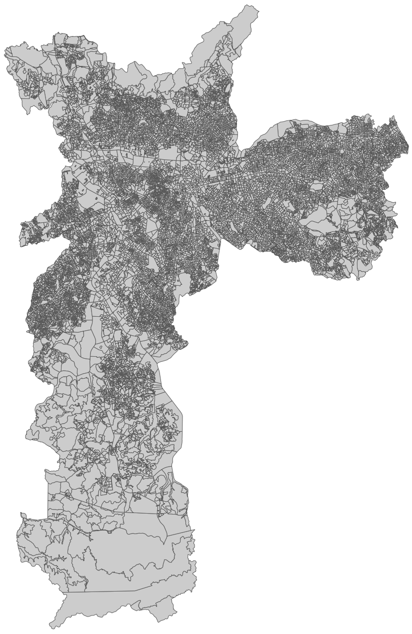
Covid-19 data at the neighborhood level: We obtained the neighborhood-level number of Covid-19 cases and deaths from the following websites:

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

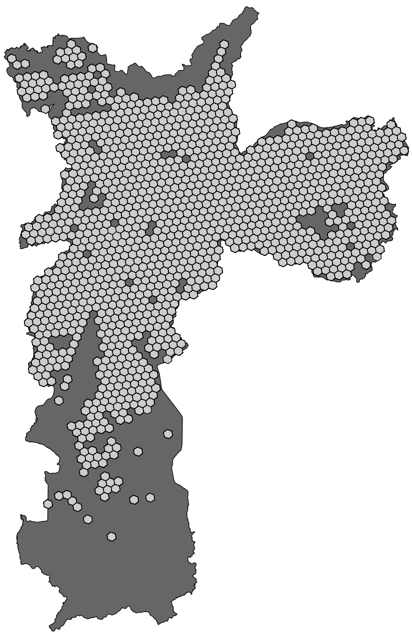
Covid-19 data at the hexagon level: Geo-referenced data on hospitalizations and deaths (until May 18, 2020) caused by Covid-19 and other acute respiratory diseases for the city of Sao Paulo is from the following website: `https://labcidadefau.carto.com/`. We use the cross-sectional geo-referenced data to create hexagon-level information on Covid-19 hospitalizations and deaths.

Figure A2: São Paulo: Census Tracts and Hexagons

(a) 17,990 Census Tracts in São Paulo



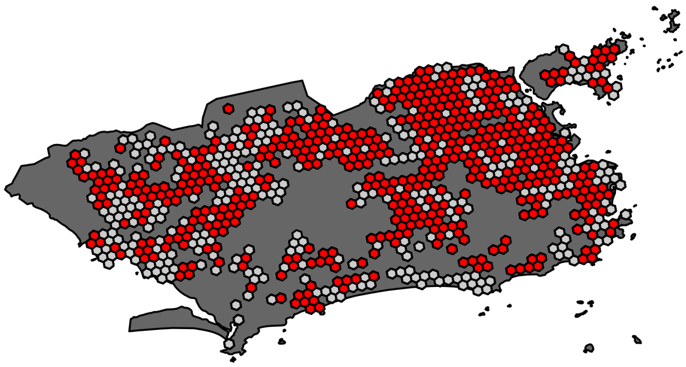
(b) 1,301 Hexagons in São Paulo



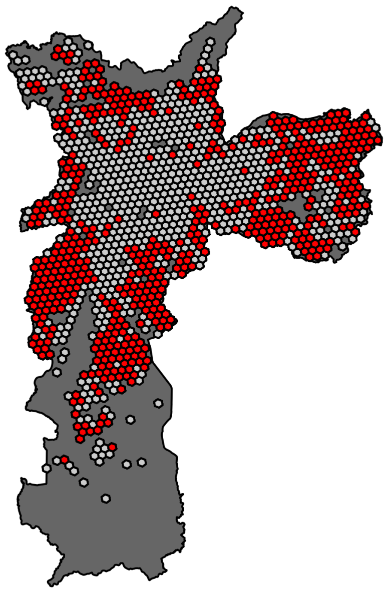
Notes. The figure shows the census tracts and the hexagons for the city of Sao Paulo.

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

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



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

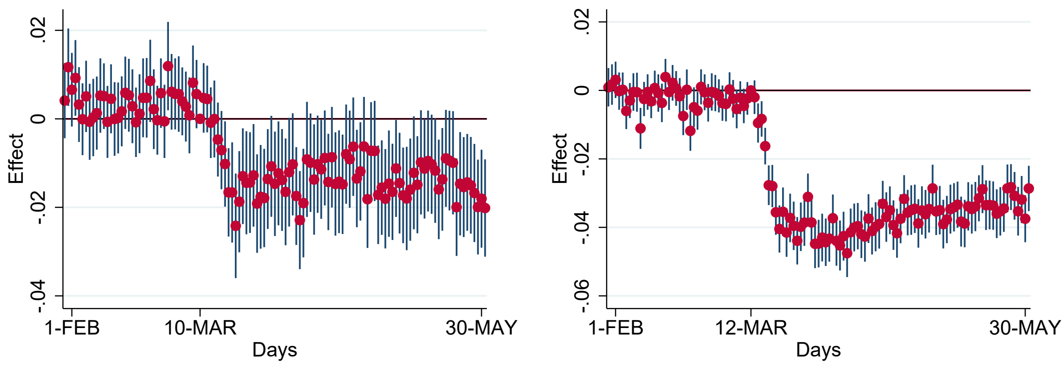


Notes. The figures show the location of the hexagons (in red) with slums. There are 510 hexagons with slums in Rio de Janeiro, and the 598 with slums in Sao Paulo.

