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Covid-19 in unequal societies

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1. Introduction

The goal of this paper is to understand the distributional and macroeconomic consequences of Covid-19 in an unequal society. We document the epidemiological and economic disparities associated with SARS-CoV-2 in Bogotá. Then we build an integrated macroeconomic and epidemiological model with heterogeneous agents, which we use to interpret the data and simulate policy counterfactuals.

We consider a society with two social groups. In the high socioeconomic stratum (SES), people have higher human capital, access to financial markets, and the digital and occupational means to work from home and shop remotely. People in the low SES own capital but do not have access to credit markets. They are more exposed to contagion as they work in more contact-intensive industries, have a decreased ability to shop online, live in more densely populated residences, and rely more on public means of transportation. We document the epidemiological and economic disparities associated with the spread of SARS-CoV-2 among these two groups in the city of Bogotá, where people in the low SES account for 85% of the population.

Our main epidemiological data source is the CoVida project, a large-scale epidemiological surveillance study that was conducted for nine months in Bogotá (Laajaj et al., 2021a). Almost 60,000 people were tested for the virus (with an RT-PCR test) and responded to a questionnaire on their socioeconomic and demographic characteristics. A problem in studying the Covid-19 pandemic is that official data on infection are often unreliable because the data fail to detect most asymptomatic cases. The CoVida data are highly valuable in that they provide reliable estimates of infections and the personal background...
of those infected. We find that by February 2021, 54% of Bogotá’s population was infected by the virus, the prevalence ratio between the two groups was two, and the fatality rate of the low SES was 50% higher than for the high SES. The reliable estimate of the prevalence rates allows us to estimate infection fatality rates by SES. We find that, although infection fatality rates conditional on age are higher for the more vulnerable group, the unconditional infection fatality rates for the adult population are similar across the two groups because of age composition effects.

We record the economic impact of the Covid-19 epidemic, drawing on official data on economic activity and labor market indicators and on a private tracker of private consumption. Economic activity in Bogotá fell by 25% in April 2020, recovered sluggishly, and was 5% below trend in April 2021. Private consumption dropped on impact and recovered faster, exhibiting a similar pattern for people in the two social groups, with the caveat that consumption in the high SES was smoother. Employment fell by 30% and hours worked by more than 50% on impact, and hours recovered to a level that was 15% below trend. In the second quarter of 2020, during the shutdown, capital income was 30% below trend and labor income was 10% below trend. Thus, to the extent that people in the high SES hold most of the capital stock, their income losses would be higher.\textsuperscript{2}

We compute the dynamic general equilibrium of a small open economy (a country or city) populated by two sets of agents with the characteristics described above. We integrate this macroeconomic model with a behavioral epidemiological SIRD model building on Eichenbaum et al. (2020) and Faroodi et al. (2020). When the epidemic breaks out, agents decide their optimal exposure to the risk of contagion, and there is a mutual feedback between the resulting health dynamics and aggregate economic outcomes (wages, employment, consumption, asset and capital accumulation).

We follow Eichenbaum et al. (2020) in assuming that exposure to contagion in the workplace and consumption venues is proportional to labor hours and consumption expenditures. We also assume that people adjust their social behavior not associated with these activities by wearing masks, socially distancing from loved ones, meeting outdoors, and so on. We model decisions balancing the risk of infection and the utility cost of this change in social behavior, reinterpreting the model in Faroodi et al. (2020). A key difference between Eichenbaum et al.’s (2020) model and ours is that we assume that when people are not working, they are consuming or engaging in other social interactions. Thus, reducing the labor supply to avoid infections is more effective if it is complemented with costly adjustments to non-work activities.

We find that in the competitive laissez-faire equilibrium the welfare cost of the epidemic outbreak is equivalent to a three-year reduction in consumption of 4.3% for the high SES and 4.9% for the low SES. These welfare costs stem from the expected cost of death, a strong reaction in social interactions, and modest changes in consumption and labor.

As Bogotá’s economic performance is inconsistent with the laissez-faire equilibrium, we consider, as our benchmark case, an economy with two policy interventions: a shutdown calibrated to track Bogotá’s output pattern and lump-sum transfers calibrated to those received by the city’s poor residents. In this case, the model is very good at predicting the epidemiological and economic patterns in the data. The welfare cost borne by high-SES agents becomes 11.4% of steady-state consumption for three years, and the one for the low-SES agents is equivalent to a three-year fall in consumption of 8.7%. Most of the fall in welfare stems from the inefficiency of the shutdown, which is very costly from an economic perspective and has little epidemiological benefit. The shutdown hurts the rich more than the poor, via the capital income channel, and the redistributive transfer further hurts high-SES individuals. To smooth consumption at the peak of the lockdown, low-SES agents sell some of their capital, paying an adjustment cost, and later repurchase it, again paying an adjustment cost.

In our model, redistributive lump-sum transfers naturally hurt the high-SES agents that pay for them to benefit the recipients. Macroeconomically, transfers have the expected effect of reducing aggregate labor and increasing consumption. Investment rises as a result of our assumption that low-SES agents do not have access to credit markets, so they choose to save the transitory income from the transfers by accumulating capital.

We exploit the richness of the CoVida epidemiological data, in combination with economic data, to internally calibrate through the simulated method of moments key epidemiological parameters and the preference parameters tied to the cost of social distancing. The rest of the parameters are exactly identified and chosen to match moments that correspond to the disease-free steady state.

We find that the basic reproductive number for Bogotá was 2.3 and, through a combination of endogenous behavior and economic restrictions, fell to 1.2 at the peak of the epidemic.\textsuperscript{3} Our internally calibrated epidemiological transmission rates imply that people in the low socioeconomic group are 41% more vulnerable to infection than those in the high SES. They are more vulnerable mainly because, while the transmission rates from people in the high SES to people in both groups are similar, people in the lower SES transmit the virus to somebody in their own group 95% more relative to transmission to their richer peers.

The model estimates that, at the peak of the pandemic, Bogotá’s inhabitants reduced their social interactions with a high risk of transmitting the virus, outside workplaces and shopping venues, by about 60%. At that point, the elasticity of consumption with respect to social distancing along an indifference curve was close to 4%. People would pay 0.04% of their weekly consumption to reduce social distancing by 1%.

\textsuperscript{2} Gupta et al. (2021) documents that the fall in capital income is an important factor in explaining why inequality in India fell during covid.

\textsuperscript{3} The basic reproductive number, or \( R_0 \), is the average number of secondary infections generated by a single infected individual in a population composed of only susceptible individuals.
Table 1
Characteristics of Socioeconomic Groups.

|                  | Low-SES | High-SES |
|------------------|---------|----------|
| % of labor force | 89      | 11       |
| % of population over 18 | 87 | 13     |
| Years of education | 10.8 | 16.1 |
| Income (USD)    | $366   | $1.513   |
| Work hours per week | 44  | 41       |
| Income/hour (USD) | $2.1 | $9.3     |

Notes: Low (high) SES is the aggregation of socioeconomic strata 1, 2, and 3 (4, 5, and 6). Reported values are the 2017-19 average of monthly surveys. Income is monthly labor income from all sources excluding transfers and capital income converted to USD with the average exchange rate from each year. Income per hour is computed multiplying hours per week by four. Source: Labor household survey from Colombia’s National Department of Statistics (Gran Encuesta Integrada de Hogares - GEIH/DANE). Population data come from The Multipurpose Survey 2017 (Encuesta Multipropósito - DANE).

Related literature. A burgeoning literature uses economic theory to enrich epidemiological models with behavioral decisions that impinge on the risk of contagion and, at the same time, learn about the impact of epidemiological dynamics on macroeconomic aggregates. This paper builds on the work of Eichenbaum et al. (2021) and Farboodi et al. (2020) to develop an epi-macro model of an unequal society. We extend their model to a multi-group SIRD in which agents differ in their transmission rates. The model also features two assets, capital and a bond, and captures the limited financial inclusion in emerging economies by excluding the low-SES group from trading the risk-free asset. Several papers address similar questions—see, for example, Eichenbaum et al. (2021), Hur (2020), and Kaplan et al. (2020). In addition to several modeling choices described above and in the text, the most distinguishing feature of our work is that we discipline the epidemiological features of the model with more reliable data on infections and fatalities. Our model delivers as a by-product the private value of a vaccine for each socioeconomic group. However, we do not compute the social planner’s allocation, so our approach does not take into account the externalities associated with vaccines, as in Garriga et al. (2020) and Boppard et al. (2021).

The rest of the paper is structured as follows. We document the epidemiological and economic impact of Covid-19 in Bogotá in section 2, present the model in section 3, the calibration strategy in section 4, the simulation results in section 5, the sensitivity analysis in section 6, and conclusions in section 7.

2. The heterogeneous impact of Covid-19 across socioeconomic groups in Bogotá

In this section, we document the heterogeneous effect of Covid-19 on health and economic outcomes. We focus our attention on the city of Bogotá because of the quality of the epidemiological data gathered by the CoVida sentinel surveillance project (Laajaj et al. (2021a), Varela et al. (2021)). From April 18, 2020, to March 29, 2021, CoVida performed almost 60,000 RT-PCR tests on a sample of the city’s population (mostly asymptomatic individuals). Participants were adults randomly drawn from large employer lists and from a convenience sample of individuals responding to a free testing public campaign. Results for the two samples are similar once the selection bias from those with symptoms and contacts with infected persons is removed from the convenience sample. Excluding the latter, the sample has 42,164 observations.

CoVida participants have to respond to a questionnaire that describes their socioeconomic background, age, occupation, contacts, and health history in order to be tested. One of the questions refers to the participant’s socioeconomic stratum (SES), which is also a question in the labor market household survey. The SES is a classification of residential units used by the government to discriminate prices for public utilities across households, dividing the population into six socioeconomic strata. We aggregate participants into two groups comprising the lower three and the top three SES. The characteristics of these two groups are described in Table 1.5

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5 Gran Encuesta Integrada de los Hogares (GEIH), D.A.N.E.
6 Table 7 in section A describes the characteristics at a more disaggregated level.
2.1. Epidemiological disparities

In this section, we document the spread of Covid-19 in Bogotá. Using CoVida’s data, in March 2021, 54% of Bogotá’s population had been infected, and the prevalence ratio in the lower SES doubled relative to the higher SES.

Figure 1 shows the epidemiological dynamics of Covid-19. The left panel, figure 1a, reports the estimates of daily new cases (inferred from positivity rates) by SES and shows two waves of infections with a higher rate of infection in the lower SES, especially in the second wave. The right-hand panel, figure 1b, shows the cumulative sum of positive cases for the aggregate as well as for each SES. The cumulative cases from June 2020 to February 2021 estimated by CoVida add up to 53.8% of Bogotá’s population, and the prevalence in the low-SES population was 58%, twice that (29%) of the higher SES population.\textsuperscript{7}

The CoVida prevalence rates reported above contrast with official counts of Covid-19 cases of only 8% of the population by the end of February 2021. The official detection rate varies significantly across social groups as well: while the official detection rate in the highest socioeconomic stratum is one in six, in the lowest stratum it is one in ten (Laajaj et al., 2021a). The CoVida project’s results have an external validation from a seroprevalence survey conducted by Colombia’s government between October 26\textsuperscript{th} and November 17\textsuperscript{th}, 2020. The serosurvey estimates a prevalence rate of 30% [27-33] of the population, while CoVida’s data yield an estimated prevalence of 29% [26-37]. The official case count at that date was of only 5% of the population.

In figure 2 we plot measures of epidemiological disparity against Covid-19 prevalence (a proxy for epidemiological time). The lines represent the odds and prevalence ratios across socioeconomic groups in Bogotá. The solid lines are the ratios for our benchmark case in which we aggregate the lowest three and the highest three SES. Dashed lines represent the same concept excluding the third SES from the low-SES group. Keeping only the most vulnerable individuals in the sample in the low-SES group significantly increases the epidemiological disparity.

Each of the two waves of infections accelerates the epidemiological disparities illustrated in figure 2. The first sharp rise in disparity in Bogotá occurs when prevalence is above 20% during the exit of the first wave as the new cases fall much faster for the more advantaged SES. The second bout in disparity is at the beginning of the second wave as new infections grow much faster for people in the more disadvantaged SES. In comparison with the literature on Covid-19 health disparities we reviewed, the health disparities measured in the CoVida project in Bogotá are relatively small.\textsuperscript{8}

We estimate infection fatality rates (IFRs) in Bogotá of 0.32%, which is in line with estimated values elsewhere (Ioannidis, 2021). Table 2 reports fatality, prevalence, infection fatality, and hospitalization fatality rates by age and SES group. For the working-age population, infection fatality rates are the same across SES. Even though IFRs conditional on age are higher for the low SES, there is a composition effect because the high-SES population is older. Covid-positive cases in adults over 60 years are 14% in the low SES and 18% in the high SES.\textsuperscript{9}

\textsuperscript{7} Laajaj et al. (2021b) documents with more detail SARS-CoV-2 infection inequalities.

\textsuperscript{8} See section A.2

\textsuperscript{9} The demographic structure of the population, the CoVida sample, and the CoVida positive cases by age is reported in table 10 in section A.2
2.2. The impact of Covid-19 on economic activity and disparities

In this section, we describe the evolution of economic activity, consumption, and labor hours in Bogotá, which is depicted in figure 3, together with the national Oxford Policy Stringency Index. The National Stringency Index aggregates the values of its components using the maximum value among sub-national jurisdictions.

Colombia imposed a strict lockdown on March 26, 2020, that lasted until the end of August. Most restrictions on economic activity were lifted at that time, and some were reimposed for a brief period on January 7, 2021, at the peak of the second wave. Economic activity in Bogotá fell by 22% in April 2020, when the quarantine was imposed, and recovered slowly while the quarantine was still in place and Covid-19 cases were rising to settle around 5% below the pre-pandemic linear trend. Aggregate consumption exhibits a smaller V-shaped fall with a faster recovery that settles around 4% below trend while the quarantine is in place and gets close to normal before the second lockdown. Consumption for individuals in high-SES recovers to 3% below trend and is smoother than the one for low SES. As DANE publishes neither consumption data disaggregated by SES nor consumption data for Bogotá, we use consumption data estimated by the private consulting firm RADDAR, which estimates consumption expenditures by income group for Bogotá at a monthly frequency. RADDAR's data include expenditures in used consumer durable goods, which the national income accounts do not. RADDAR's consumption...
Table 2  
Infection Fatality Rate.

| Fatality Rates (100k) | Aggregate | Low-SES | High-SES | L/H ratio |
|----------------------|-----------|---------|----------|-----------|
| All ages             | 170       | 178     | 122      | 1.46      |
| 18-59                | 55        | 60      | 21       | 2.83      |
| 18-39                | 13        | 15      | 4        | 3.83      |
| 40-59                | 113       | 127     | 40       | 3.13      |
| 60+                  | 1212      | 1341    | 643      | 2.09      |

Prevalence Rate (% population)  
| All ages             | 54        | 58      | 29       | 1.99      |
| 18-59                | 53        | 59      | 21       | 2.81      |
| 18-39                | 54        | 62      | 17       | 3.66      |
| 40-59                | 50        | 54      | 26       | 2.05      |
| 60+                  | 61        | 51      | 59       | 0.87      |

Infection Fatality Rate (100k infected)  
| All ages             | 317       | 309     | 422      | 0.73      |
| 18-59                | 104       | 103     | 102      | 1.01      |
| 18-39                | 24        | 24      | 23       | 1.05      |
| 40-59                | 226       | 234     | 153      | 1.53      |
| 60+                  | 1983      | 2636    | 1098     | 2.4       |

Hospital Fatality Rate (%)  
| All ages             | 27        | 26      | 33       | 0.79      |

Notes: Fatality (Servicio de Salud Bogotá) and prevalence rates (CoVida) are percentages of the population of each group computed with data up to February 2021. Infection fatality rates are the ratio of fatality and prevalence rates. Hospital fatality rates (Covid-related deaths/Covidrelated hospitalizations) are based on Eslava et al. (2020).

Fig. 3. Impact of Covid-19 on Economic Activity and Disparities. Notes: Economic data in panel (a) are log deviations from the pre-pandemic (2017-19) linear trend. Labor hours are the percentage difference from the 2019 average of seasonally adjusted data. Nominal consumption expenditure was deflated by the Consumer Price Index. Consumption and labor hours are seasonally adjusted with the US Census X13 method. Sources: Output in Bogotá is real seasonally adjusted Indicador de Seguimiento Económico from DANE. Consumption is from RADDAR. Consumption includes household expenditures on previously produced goods (not counted in GDP). Oxford Stringency Index downloaded from Ritchie et al. (2020). Labor hours are computed with household survey data (Gran Encuesta Integrada de Hogares (GEIH) - DANE).

estimates fall less than consumption in the national accounts in the second quarter of 2020 because during the lockdown there was an increase in the expenditure on used goods relative to normal times, especially for computers and vehicles.\(^\text{12}\)

The dynamics of employment during the pandemic are shown in figure 3b. The introduction of the strict lockdown in late March induced a fall in hours worked of 54% from their average value in 2019 in April 2020, with a subsequent sluggish recovery that is still around 15% below the 2019 average at the end of 2020. Although the time pattern of labor dynamics is qualitatively similar to that of output, the trough is deeper and the recovery value smaller than what would be expected with a constant returns to scale technology and a labor share of 2/3, indicating an increase in total factor productivity during the pandemic.

Unfortunately, the household survey data are inadequate to draw conclusions about the disparities in hours worked (or employment) during the lockdown because, between March and July, DANE conducted an abridged survey in which it did

\(^{12}\) See figure 18 in section A.3 for a comparison of Raddar and NIPA consumption data during 2020. In normal times the correlation between the two data sources is about 0.85.
not ask respondents for their SES.\textsuperscript{13} Moreover, the data for individuals in higher SES (10\% of the labor force) are very noisy. With these caveats, we observe that after the lockdown, labor hours are on average slightly higher for the high-SES group relative to the low-SES group.

The functional distribution of income depicted in figure 4 shows a large drop in capital income in the second quarter of 2020, which is more than three times larger than the fall in labor income.

2.2.1. Transfer policies

During 2020-1, Colombia’s government set in motion a battery of new social programs and enhanced existing ones (Lustig et al., 2021), which add up to 4.6\% of average pre-pandemic labor income per person for individuals in the low-SES group (SES 1, 2, and 3).\textsuperscript{14} If we assume these payments are targeted at the two lowest SES, they amount to 8.3\% of per person pre-pandemic labor income.\textsuperscript{15}

3. Model

The model we propose integrates economics and epidemiology by incorporating in the analysis behavioral responses that influence the disease’s transmission rate. It interlaces the basic SIR model of epidemics proposed in McKendrick and Kermack (1927) with a macroeconomic model, as in Eichenbaum et al. (2020). The latter departs from the standard epidemiological model because it explicitly takes into account how infection dynamics depend on economic activity. It extends

\textsuperscript{13} DANE has a project to recover the missing data in 2020 and is expected to publish the results by the end of 2021.

\textsuperscript{14} Ingreso solidario, a new program, paid COP 160,000 (USD 42) each month between April and December 2020, to 3 million informal workers with no bank accounts. Familias en Acción, a conditional cash program for underprivileged children and adolescents, was expanded with five extra payments of COP 145,000 (USD 42) to approximately 2.6 million people. Jóvenes en Acción, targeted to disadvantaged young adults (16 to 24) so that they will complete their studies, issued five extra payments of COP 356,000 to 204,000 individuals. The local Bogotá government created a new assistance program that made five bimonthly payments of COP 233,000 to 251,000 beneficiaries. We exclude Colombia Mayor, a cash transfer for older adults without pension or living in extreme poverty, that expanded with five extra payments of COP 160,000, to 17 million people because we don’t have retired persons in our model.

\textsuperscript{15} The labor household survey (GEIH) asks respondents about the transfer payments they receive which average approximately 11\% of income for individuals in both the SES 1 and 2 group and the SES 1, 2, and 3 group. There is no change between the average transfer received during the period August 2020-February 2021 and the average for the same months in the previous two years. This means the either respondents do not report transfers associated to covid-19 or that the transfers did not reach them. We assume the former.

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**Fig. 4.** Functional Distribution of Income. Note: Nominal income figures are deflated with the implicit price deflator. Mixed income is assigned two-thirds to labor and one-third to capital. Trend is the 2018-19 linear trend. Source: DANE.
the work of Eichenbaum et al. (2020) by incorporating endogenous social practices that mitigate the risk of infection at the cost of a lower utility and by incorporating capital.

3.1. A behavioral multigroup epidemiological SIRD model

The population is normalized to one. A fraction $\lambda \in [0, 1]$ of the population belongs to the low SES while the fraction $1 - \lambda$ belongs to the high SES. In our benchmark model, we assume that people in the low SES differ from those in the high SES in that (i) they have less human capital (earn less) and (ii) they do not have access to financial markets. We use the subscripts $\{L, H\}$ as indicators of each type.