B Additional Tables and Figures

Figure B4: **Event-Study Analysis (results without weights): Rio de Janeiro and Sao Paulo**

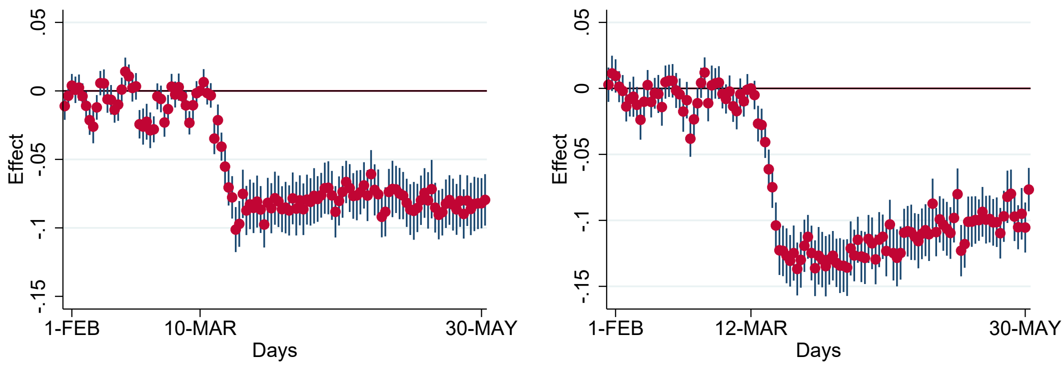
(a) Rio de Janeiro (b) Sao Paulo



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: **Event-Study 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%.

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 Feb 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

Table B2: Cross-Section Analysis: Correlation between slums and hospitalizations/deaths

Dependent variable:	Covid-19		Acute Respiratory Disease	
in logs	Hospitalization	Death	Hospitalization	Death
	(i)	(ii)	(iii)	(iv)
Slum Dummy	0.1115**	0.1010***	0.3588***	0.0731**
	(0.0463)	(0.0378)	(0.0435)	(0.0339)
Observations	1,301	1,301	1,301	1,301
Number of Hexagons	1,301	1,301	1,301	1,301
City	Sao Paulo	Sao Paulo	Sao Paulo	Sao Paulo

Notes. Each column displays the results from a separate cross-section regression. This table presents results from the estimation of the following specification: $Y_h = \alpha + \gamma I_h + \epsilon_h$, where Y_h is the outcome variable (hospitalizations and deaths) for each hexagon h and the "Slum Dummy" I_h equals one for hexagons with slums and zero otherwise. The unit of observation is a hexagon. There are 1,301 hexagons in Sao Paulo. Robust standard errors (in parentheses). The dependent variables in the regressions are the total (accumulated) number of hospitalizations and the total number of deaths (from Jan 2020) until May 18, 2020. See Appendix A for more details on the data.

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

C Laws of Motion

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

To account for infected people, one counts those who started last period healthy and get infected this period, but also those who started last period infected who neither develop severe symptoms nor recover:

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

People with severe symptoms comprise those who entered last period infected and do not recover but instead develop more severe symptoms, as well as severely symptomatic individuals from the previous period who neither die nor recover:

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

Recovered and therefore resistant individuals comprise those who were infected and recover, those with severe symptoms who do not die but recover, and resistant individuals from the previous period:

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

The right hand sides of equations (16) to (18) gives 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:

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

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

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

D Details on Calibration

D.1 Basic Reproduction Number - R_0

The probability that an infected agent leaves such state is: $\phi(0) + (1-\phi(0))\alpha$. This is the probability of recovery and the probability that the agent switches to the serious symptoms case. Hence, the expected amount of time one stays in state i is:

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

The probability that an agent with serious symptoms 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 s is:

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

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

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

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

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 with serious symptoms. 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 healthy.

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

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

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

Consider an agent that is infected with Covid-19. He may recover with probability $\phi(0)$ or develop serious symptoms with probability α. These are functions of g also, but we supress this dependence for notational convenience. The following table gives what happens to a measure 1 of agents that 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	...	...	...

Thus, the fraction of people that will develop symptoms F_s is given by

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

Solving out for α gives

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

where $B = F_s/(1-\phi(0))$. With $\phi(0)$ given by the average time for recovery, one can use the formula above to get α.

We can do similarly for agents with symptoms 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 above and denoting the fraction that 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	Non-infected	Infected
25%	1.88	0
50%	6.45	4.46
75%	33.4	31.45