At the beginning of the pandemic, the population is partitioned into four compartments: the persons that are susceptible of contagion, denoted by $\{S_{Ht}, S_{Lt}\}$; the persons that are infectious, denoted by $\{I_{Ht}, I_{Lt}\}$; and the persons that are removed from the pandemic either because they acquired immunity, $\{R_{Ht}, R_{Lt}\}$, or because they died, $\{D_{Ht}, D_{Lt}\}$. Let $\{\Gamma_{Ht}^j, \Gamma_{Lt}^j\}$ denote the vector of aggregate economic choices made by susceptible and infected agents of type $j \in \{H, L\}$. Then, given initial conditions $\{S_{j,0}, I_{j,0}, R_{j,0}, D_{j,0}\}$ for each group $j \in \{H, L\}$, the disease dynamics in our model are governed by the following equations:

$$S_{jt+1} - S_{jt} = - (\tilde{\beta}^{Hj}(\Gamma_{jt}^S, \Gamma_{Ht}^j)I_{Ht} + \tilde{\beta}^{Lj}(\Gamma_{jt}^S, \Gamma_{Lt}^j)I_{Lt})S_{jt},$$  \hspace{1cm} (1a)

$$I_{jt+1} - I_{jt} = (\tilde{\beta}^{Hj}(\Gamma_{jt}^S, \Gamma_{Ht}^j)I_{Ht} + \tilde{\beta}^{Lj}(\Gamma_{jt}^S, \Gamma_{Lt}^j)I_{Lt})S_{jt} - (\pi^R + \pi^D)I_{jt},$$  \hspace{1cm} (1b)

$$R_{jt+1} - R_{jt} = \pi^R I_{jt},$$  \hspace{1cm} (1c)

$$D_{jt+1} - D_{jt} = \pi^D I_{jt},$$  \hspace{1cm} (1d)

where $\pi^R$ is the rate at which infected individuals recover and $\pi^D$ the rate at which they die. The key feature of our model is that transmission rates are endogenous and depend not only on the aggregate economic choices of the susceptible and the infected but also on their individual choices. Furthermore, we assume the transmission rate between an infected individual of type $i$ and a susceptible one of type $j$ has three additive components that represent the transmission that occurs at consumption venues, workplaces, and other spaces of social interaction:

$$\tilde{\beta}^{ij}(\Gamma_{jt}^S, \Gamma_{jt}^L) = \beta_{ij}^L(\Gamma_{jt}^S, \Gamma_{jt}^L) + \beta_{ij}^H(\Gamma_{jt}^S, \Gamma_{jt}^L) + \beta_{ij}^A(\Gamma_{jt}^S, \Gamma_{jt}^L).$$  \hspace{1cm} (2)

Following Eichenbaum et al. (2020), we assume that the first two terms depend on contact intensity at consumption venues and workplaces, which is proportional to the intensity of consumption and hours worked by each group. The last term is a reinterpretation of Farboodi et al. (2020) that captures other social interactions and depends on mitigating actions of susceptible and infected individuals, such as reduced meetings among family and friends, interacting outdoors, mask wearing, and limiting the number of contacts. The exact functional form for $\tilde{\beta}^{ij}(\Gamma_{jt}^S, \Gamma_{jt}^L)$ is described in equation (21) in Section 4.

The heterogeneity in transmission rates is meant to capture the conventional wisdom that low-SES households are more vulnerable to contagion because they have a reduced ability to shop online and stock up on goods, are more likely to work in contact-intensive industries, have fewer opportunities to work from home, and live in more densely populated quarters. An immediate implication of our formulation is that the evolution of the disease will depend on household heterogeneity.

3.1.1. Transition probabilities, individual choices, and health dynamics

When agents make choices, they take into account how these choices may affect their health status in the future. In the case of infected and recovered agents, their decisions have no effect on their health. For susceptible agents, however, the probability of becoming infected does depend on their choices. We use $\pi^i_j(\gamma_t, \Gamma_{Ht}^i, \Gamma_{Lt}^i)$ to denote the probability that a susceptible agent of type $j$, with individual choices $\gamma_t$, becomes infected next period given aggregate choices $\Gamma_{Ht}^i$ and $\Gamma_{Lt}^i$. Aggregation requires:

$$\pi^i_j(\gamma_t, \Gamma_{Ht}^i, \Gamma_{Lt}^i) = \tilde{\beta}^{ij}(\gamma_t, \Gamma_{Ht}^i, \Gamma_{Lt}^i)I_{Ht} + \tilde{\beta}^{Lj}(\gamma_t, \Gamma_{Ht}^i, \Gamma_{Lt}^i)I_{Lt}.$$  \hspace{1cm} (3)

The probability of becoming infected depends on the interaction between the susceptible decision maker and the aggregate number of infectious agents in the different social interaction activities. Thus, agents can reduce the probability of becoming infected by reducing their exposure to infected individuals in consumption venues and workplaces or by engaging in other social interactions. At the same time, an externality arises because each individual takes the aggregate as given and does not take into account the impact of his or her actions on the aggregate. Using equation (3), equilibrium disease dynamics in equations (1) can be rewritten as follows:

$$S_{t+1} = (1 - \pi^i_j(\Gamma_{jt}^S, \Gamma_{Ht}^i, \Gamma_{Lt}^i))S_t,$$  \hspace{1cm} (4a)

$$I_{t+1} = (1 - \pi^R - \pi^D)I_t + \pi^i_j(\Gamma_{jt}^S, \Gamma_{Ht}^i, \Gamma_{Lt}^i)S_t.$$  \hspace{1cm} (4b)
\[ \begin{align*}
R_{t+1}^j &= R_t^j + \pi^R_t^j, \\
D_{t+1}^j &= D_t^j + \pi^D_t^j.
\end{align*} \tag{4c, 4d}
\]

The first equation describes the dynamics of susceptible households. The share of susceptible households of type \( j \) next period, \( S_{t+1}^j \), is simply the fraction of households that do not get infected in the current period, \( (1 - \pi_t^j)S_t^j \). Likewise, the share of infected households of type \( j \) next period equals those that did not recover or die, plus the susceptible households that got infected.

3.2. Government

The government in this economy plays two roles. First, it may impose restrictions on economic activity aimed at reducing social interactions and contagion. Second, it uses lump-sum taxes and transfers to redistribute income from high-SES to low-SES consumers to alleviate the economic impact of the former restrictions.

A government policy consists of a sequence \( \{\xi_t, \tau_t\}_t^{\infty} \), where \( 0 < \xi_t \leq 1 \) represent limits on firm production and \( \tau_t \geq 0 \) represent lump-sum transfers to \( \lambda \) low-SES consumers, which are paid with lump-sum taxes on \( 1 - \lambda \) high-SES agents.

3.3. Production

The production side of the economy is very simple. A representative firm combines capital and labor to produce the final consumption good according to the following Cobb-Douglas technology:

\[ y_t = ZK_t^\alpha n_t^{1-\alpha}, \tag{5} \]

where \( Z \) denotes total factor productivity. In the context of a pandemic, the firm could be subject to an epidemiological policy restriction of the following type:

\[ y_t \leq \xi_t. \tag{6} \]

All markets are perfectly competitive. We use the consumption good as the numeraire and normalize its price to one. The firm chooses capital and labor in order to maximize profits. Formally, the firm’s problem is

\[ \max_{\{n_t, k_t\}} y_t - w_t n_t - v_t k_t \tag{7} \]

subject to (5) and (6), where \( w_t \) is the wage and \( v_t \) is the rental rate of capital.\(^\text{16}\) First-order conditions imply that factor prices must satisfy

\[ w_t = (1 - \varphi_t)(1 - \alpha)ZK_t^\alpha n_t^{1-\alpha}, \tag{8a} \]

\[ v_t = (1 - \varphi_t)\alpha ZK_t^{\alpha-1} n_t^{1-\alpha}, \tag{8b} \]

where \( \varphi_t \) is the Lagrange multiplier on the epidemiological policy capacity constraint (6). Binding capacity constraints, \( \varphi_t > 0 \), reduce the demand for labor and capital.

3.4. Consumers

People differ in terms of their human capital and access to financial markets. Regardless of their type, each household can be in one of three possible health states: susceptible, infected, or recovered. In what follows, we use \( \sigma \in \{s, i, r\} \) as an indicator of the individual health status and \( j \in \{L, H\} \) as an indicator of consumer type.

All household have identical, time-separable preferences, which are defined over streams of consumption, labor, and social activities. The instantaneous utility function is denoted by \( u(c, n, a) \).

Before laying out the problem of each type of consumer in recursive form, we briefly discuss an assumption that we impose to simplify the numerical computation of the model. Since the individual transition across health states is stochastic, absent any insurance mechanism, there is idiosyncratic risk and heterogeneity across agents that belong to different health states. Since our objective is not to study this particular form of heterogeneity, and doing so would require us to keep track of the entire distribution of assets within each health group, we simplify the model by assuming that all consumers can insure ex ante, at time \( t = 0 \), against the risk of becoming infected at different dates in time. The advantage of imposing this assumption is that we can consider the problem of a representative agent for each of the health groups. Appendix D sketches the details of this insurance arrangement.

\(^\text{16}\) The international interest rate \( r_t \) and the rental cost of capital \( v_t \) may differ in the short-run because capital accumulation is subject to adjustment costs to investment.
To set up the consumer’s problem recursively, we use $\Sigma_t$ to denote the vector of all aggregate state variables that are relevant to the consumer at period $t$, and $\mathcal{H}$ to denote its law of motion, that is,

$$\Sigma_{t+1} = \mathcal{H}(\Sigma_t).$$  \hfill (9)

This transition function must allow consumers to predict the epidemiological variables in (4) and factor prices in (8). The individual state variables consist of the health status $\sigma_t$, the stock of capital holdings $k_t$, and the stock of bond holdings $b_t$.

The capital accumulation technology entails an adjustment cost so that capital evolves according to

$$k_{t+1} = (1 - \delta)k_t + x_t - \Phi(k_t, k_{t+1}).$$  \hfill (10)

### 3.4.1. High-SES consumers

In each period, a high-SES consumer with health status $\sigma_t$ decides consumption $c_t$, savings $b_{t+1}$, investment $x_t$, and labor supply $n_t$ so as to satisfy the budget constraint

$$c_t + x_t + b_{t+1} = w_t n_t + v_t k_t + (1 + r(b_t))b_t - \frac{\lambda}{1 - \lambda} T_{t+1}^H(\sigma_t, \Sigma_t)$$  \hfill (11)

where $w_t$ is the wage rate, $v_t$ is the return to capital, and $r(b_t)$ is the interest rate schedule faced by each agent,\footnote{The interest rate $r(b)$ is the sum of a foreign interest rate $r^*$ and a risk premium that depends on the stock of debt $b$. We assume that $dr(b)/db$ is a small positive number that induces consumption and asset holdings to be stationary following Schmitt-Grohe and Uribe (2003).} and $T_{t+1}^H$ are insurance transfers that break the link between the health status and wealth described in Appendix D. A borrowing limit that bounds consumption completes the constraint set of high-SES agents.

An individual’s welfare at period $t$ satisfies the following recursive expression:

$$V_{t+1}^H(\sigma, k; b, \Sigma) = \max_{c(n, k, a, b)} u(c, n, a) + \frac{1}{1 + \rho} \mathbb{E}\left[V_{t+1}^H(\sigma', k', b'; \Sigma') \mid \sigma \right]$$  \hfill (12)

where the optimization problem on the right-hand side is subject to the capital accumulation technology (10), the budget constraints (11), the borrowing constraint, and the aggregate law of motion (9). Importantly, the expectation on the right-hand side of equation (12) is taken with respect to the next period’s health status and constitutes the only difference in the problems faced by each type of agent. The decision problem of a recovered agent is the simplest one, as the next period’s health status is known and independent of current actions. Thus, we have

$$\mathbb{E}\left[V_{t+1}^H(\sigma, k; b, \Sigma) \mid \sigma \right] = V^H(\sigma, k; b, \Sigma).$$

An infectious consumer does face uncertainty, but it is independent of current choices. The continuation value is

$$\mathbb{E}\left[V_{t+1}^H(\sigma, k; b, \Sigma) \mid i \right] = (1 - \pi^D - \pi^I) V^H(i, k; b, \Sigma) + \pi^I V^H(\sigma, k; b, \Sigma),$$

where we should note that with probability $\pi^D$, this value drops to zero if the infectious consumer dies. Finally, the continuation value of a susceptible consumer is

$$\mathbb{E}\left[V_{t+1}^H(\sigma', k'; b'; \Sigma') \mid s \right] = \pi^I f_i(c(n, a)) V_{t+1}^H(i, k; b, \Sigma) + (1 - \pi^I f_i(c(n, a))) V_{t+1}^H(s, k; b, \Sigma).$$

Thus, the decision problem of a susceptible consumer entails health as well as economic considerations. This is because the time spent shopping, at work, and engaging in other social activities affects the probability of becoming infected, which has an impact on future welfare.

### 3.4.2. Low-SES consumers

Low-SES consumers solve a simpler decision problem as they choose consumption, investment, labor supply, and the amount of other social activities. Their budget constraint reads

$$c_t + x_t = w_t n_t + v_t k_t + \tau_t + T_{t+1}^I(\sigma_t, \Sigma_t)$$  \hfill (13)

where the parameter $\omega \leq 1$ captures the fact that low-SES consumers may have lower human capital. Their problem is equivalent to that of high-SES agents but imposing $b_t = 0$ for all $t$ in equation (11). Individual welfare at period $t$ must satisfy the following recursion:

$$V_{t}^L(\sigma, k; \Sigma) = \max_{c(n, n, a)} u(c, n, a) + \frac{1}{1 + \rho} \mathbb{E}\left[V_{t+1}^L(\sigma', k'; \Sigma') \mid \sigma \right]$$  \hfill (14)

for all $t$, where the problem on the right-hand side is subject to the capital accumulation technology (10), the budget constraints (13), and the law of motion for the aggregate state (9). As was the case for the high-SES agent, the continuation value on the right-hand side depends on the health status of the decision maker, as does the solution to the optimization problem.
3.5. Aggregation

We use capital letters to denote aggregates. An agent of type \( j \in \{ L, H \} \) with health status \( \sigma \in \{ s, i, r \} \) is representative of her group. This means that at every period \( t \), we must have

\[
C^\sigma_{jt} = c^\sigma_{jt}, \quad N^\sigma_{jt} = n^\sigma_{jt}, \quad A^\sigma_{jt} = a^\sigma_{jt}, \quad X^\sigma_{jt} = x^\sigma_{jt}, \quad K^\sigma_{jt+1} = k^\sigma_{jt+1},
\]

(15)

for all \( j \) and \( \sigma \), and

\[
B^\sigma_{jt+1} = b^\sigma_{jt+1}.
\]

(16)

for all \( \sigma \). Aggregate consumption, investment, capital, labor, and social interaction are computed as follows:

\[
C_t = C^H_{Lt}S_{Lt} + C^I_{Lt}I_{Lt} + C^R_{Lt}R_{Lt} + C^S_{Lt}S_{Lt} + C^I_{Lt}I_{Lt} + C^R_{Lt}R_{Lt},
\]

(17a)

\[
N_t = N^H_{Lt}S_{Lt} + N^I_{Lt}I_{Lt} + N^R_{Lt}R_{Lt} + N^S_{Lt}S_{Lt} + N^I_{Lt}I_{Lt} + N^R_{Lt}R_{Lt},
\]

(17b)

\[
A_t = A^H_{Lt}S_{Lt} + A^I_{Lt}I_{Lt} + A^R_{Lt}R_{Lt} + A^S_{Lt}S_{Lt} + A^I_{Lt}I_{Lt} + A^R_{Lt}R_{Lt},
\]

(17c)

\[
X_t = X^H_{Lt}S_{Lt} + X^I_{Lt}I_{Lt} + X^R_{Lt}R_{Lt} + X^S_{Lt}S_{Lt} + X^I_{Lt}I_{Lt} + X^R_{Lt}R_{Lt},
\]

(17d)

\[
K_t = K^H_{Lt}S_{Lt} + K^I_{Lt}I_{Lt} + K^R_{Lt}R_{Lt} + K^S_{Lt}S_{Lt} + K^I_{Lt}I_{Lt} + K^R_{Lt}R_{Lt}.
\]

(17e)

Since only high-SES agents can trade bonds, aggregate bond holdings are obtained by aggregating only across such agents. Thus, we have

\[
B_t = B^H_{jt}S_{Lt} + B^I_{jt}I_{Lt} + B^R_{jt}R_{Lt}.
\]

(18a)

3.6. An epidemiological and economic equilibrium

Given a government policy \( \{ \xi, \tau_1 \} \), an interest rate \( r^* \), initial epidemiological conditions \( \{ S_j, I_j, R_j, D_j \}_{j \in \{L,H\}} \), and initial stocks of government debt, capital stock, and bond holdings \( \{ B_0, K_0 \}_{j \in \{L,H\}} \), an equilibrium for this economy is a collection of sequences for factor prices \( \{ w_t, v^i_{t+\rho} \}_{t=0}^\infty \), value functions \( \{ V^H_{t+\rho}, V^I_{t+\rho} \}_{t=0}^\infty \); optimal choices for high- and low-SES agents \( \{ c_t, n_t, a_t, k_{t+1}, b_{t+1} \}_{t=0}^\infty \) and \( \{ c_t, n_t, a_t, k_{t+1} \}_{t=0}^\infty \); macroeconomic aggregates \( \{ C_t, N_t, A_t, X_t, K_{t+1}, B_{t+1} \} \); and epidemiological aggregates \( \{ S_t, I_t, R_t, D_t \}_{t=0}^\infty \) such that:

1. value functions and optimal choices solve the consumers’ problem,
2. factor prices satisfy \((8a)\) and \((8b)\),
3. macroeconomic variables satisfy \((17), (18)\),
4. Epidemiological variables satisfy \((4)\), and
5. labor and capital markets clear.

There is an aggregate equilibrium intertemporal budget constraint for the whole economy instead of a market clearing condition for final goods, which is derived from the individual budget constraints by Walras’ law. The government’s budget constraint is embedded in the individual ones.

3.6.1. Individual trade-off: economic activity and risk of infection.

As mentioned above, the decision problem of susceptible consumers entails health and economic considerations. To highlight this property, we use the first-order conditions of their respective problem. To start with, it is useful to define the holistic marginal utility of consumption, work, and other social activities as

\[
\bar{u}^H_{k,b}(c, n, a, b') = u_k(c, n, a) + \frac{\partial \pi^H_{k,b}(c, n, a)}{\partial x} \left[ V^H_{t+1}(i, k', b'; \Sigma) - V^H_{t+1}(i, k, b'; \Sigma) \right] / (1 + \rho),
\]

(19a)

\[
\bar{u}^I_{k,b}(c, n, a, k') = u_k(c, n, a) + \frac{\partial \pi^I_{k,b}(c, n, a)}{\partial x} \left[ V^I_{t+1}(i, k', \Sigma) - V^I_{t+1}(i, k, \Sigma) \right] / (1 + \rho)
\]

(19b)

for \( x \in \{ c, n, a \} \). The term in square brackets on the right-hand side of both expressions represents the discounted welfare loss of becoming infected. Hence, the holistic marginal utility takes into account the health consequences of economic choices. For instance, in the case of consumption, it is equal to the sum of the marginal utility of consumption and the
marginal impact of the additional time spent shopping on the probability of suffering a welfare loss from becoming infected.

The solution of each consumer’s optimization problem, equation (12) or equation (14), entails the following intratemporal first-order conditions:

\[-\frac{\hat{u}_{a,t}(s)}{\hat{u}_{c,t}(s)} = \omega W_t, \quad \text{(20a)}\]

\[\hat{u}_{a,t}(s) = 0, \quad \text{(20b)}\]

for all t, where we introduced the shorthand notation \(\hat{u}_{x,t}(s)\) to denote the holistic marginal utility in activity \(x\) and omitted the arguments and the group identity for convenience and the fact that the wage of the low-SES agents is \(\omega W_t\). Condition (20a) equates the real wage to the holistic marginal rate of substitution between consumption and leisure. In the context of a pandemic, where there is positive infection risk and the welfare loss of becoming infected is positive, the holistic marginal rate of substitution is larger in absolute value than the standard one. Intuitively, this occurs because the welfare loss from infection increases the marginal disutility of labor (e.g., \(-\hat{u}_{a,t}(s) < -\hat{u}_{c,t}(s)\)) and decreases the marginal utility of consumption (e.g., \(\hat{u}_{c,t}(s) < \hat{u}_{c,t}(s)\)). As a result, the holistic indifference curves between consumption and leisure are steeper than the standard ones, and agents will prefer to work and consume less at any given wage than without the risk of becoming infected. The strength of this effect will depend on the prevalence of infection at shopping venues and at work, and it will change over the course of the epidemic. Figure 5 illustrates this description.

Likewise, condition (20b) equates the holistic marginal utility of other social activities to zero. Because there is a potential utility loss of becoming infected, susceptible consumers will reduce other social activities relative to a world without the pandemic since \(\hat{u}_{a,t}(s) < \hat{u}_{a,t}(s)\) for all \(a\) and \(u_{a,t} = 0 \Rightarrow \hat{u}_{a,t} < 0\).

4. Calibration

One period in the model represents one week. We assume the economy starts at the disease-free steady state in period 0 and then suffers an unexpected pandemic shock: a fraction \(\epsilon\) of consumers become infected. The dynamics of the pandemic unfold from period 1 onward. In our simulation, period 0 corresponds to the first week of February 2020.

The calibration strategy targets the economic and epidemiological performance in the city of Bogotá. We first describe the functional form assumptions. Most of the parameters are chosen to match moments that correspond to the disease-free steady state. In most cases, these parameters are exactly identified. To calibrate the remaining parameters, we use the simulated method of moments.

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18 This logic presumes that the probability of infection is increasing in every argument.
4.1. Functional forms

4.1.1. Transmission rates

We assume that contagion at consumption venues and in spaces of social interaction is proportional not only to consumption and social interaction but also to the amount of time allocated to leisure. The transmission rate from an infectious of type $i$ to a susceptible of type $j$ for $i,j \in \{L,H\}$ in our model is

$$\tilde{\beta}^{ij}(\Gamma^S_{j,t}, \Gamma^L_{i,t}) = \beta^N_{ij} N^S_{jt} N^L_{it} + \left( \beta^C_{ij} C^S_{jt} C^L_{it} + \beta^K_{ij} A^S_{jt} A^L_{it} \right) \frac{1 - N^S_{jt}}{1 - N^S_j} \frac{1 - N^L_{it}}{1 - N^L_i},$$

(21)

where the variables with a “$\tilde{\phantom{a}}$” denote disease-free steady-state values. This specification is convenient because it clarifies that the dynamics of the model will differ from the standard epidemiological SIRD model precisely because it induces a behavioral change. In the absence of any behavioral change $\tilde{\beta}^{ij}(\Gamma^S_{j,t}, \Gamma^L_{i,t}) = \beta^N_{ij} + \beta^C_{ij} + \beta^K_{ij}$.

4.1.2. Instantaneous preferences

We consider an instantaneous utility function that is separable in the three arguments:

$$u(c, n, \alpha) = \log(c) + v^1_j \left( \frac{\bar{n} - n}{1 - 1/\bar{\zeta}} \right) + \kappa \left( \log(\alpha) - a + 1 \right) + \tilde{u}$$

(22)

for $j \in \{L, H\}$. The term $\tilde{u}$ measures the flow utility of being alive, normalizing the utility of being dead to zero. We also follow Farboodi et al. (2020) in considering the utility of social activities as a function that has a global maximum when $a = 1$, at which point the flow utility of optimal social interaction is just zero. This specification introduces the parameters \{\nu_L, \nu_H, \kappa, \zeta, \tilde{u}\}, and the only source of heterogeneity in preferences comes from $v_j$.

4.1.3. Capital adjustment costs

The functional form of capital adjustment costs is

$$\Phi(k, k') = \phi \left( \frac{k' - k}{k} \right)^2 k,$$

(23)

which is standard in the literature. To set the capital adjustment cost parameter $\phi$, we generate a time series of a TFP process that follows an AR(1) with persistence of 0.944 per quarter and a standard deviation of innovations of 0.028. This series is then used in the disease-free version of the model, and $\phi$ is chosen so that the standard deviation of investment relative to the standard deviation of GDP equals 3.75.19

4.1.4. Interest rate schedule

The interest rate schedule is

$$r(b) = r^* + \chi \left( \exp \left( \frac{\bar{y} - b}{\bar{b}} \right) - 1 \right),$$

(24)

where $r^*$ represents the exogenously given international interest rate, $\bar{y}$ is the steady-state level of output, and $\chi$ is a small positive constant. Thus, the interest rate is decreasing in the financial asset position of consumers. The role of $\chi$ is to induce a stable steady state in the problem of the high-SES agent following Schmitt-Grohe and Uribe (2003). We set $\bar{b} = 0$, $r^* = 0.015/52$ and $\chi = 0.0001$.

4.2. Parameters

We set the share of low-SES agents to $\lambda = 0.89$ as in table 1.

4.2.1. Epidemiological parameters

We set the infection fatality rate $\pi^D(\pi^R + \pi^D)$ to 0.032% as reported in table 2 for Bogotá and impose $\pi^R + \pi^D = 7/18$, following Atkeson (2020). This gives us two equations that pin down $\pi^D$ and $\pi^R$.

To capture the heterogeneity in transmission rates, we proceed as follows. First, we consider the possibility of segmentation in the transmission of the disease, which means that a susceptible agent of type $j \in \{L, H\}$ becomes more easily infected through contacts with agents of her own type. This assumption is parameterized with a single parameter $\eta_1$, by imposing that

$$\beta^{LL}_L = \eta_1 \beta^{HH}_L,$$

(25a)

$$\beta^{HL}_H = \eta_1 \beta^{HL}_H,$$

(25b)

19 García-Schmidt and García-Cicco (2020), García et al. (2019)
for \( x \in \{C, N, A\} \). In addition, we consider the possibility of asymmetric interaction, which means that the transmission resulting from cross-type interactions could depend on the identity of the susceptible. This assumption is also parameterized with a single parameter \( \eta_2 \), through the following condition:

\[
\beta^{H,i}_x = \eta_2 \beta^{L,H}_x,
\]

(26)

for \( x \in \{C, N, A\} \). Equations (25) and (26) imply that \( \beta^{H,H}_x = \eta_1 \eta_2 \beta^{L,H}_x \) so all the parameters \( \beta^{L,i}_x \) can be expressed in terms of \( \beta^{L,H}_x \).

To calibrate \( \beta^{H}_x \) in each activity, we follow Eichenbaum et al. (2020) in assuming that, at the onset of the pandemic, one-sixth of the infections stem from contacts in consumption venues and workplaces, whereas two-thirds come from contacts at spaces of social interaction. We will write each \( \beta^{L,H}_x \) as a function of \( R_0 \).

We start by writing the basic reproduction number for infectious agents of type \( i \in \{L, H\} \),

\[
R_0^i = \sum_x \beta^{L,i}_x \lambda + \frac{\beta^{H,i}_x (1 - \lambda)}{\pi^R + \pi^D}.
\]

Observe that with no consumer heterogeneity and without different sectors, this expression collapses to the standard definition in the literature (e.g., \( R_0 = \beta / (\pi^R + \pi^D) \)). At the outset of the pandemic, assuming that the initial infectious is a low-(high-) SES consumer with probability \( \lambda (1 - \lambda) \), the basic reproduction number is

\[
R_0 = \lambda R_0^L + (1 - \lambda) R_0^H.
\]

(27)

The transmission rates \( \beta^{L,H}_x \) then can be written as

\[
\beta^{L,H}_L = \frac{1}{6} \lambda^2 \eta_1 + \lambda (1 - \lambda)(1 + \eta_2) + (1 - \lambda)^2 \eta_1 \eta_2 R_0.
\]

(28a)

\[
\beta^{L,H}_H = \frac{2}{3} \lambda^2 \eta_1 + \lambda (1 - \lambda)(1 + \eta_2) + (1 - \lambda)^2 \eta_1 \eta_2 R_0.
\]

(28b)

\[
\beta^{L,H}_A = \frac{1}{6} \lambda^2 \eta_1 + \lambda (1 - \lambda)(1 + \eta_2) + (1 - \lambda)^2 \eta_1 \eta_2 R_0.
\]

(28c)

Hence, the epidemiological block requires the calibration of four parameters: \( \{R_0, \eta_1, \eta_2 \} \).

4.2.2. Economic parameters

We set the ratio of labor income between workers in low and high SES to \( \omega = 0.22 \) to match the household survey data reported in table 1.

The preference parameters that govern the labor supply, \( \{v_H, v_L, \xi \} \), are set to match a Frisch elasticity of 1.5 and to guarantee that both types of consumers use 20% of total available time to work.\(^{21}\)

To calibrate \( \bar{u} \), we use an estimate of the value of a statistical life (VSL) lost from Covid-19 that is six times the steady-state level of consumption, following Hall et al. (2020). Hence, in our model we must have

\[
6C = \lambda \left[ \frac{u(c^H, n^H, a^H)}{u(c^L, n^L, a^L)} \right] + (1 - \lambda) \left[ \frac{u(c^H, n^H, a^H)}{u(c^L, n^L, a^L)} \right].
\]

We evaluate this expression at the disease-free steady state and solve for \( \bar{u} \). See Appendix B for details.

The rate of time preference, which is derived from the steady-state Euler equation for bond holdings, satisfies \((1 + \rho)^{52} = (1 + r)^{52} - \chi \frac{b}{G} \), which implies \( \rho = \left( (1 + r)^{52} - \chi \frac{b}{G} \right) \frac{\tilde{\pi}}{\bar{\pi}} - 1 \).

As we do not have data on the distribution of wealth in Bogotá or Colombia, we make an informed guess based on US data from Smith et al. (2021) for the US, who find that the top 1%, the 90-99th percentiles, and the bottom 90% of the wealth distribution each hold about one-third of the wealth. We assume the skewness in the top 1% is not present in Bogotá (or in our data) and assign one-half of the capital to each of our two groups. Since we set \( \lambda = 0.89 \), this implies that the top 11% of the distribution holds in the aggregate the same amount of capital as the bottom 89%. Under these assumptions, a representative high-SES agent owns eight times more capital than a low-SES individual.

\(^{20}\) Notice that, while any \( \eta_2 \) different from one would indicate asymmetric interaction, segmentation requires \( \eta_1 \) to be strictly greater than one.

\(^{21}\) Considering an employment to population ratio of 0.6 and that agents use 1/3 of their time to work delivers 20%.
Table 3
Calibrated parameters.

| Parameter | Description                                      | Value | Source/Comment |
|-----------|--------------------------------------------------|-------|---------------|
| $\rho$    | Rate of time preference                          | 0.0003| $(1 + r)^2 - \chi / 4$ |
| $r^*$     | Interest rate (annualized)                       | 0.015 |               |
| $\chi$    | Elasticity credit supply                         | 0.0001|               |
| $\lambda$ | Share of low-SES                                 | 0.89  |               |
| $\omega$  | Efficiency units for low-SES                     | 0.22  | Table 1       |
| $v_L$     | Labor preference parameter                       | 2.76  |               |
| $v_W$     | Frisch labor parameter                           | 2.07  |               |
| $\phi$    | Investment adjustment cost                       | 0.38  | Garcia et al. (2019) |
| $\delta$  | Weekly dep. rate (4% p.a.)                       | 1 – 0.96 | Garcia et al. (2019) |
| $K_{t0}/K_0$ | 90/10 capital stock ratio                       | 1     | Smith et al. (2021) |
| $\bar{u}$ | Joy of life                                      | 8.26  | SVL= 6C in Hall et al. (2020) |
| $\xi_1$   | Output limits                                    | 0.25  |               |
| $\xi_2$   | Transmission rate parameters                     | 0.12  |               |
| $\xi_3$   |                                                   | 0.04  |               |
| $\xi_4$   |                                                   | 0.02  |               |
| $\kappa$  | Social Preference parameter                      | 0.053 |               |
| $\eta_1$  | Transmission rate parameters                     | 1.38  |               |
| $\eta_2$  |                                                   | 0.71  |               |
| $R_0$     | Basic Reproduction number                        | 2.36  |               |
| $\epsilon$| Fraction of initial infected                     | 0.05% |               |

Table 4
Model Performance.

| Targeted Moments | Model | Data |
|------------------|-------|------|
| Output (relative to SS) | 0.77  | 0.77 |
| Last week of Mar-20 | 0.88  | 0.89 |
| Last week of Aug-20 | 0.96  | 0.96 |
| First week of Jan-21 | 0.99  | 0.99 |
| First week of Feb-21 | 0.21  | 0.21 |
| Prevalence rate | 0.25  | 0.25 |
| First week of Sep-20 | 0.26  | 0.26 |
| First week of Oct-20 | 0.30  | 0.30 |
| First week of Nov-20 | 0.33  | 0.34 |
| Prevalence ratio | 1.72  | 1.73 |

4.2.3. Government policy

Transfers to low-SES agents during the pandemic represented 4.6% of total income and lasted for approximately 10 months, from the end of March 2020 to the end of December 2020 (see section 2.2.1). This fact and the government budget constraint set the values for $\{\tau_i\}_{i=0}^\infty$.

We parameterize the path of output limits during the pandemic as a piece-wise linear function, for which we fix the values at four points in time as follows. Between the end of March 2020 and the end of February 2021, economic restrictions were imposed in two different periods: between the last week of March 2020 and the last week of August 2020, and between the first week of January and the last week of February 2021. Although in the interim period comprising September-December many restrictions were lifted, we assume output limits in the model were still positive to capture the fact that some restrictions were still in place and were potentially limiting economic activity. Thus, we need to define the limits that correspond to the first and last week of each lockdown period, which we denote $\{\bar{\xi}_1, \bar{\xi}_2, \bar{\xi}_3, \bar{\xi}_4\}$.

4.3. Joint calibration of the remaining parameters

We use the simulated method of moments to calibrate the vector $\{ar{\xi}_1, \bar{\xi}_2, \bar{\xi}_3, \bar{\xi}_4, \kappa, \eta_1, \eta_2, R_0, \epsilon\}$. The targets in the data are: output at each point in time for which we impose restrictions, the prevalence rate between August 2020 and November 2020 (four observations), and the average prevalence ratio for the CoVida sample. The resulting calibration and the performance of the model are summarized in table 3 and table 4, respectively.

**Epidemiological Parameters: interpretation and implications**

The epidemiological block of the calibration yields values for $\{R_0, \eta_1, \eta_2, \epsilon\}$ reported in table 3.

The value of $R_0$ at the beginning of the outbreak without any behavioral adjustment is $R_0 = 2.36$. This number is not as important as in the non-behavioral SIRD model as the epidemiological dynamics or governed by the behaviorally adjusted reproduction number. The model estimates 50 cases per 100,000 inhabitants in the first week of February 2020.
The calibrated values for $\eta_1$ and $\eta_2$ reported in Table 3, together with equations (25)-(26), imply that the transmission matrix from each source of exposure ($x$) is proportional to

$$
\begin{pmatrix}
\beta^L_L & \beta^L_H \\
\beta^H_L & \beta^H_H
\end{pmatrix}
\propto
\begin{pmatrix}
1.38 & 1 \\
0.71 & 0.98
\end{pmatrix}
$$

(29)

The estimated transmission rates have several implications. (i) Low-SES individuals are 40% more vulnerable to the virus, a consequence of the fact that the ratio $\frac{(\beta^L_L + \beta^L_H)}{(\beta^H_L + \beta^H_H)} = 1.4$ captures the difference in the vulnerability to infection across SES. (ii) The number of infections induced by one individual is independent of his or her SES, a consequence of the fact that the ratio $\frac{(\beta^L_L + \beta^L_H)}{(\beta^H_L + \beta^H_H)} = 1.06$ measures the difference in the infections induced by individuals in each group. (iii) Finally, while low-SES consumers transmit the virus 95% more to persons in their own group, high-SES consumers transmit the virus equally to both groups. The ratios $\frac{\beta^L_L}{\beta^H_L} = 1.95$ and $\frac{\beta^L_H}{\beta^H_H} = 1.02$ capture the heterogeneity in vulnerability to an infectious person in the low- and high-SES groups, respectively.

5. Simulations and counterfactuals

We first report the performance of the model for the benchmark case with output restrictions and redistributive policies. Then we conduct a series of counterfactual exercises to understand the macroeconomic and epidemiological implications of policy interventions. Finally, we compute the welfare effects of the different exercises performed.

5.1. Benchmark: output restrictions and redistributive transfers

We first show the behavior of aggregate variables, then individual behavior, and finally close with the model’s implications on the cost of social distancing and the private value of a vaccine.

5.1.1. Aggregate variables

The aggregate economic predictions of the model are depicted in Figure 6, where we show output, employment, consumption, and the change in social interactions along with their corresponding data counterparts whenever possible. Output in the model is aligned with the data and driven by the binding output constraints, which are also the driving force behind the labor demand. The labor supply falls because of the risk-avoiding behavior of workers, but as the effect is small relative to the fall in demand, the latter dominates and wages fall. The model is, by and large, consistent with the behavior of employment but underpredicts the fall in hours. The model tracks well the path of consumption, which is driven by the
combination of the low-SES agents’ transitory fall in income with the financial frictions they face in the model. Social interaction is displayed in the bottom right panel, which shows that, as soon as the epidemic starts, rational forward-looking agents change their social behavior. We are hesitant to contrast the evolution of this variable with data, such as measures of mobility from mobile telephones,\footnote{e.g. Google Mobility, Safe Graph, Facebook, etc.} because we think it encompasses behavior that is not observable (wearing masks, social distancing within homes, or changing social and religious practices, among many others). Overall, these aggregate figures suggest that consumers reduce the risk of infection mostly by reducing the amount of social interactions and by working less. This adjustment in behavior affects the dynamics of the pandemic, as we show next.

The epidemiological dynamics are summarized in figure 7. The top left panel shows the prevalence rate for the aggregate and for each SES in the benchmark model as well as the aggregate prevalence in the non-behavioral SIRD with an \( R_0 = 2.36 \). The model captures well the aggregate prevalence as well as the one for each SES for the first wave of the pandemic (February-November). The top right panel shows that in the data, the number of new cases increases very sharply at the peak of the pandemic, a feature that the model does not capture. The epidemiological dynamics in the non-behavioral SIRD model, depicted in grey, in the top two graphs go off-scale in overpredicting the speed of infections as they do not take into account the endogenous mitigating behavior.

At this point, it is useful to distinguish the basic reproduction number \( R_0 \) from the behavioral reproduction number \( \bar{R}_{0,t} \). The latter is defined as

\[
\bar{R}_{0,t} = \frac{R_0}{R_0 ( \sum_x \bar{p}^{L,H} \frac{S^x}{S^x} + \bar{p}^{H,H} \frac{S^x}{S^x} ) + \frac{\mu}{\tau} ( \sum_x \bar{p}^{L,H} \frac{S^x}{S^x} + \bar{p}^{H,H} \frac{S^x}{S^x} )},
\]

In contrast to the basic reproduction number, the behavioral reproduction number \( \bar{R}_{0,t} \) takes into account the behavioral responses of each type of agent as well as the shares of susceptible and infected agents of each type throughout the pandemic. In a model with homogeneous agents, it collapses to \( \bar{R}_{0,t} = ( \sum_x \bar{p}_x ) / (\pi^R + \pi^D) \). Estimates of \( R_0 \) are based on observational data such as the estimate for the rate of growth of cases, \( R_{0,t} \), not \( R_0 \). The effective reproductive number is \( \bar{R}_t = \bar{R}_{0,t} S_t \), which represents the number of new cases per each infected individual.
Fig. 8. Microeconomic choices (monthly). Note: Shaded bars identify the shutdown period. Light shaded areas identify the interim period in which some restrictions were lifted. In the case of labor, the solid lines represent the time average for the period in which data are available.

The lower left panel in figure 7 depicts the basic reproduction number $R_0$, the behavioral reproductive number $R_{0,H}$, and the effective behavioral reproduction number $R$. It shows how the behavioral reaction to the risk of infection and death immediately reduces the aggregate basic reproduction number, illustrating how forward-looking susceptible agents behave in this model. The main driver for this result is the change in non-economic social activities.

The behavioral adjustment predicted by the model aligns well with estimates of the effective reproduction number for Bogota during April-May, $R_0 = 1.68$, estimated in Laajaj et al. (2021a). As the number of active cases, $I_t$, increases, the behavioral adjustment deepens. Susceptible agents, the majority of the population, reduce their labor and consumption and engage in safer social interactions. When the number of active cases peaks, the behavioral reproductive number $R_{0,H}$ defined in equation (30) falls to a minimum of 1.19. Interestingly, the effective reproduction number, the product of the behavioral reproduction number and the population’s share of susceptible subjects, $R_{0,S}$, falls below 1 after five months and stays just under 1 for the remainder of the outbreak. This is consistent with the empirical findings in Atkeson et al. (2020) and with the theoretical results in Farboodi et al. (2020). The behavioral adjustment slows down and contains the spread of disease at the expense of lengthening the epidemic.

The model captures well the epidemiological disparities found in the CoVida data before the second wave, as the prevalence rates for high- and low-SES groups in the top left panel shows. The heterogeneity in transmission rates reported in equation (29) is a key factor driving this result. The bottom right panel of figure 7 shows the evolution of the prevalence ratio. The averages of the simulated prevalence ratio and the actual are similar as they are a calibration target. The model’s predictions differ from the data because the latter exhibits a monotonically increasing prevalence ratio. The prevalence ratio in the model is humped shaped because the disease progresses faster in the low-SES group, but at some point, there are relatively fewer susceptible low-SES agents, and thus the disease spreads faster among high-SES agents.

5.1.2. Microeconomic behavior

The sequence of choices for consumption, labor, and forms of social interaction for six types of agents according to their health status (susceptible, infected, recovered) and socioeconomic stratum is depicted in figure 8. These choices are induced by the epidemiological dynamics, policy interventions, and equilibrium prices. The figure also shows the data for labor and consumption aggregated across health states for each SES.

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23 The endogenous initial behavioral adjustment that reduces the basic reproductive number is similar to the one imposed in the calibration in Glover et al. (2020).

25 The model could incorporate waning immunity and shifts in $\beta$’s due to new more infectious SARS-CoV-2 variants to capture the second wave.

26 The incidence for the low-SES individuals is always higher than in the high-SES in the data—(figure 1).
Susceptible agents. Susceptible low-SES consumers mitigate the risk of contagion by reducing all three activities that contribute to disease transmission, as shown in the top panels of figure 8. While social activities voluntarily drop sharply and remain low throughout the epidemic outbreak, the adjustment of consumption and the labor supply is less persistent and is largely driven by the shutdown, as will become evident in the next section. The shutdown reduces labor demand (in excess of the reduction in labor supply) so that both hours worked and wages fall. Capital income also falls in response to the shutdown (see figure 9). The model’s prediction for low-SES consumption is well aligned with the data but recovers faster in the model than in the data.27 Low-SES consumption is smoothed through negative investment.

The response of high-SES agents to the epidemic and policy interventions is similar to the one for the low-SES ones, but with some differences. Consumption is naturally smoother thanks to their access to the bond market, their labor adjustment is stronger than for low-SES agents in spite of the lower risk of infection, and risk mitigation in social activities is similar. At the peak stringency of the lockdown, consumption of high-SES agents is smoother in the model than in the data, probably because the model abstracts from non-traded goods that are affected by the shutdown. After the sharp drop, high-SES labor has an average recovery value similar to the data.

Infectious and recovered. The behavior of the infected and recovered highlights the role played in this model by the health externality, health immunity after infection, the financial exclusion of people in the low SES, and prices. In aggregate terms, the infectious are always a small share of the population, and as the pandemic runs its course, the recovered become the majority of the population.

The behavior of the infectious and recovered is almost identical, illustrating the health externality in this model. Infectious agents do not isolate even though they know they are putting others at risk, behaving like immune agents that are not infectious.

The difference between the behavior of the recovered and susceptible shows the role played by epidemiological considerations in driving the response of the susceptible, as both groups face the same prices. Figure 8 shows how the risk of death drives the susceptible to always consume and work less than the recovered.

The role of capital is interesting as it simultaneously amplifies and dampens the economic effect of the shutdown, as shown in figure 9. The left panel shows how capital income amplifies the effect of the shutdown by reducing the rental rate of capital (see equation (8b)). Capital income falls by about 50% for both groups. Capital accumulation also moderates the effect of the shutdown on consumption as households are able to divert resources from investment to consumption. This effect is quite strong and results in a current account surplus (for the city). For low-SES agents, the sale of used capital

27 See Buera et al. (2021) for an analysis of the speed of recovery from shutdowns.
in April frees up to 35% of pre-pandemic steady-state income for consumption, about seven times the size of the transfers in Bogotá. The lower investment is an important source of consumption smoothing for low-SES agents throughout the pandemic. Investment in the data falls by less than in the model.

5.1.3. Some implications of the model and the calibrated parameters

The model has some interesting implications we want to highlight. The equilibrium value functions of the recovered and infected individuals can be used to measure the private value of a vaccine, and the parameter $\kappa$ can be used to price social distancing in terms of consumption. The private value of a vaccine

A perfect vaccine makes a susceptible person immune (recovered). Our model allows us to compute the **private value** of a perfect vaccine.\(^{28}\) To do this, we proceed in two steps. First, at each time period, we compute the utility gain of becoming immune, $V_i^r(\tau_i, \Sigma_i) - V_i^s(s_i, \Sigma)$, and transform this variation into steady-state consumption units.\(^{29}\) Then we take the present value of that perpetuity. This procedure delivers the following expression for the private value of a perfect vaccine for a consumer of type $i$ and time $t$:

$$V_i^r = \frac{1 + \rho}{\rho} \left( \exp \left( \frac{\rho}{1 + \rho} \left( V_i^r(\tau_i, \Sigma_i) - V_i^s(s_i, \Sigma_i) \right) \right) - 1 \right) \bar{C}_i,$$

where $\bar{C}_i$ denotes the steady-state consumption.

Considering a steady-state weekly consumption level in Bogotá of USD 115, we can obtain steady-state consumption levels for each SES group, using the fraction of consumption accounted for by each group in the disease-free steady-state version of the model. In figure 10, we report the results. Low- and high-SES agents would have paid USD 627 and USD 2,481, respectively, at the onset of the pandemic in February 2020 to become immune, whereas they would have paid only USD 344 and USD 1,149 when vaccines became available at the end of December, in the 48th week of the pandemic. As the epidemic progresses and the risk of infection falls, so does the value of the vaccine.

The value of the vaccine computed here assumes the vaccine arrives unexpectedly and is immediately distributed. If people anticipate the arrival of the vaccine, they will change their behavior, which will have an effect on the epidemiological dynamics and the value of the vaccine, as analyzed by Garriga et al. (2020). This does not affect the time profile of the value of the vaccine in figure 10.

\(^{28}\) The **social value** of the vaccine measures the change in welfare from the effect of the vaccine on the aggregate health state $\Sigma$.

\(^{29}\) Assuming log preferences, this transformation yields $\left( \exp \left( \frac{\rho}{1 + \rho} \left( V_i^r(\tau_i, \Sigma_i) - V_i^s(s_i, \Sigma_i) \right) \right) - 1 \right) \bar{C}_i$.
The cost of social distancing

The model allows us to measure the welfare cost of social distancing in terms of consumption by computing how much consumption a person would give up in order to reduce social distance by 1% and have the same level of welfare. The elasticity of consumption with respect to social interaction, keeping utility constant for the preferences in equation (22), is

$$\frac{dc}{da} \bigg|_{da=0} = -\kappa \left( \frac{1}{a} - 1 \right) a.$$  \hspace{1cm} (31)

In August, at the epidemic’s peak, the value of $a$ is approximately $a^d = 0.31$ and $a^t = 0.30$, whereas it is $\kappa = 0.053$ in the calibration. This implies that persons in the low-SES group would give up 3.7% of weekly consumption or 3 USD to increase $a$ by 1% for a week, whereas people in the high-SES group would pay 3.6% of weekly consumption or 14 USD. The evolution of this cost, expressed in terms of the fraction of forgone weekly consumption, is displayed in figure 11.

5.2. The role of policy interventions

We now analyze the effect of policy interventions. We compare the economic and epidemiological outcomes of the benchmark economy to those of a collection of fictitious economies: a laissez-faire economy without intervention and other economies that differ in the shutdown and in the redistributive policies. Figure 12 reports the aggregate economic results of these counterfactuals, and epidemiological outcomes are reported in figure 13.

Shutdown. To isolate the effect of the shutdown, we consider an economy without transfers and with an initial shutdown of 25% in March 2020 that is gradually released in a stepwise linear fashion to 12% in September 2020, 4% in January 2021, and 2% by the end of February 2021. We compare this counterfactual shutdown-only economy with the laissez-faire equilibrium.

The shutdown has a direct effect on economic activity and a minor effect on epidemiological outcomes. In our calibration, the specification of transmission rates in equation (21) takes into account that if people do not go to work, they spend their time somewhere else, engaging in consumption or other social activities (including at home), where they might get infected. Hence, restrictions on work activity have to take into account the transmission of SARS-CoV-2 outside the workplace.

To illustrate this interaction, the following equation displays the partial derivative of the transmission rate in equation (21) with respect to the labor choice:

$$\frac{d(\Gamma_j^L)}{dn_{j,t}} = \beta^L \frac{1}{N_j} N_{j,t} - \left( \beta^C \frac{C_j^t C_j^t}{C_i^t C_i^t} + \beta^A \frac{A_j^L}{A_j} \frac{A_i^L}{A_i^L} \right) \frac{1}{1 - N_j} \frac{1 - N_{i,t}}{1 - N_i}. \hspace{1cm} (32)$$
Fig. 12. Counterfactuals: Aggregate Dynamics (monthly). Note: Shaded bars identify the shutdown period. Light shaded areas identify the interim period in which some restrictions were lifted.

Fig. 13. Counterfactuals: Epidemiological Dynamics (monthly). Note: Shaded bars identify the shutdown period. Light shaded areas identify the interim period in which some restrictions were lifted.
for $j \in \{L, H\}$ and $i \in \{L, H\}$. The direct impact of changes in labor hours on the transmission rate from a type-$i$ infected to a type-$j$ susceptible is captured by the first term on the right-hand side. This direct effect is moderated by the second term, which captures the fact that the time not spent working is allocated to consumption and social activities.\(^{30}\) This interaction is also optimally taken into account by susceptible individuals as they assess how their labor supply choice affects the probability of becoming infected, displayed in equation (3). Changing hours worked by a susceptible individual has two effects on the probability of infection of each consumer type, as depicted in figure 14. It shows that this derivative flips signs and is much smaller in absolute value than the derivative of the probability of infection with respect to contacts at the workplace.

The restrictions on economic activity have an important effect on employment, wages, capital income, investment, and output. The fall in employment is much larger under a shutdown than in the counterfactuals without one (see figures 12 and 16). In the first case, the fall in labor demand induces a fall in wages of 25% at the peak of restrictions, whereas in the case without a shutdown, wages moderately increase as a result of the effect of the risk of infection on the labor supply (see figure 15). As the shutdown has a strong effect on labor and consumption activity, the mitigation in other social interactions is moderated (see figure 16). The fall in capital income and investment is also much larger in response to the shutdown (see figure 17).

The shutdown has a moderate impact on the epidemiological outcome of “flattening the curve” and no effect on the prevalence ratio between different SES, as shown in figure 13. The figure shows that the shutdown reduces the behavioral reproduction number $R_0$, and as a result, the prevalence rate and the peak in new cases are smaller than under laissez faire. Table 6 shows that at week 40 (before the start of the second wave in the data), the shutdown reduces deaths by 10%. When the epidemic runs its course, the shutdown has no effect on the cumulative number of deaths or on the cumulative number of infections.

**Transfer policies.** We analyze the effects of redistributive transfers in two ways. We compare the laissez-faire economy with an economy with only transfers, and we compare the shutdown-only economy with the benchmark economy (with the shutdown and transfers) and with another economy with shutdown and transfers that are twice as large as in the benchmark. The benchmark transfer is 4.6% of the low-SES’s labor income in the disease-free steady state for 10 months.

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\(^{30}\) An analogous trade off to that in equation (32) was considered in the debate over school closures in which some people argued that students might engage in riskier behavior socializing outside schools than in the more regulated and contained school environment.
Fig. 15. Counterfactuals: Factor Prices (monthly). Note: Shaded bars identify the shutdown period. Light shaded areas identify the interim period in which some restrictions were lifted.

Fig. 16. Counterfactuals: Microeconomic Behavior of Susceptible (monthly). Note: Shaded bars identify the shutdown period. Light shaded areas identify the interim period in which some restrictions were lifted.
Fig. 17. Counterfactuals: Capital income and investment (monthly). Note: Shaded bars identify the shutdown period. Light shaded areas identify the interim period in which some restrictions were lifted.

Table 5
Welfare Cost (% of three years of steady state consumption).

|                      | Aggregate | Low-SES | High-SES | Ratio |
|----------------------|-----------|---------|----------|-------|
| Laissez-faire        | 4.9       | 4.9     | 4.3      | 1.1   |
| Transfer only        | 4.1       | 3.9     | 6.2      | 0.6   |
| Shutdown only        | 9.9       | 9.9     | 10.1     | 1     |
| Shutdown and transfer (Benchmark) | 9       | 8.7     | 11.4     | 0.8   |
| Shutdown and 2x transfer | 8.3     | 7.6     | 13.5     | 0.6   |

Note: The welfare cost is the fraction of pre-epidemic steady-state consumption that a susceptible agent would be willing to forgo over the course of three years to avoid the epidemic. Aggregate welfare is the weighted average of the welfare cost to each agent. We choose three years because aggregate labor and consumption are then within 1% of their steady-state value, the aggregate level of social interaction is 93% of its steady-state value, and the number of new infections is smaller than the initial number of infections at the outset of the pandemic.

Table 6
Deaths.

|                      | Aggregate | Low-SES | High-SES | Ratio |
|----------------------|-----------|---------|----------|-------|
| Deaths at week 40 (per 100K) |           |         |          |       |
| Laissez-faire        | 115       | 120     | 72       | 1.67  |
| Transfer only        | 115       | 120     | 72       | 1.67  |
| Shutdown only        | 101       | 106     | 63       | 1.69  |
| Shutdown and transfer (Benchmark) | 102   | 106     | 63       | 1.69  |
| Shutdown and 2x transfer | 102  | 107     | 63       | 1.69  |
| Data                 | 104       | 110     | 67       | 1.64  |
| End of Sample Deaths (per 100K) |         |         |          |       |
| Laissez-faire        | 185       | 192     | 127      | 1.51  |
| Transfer only        | 182       | 189     | 125      | 1.51  |
| Shutdown only        | 182       | 189     | 125      | 1.51  |
| Shutdown and transfer (Benchmark) | 182     | 189     | 125      | 1.51  |
| Shutdown and 2x transfer | 182  | 189     | 125      | 1.51  |

Note: The table shows deaths for 100,000 people computed in the model at two points in time: after a year of the pandemic and at the end of the simulation time span (five years). For each type of consumer, the statistic reported is calculated relative to corresponding type, not the whole population.
In all cases, the redistributive transfers reduce aggregate labor supply and output and increase consumption and investment. In the background, the city's current account deficit increases. The transfer induces low-SES agents to work less, invest more, and consume more. The fall in the labor supply for 90% of the labor force causes wages to increase, which leads to an increase in the labor supply of the high-SES agents. In the economy with the shutdown, the wage effect is quantitatively larger because the labor demand is inelastic as a result of the binding constraint on output. The transfer increases investment because the low-SES agents use capital as a vehicle to save a portion of it and smooth consumption. The high-SES agents smooth the tax in the bond market. The epidemiological impact of the redistributive transfers is negligible, as shown in figure 13 and table 6.

5.3. Welfare implications

We measure the epidemic's welfare cost as the fraction of non-disease steady-state consumption that would make susceptible agents of each type indifferent between living in an economy with an epidemic outbreak and living in one without the disease. It is computed as the difference between the value function of a susceptible individual of either type at period $t = 1$ and her value function in a disease-free steady state. This difference is then converted to units of consumption by asking how much more consumption during the epidemic would leave her indifferent between the two worlds. We choose a span of three years of consumption as our preferred measure of the welfare cost of the epidemic because this is the time it takes for the epidemic to fade in our benchmark case.\(^{31}\)

The epidemic's welfare costs are summarized in Table 5. We aggregate the individual welfare costs, adding them with equal weights for each person so the people in the high-SES group have a weight of 11% and those in the more disadvantaged group a weight of 89%.

The welfare cost of the epidemic outbreak under laissez faire is equivalent to reducing steady-state consumption by 4.9% during three years for the low-SES individuals and reducing it by 4.3% for the high-SES ones. The distributional impact of the epidemic under laissez faire is not surprising. People in the high-SES group have a lower risk of infection and more flexibility than low-SES agents to shift labor and consumption across time. The epidemiological risk disparity is also reflected in the fact that the fatality rate in the model is 50% higher for the low-SES agents.

The shutdown reduces welfare across all social groups. It has a large economic cost as everybody loses labor and capital income. The shutdown multiplies the cost of the epidemic by 2 for the low-SES agents and by 2.3 for the high-SES ones. The high-SES agents are affected more because they hold most of the capital and take the brunt of the fall in capital income. The shutdown reduces the number of deaths in the short run, as shown in Table 6, but has no long-run epidemiological benefit.

Redistributive transfers increase welfare for our additive equal weights welfare criterion by taking resources from the 11% of people in the high-SES group and giving them to the 89% in the low-SES group. Welfare is increasing in transfers for the recipients, at the cost of reducing welfare for the high-SES agents who pay for them.

One could alternatively measure the welfare cost of the pandemic by focusing on lives lost. We do this in Table 6 for the different exercises proposed. We report deaths per 100,000 persons in each group. The top panel shows the number of deaths per 100,000 40 weeks after the epidemic outbreak (before the second wave in the data) and the bottom panel for the whole course of the epidemic. We interpret these statistics as corresponding to the short- and long-run cost of the epidemic in terms of lives.

In the long run, neither the shutdown nor the transfer policies have a sizeable effect, either on the number of deaths or on their heterogeneity across social groups. In the short run, the shutdown does flatten the curve and reduces the number of deaths from 115 per 100,000 to 101 at week 40.

6. Sensitivity to the Value of a Statistical Life

In this section, we briefly comment on the sensitivity of our main results to different assumptions about the value of a statistical life (VSL). We find that the welfare costs of the epidemic, the value of the vaccine, and individual mitigation actions are all increasing functions of the value of life.

Our benchmark VSL is six times the steady-state level of consumption, as in Hall et al. (2020). Following Alvarez et al. (2021), we use alternative values of a statistical life that are 4.5, 7.5, and 10.5 times the steady-state level of consumption, and we simulate the model for these different VSL measures, keeping all other parameters constant.

We find that the epidemic’s welfare cost seems to be linear in the VSL, with an increase of 0.67% of steady-state consumption over three years for each unit increase in the VSL. Table 11 in Appendix E reports an aggregate welfare cost of 8%, 9%, 10%, and 12% of consumption for VSLs of 4.5, 6, 7.5, and 10.5, respectively. This linearity also applies to the epidemic’s welfare cost for each group.

The higher welfare cost stemming from the increase in the assumed VSL has two sources: the direct effect of increasing the cost of deaths caused by the epidemic and an indirect cost derived from agents’ mitigating strategies to cope with the

\(^{31}\) After 2.8 years the number of new infections is smaller than the initial number of infections at the outset of the pandemic. Aggregate labor and consumption are within 1% of their steady state value, and the aggregate level of social interaction is at 93% of its steady state value.
costlier risk of infection. The latter contributes to moderate the first. In our benchmark case, consumption and labor are restricted by the lockdown, so the bulk of the mitigation comes from social distancing. This, in turn, reduces the behavioral reproductive number $R_0$ for all $t$ and, hence, the epidemic's fatalities. Figure 19 in Appendix E illustrates the behavioral response of agents under different assumption for the VSL in the benchmark case, and figure 21 is the analogue under laissez-faire.

The mitigating behavioral response to higher values of life translates into fewer deaths in the long run. In our simulations, the number of deaths per 100,000 people at the end of the pandemic for the values of the VSL considered are 186, 182, 177, and 167. Thus, the marginal decrease in deaths resulting from an increase in one unit of consumption in the VSL is 2.8, 3.1, and 3.3 deaths per 100,000 for the VSL values 4.5, 6, and 7.5, respectively. The modest response of deaths to the VSL (with an elasticity smaller than one) is behind the increase in the epidemic's welfare cost when the VSL increases.

The private value of the vaccine is naturally sensitive to the VSL, as also reported in Garriga et al. (2020) and Boppart et al. (2021). The value of the vaccines at the onset of the pandemic for the high-SES agents for the four values of the VSL considered is USD 2,093; 2,614; 3,102; and 3,978. For the low-SES agents, the numbers are USD 443; 602; 753; and 1,030. The behavioral response to mitigate risk to different assumptions on the value of life makes the epidemic last longer, and, hence, it makes the value of the vaccine more persistent. The trajectory of the vaccine’s private value for different assumptions on the VSL for the benchmark case is reported in figure 20 in Appendix E.

7. Conclusions

We documented the heterogeneous impact of Covid-19 on epidemiological and economic outcomes in Bogotá and developed a quantitative macroeconomic model of a small open economy with heterogeneous agents to estimate the welfare cost of the epidemic and to evaluate policy interventions. We find that epidemic outbreaks are a welfare distribution shock driven mainly by the heterogeneity in exposure to contagion.

The welfare cost of an epidemic outbreak in the laissez-faire equilibrium is 14% higher for people that belong to the more vulnerable socioeconomic stratum. The fatality rate for more vulnerable groups is 50% higher than that of the high-SES group by the time the epidemic runs its course. The inference of the model’s epidemiological parameters through simulated moments reveals that at the root of this heterogeneity is the fact that people in the low socioeconomic group are 41% more vulnerable to infection. They are more vulnerable because, while people in the high SES are just as likely to infect people in both groups, people in the lower SES transmit the virus to somebody in their own group 95% more relative to transmission to their richer peers.

We evaluate two policy interventions through computational experiments: restrictions on economic activity aimed at reducing contacts at the workplace and consumption venues and redistributive transfers. Shutdowns reduce welfare since they impose a large economic cost on society with little epidemiological benefit. The cost of the shutdown is larger for the higher socioeconomic stratum because they are more affected by the impact of the shutdown on capital income.

Redistributive lump-sum transfers from rich to poor have no epidemiological consequence, reduce output and employment (under laissez faire), and increase consumption and investment. Under a shutdown, transfers don’t affect output or aggregate employment, which are constrained by the government.

Supplementary material

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