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Covid-19 in Unequal Societies

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Covid-19 in Unequal Societies*

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Abstract

We document the heterogeneous effect of covid-19 on health and economic outcomes across socioeconomic strata in Bogotá. We assess its distributional impact and evaluate policy counterfactuals in an heterogeneous agent quantitative dynamic general equilibrium model intertwined with a behavioral epidemiological model.

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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 with which we interpret the data and simulate policy counterfactuals.

We consider a society with two social groups. In the high socioeconomic stratum (SES), people have a 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, and are more exposed to contagion as they work in more contact intensive industries, have less ability to shop online, live in more densely populated residences, and rely more on public means of transportation.[1] 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 the low SES account for 89% of the population.

Our main epidemiological data source is the CoVida project: a large scale epidemiological surveillance study that was carried out for nine months in Bogotá (Laajaj et al., 2021). 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 is often unreliable because it fails to detect most of the asymptomatic cases. The CoVida data is highly valuable in that it provides 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 is similar across the two groups due to 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 25% in April, recovered sluggishly and it 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 30% and hours worked by more than 50%

[1]There is a growing literature documenting these facts that includes Dingel and Neiman (2020), Mongey et al. (2020), Bartik et al. (2020), Harris (2020), Papageorge et al. (2020), Bartik et al. (2020), Montenovo et al. (2020), and Leyva and Urrutia (2021).

on impact, and hours recovered to a level 15% below trend. In the second quarter of 2020, during the shutdown, capital income was 30% below trend while 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.[2]

We compute the dynamic general equilibrium of a small open economy (a country or a 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 Farboodi 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 to consumption expenditures. We also assume that people adjust their social behavior not associated to 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 Farboodi 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 there are modest reductions in output, labor and consumption and a very strong reaction in social interactions, which deviate by 60% from the normal ones. The welfare cost of the epidemic outbreak under laissez faire is equivalent to a permanent reduction of 0.38% of consumption for the high SES and of 0.43% for the low SES. This welfare costs include the expected cost of dying that depends on the probability of death at the onset of the epidemic outbreak and the value of life which we calibrate based on the statistical value of life in Hall et al. (2020).

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 born by high SES agents becomes 1.08% of steady state consumption and the one for the low SES agents is 0.79%.

[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.

Most of the fall in welfare stems from the inefficiency of the shutdown, which is very costly from the 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 the high SES individuals. In order to smooth consumption at the peak of the lockdown, low SES agents sell some of their their capital, paying an adjustment cost, and later re-purchase 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 due to 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, it fell to 1.2 at the peak of the epidemic. 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. This is mainly because, while the transmission rates from people in the high socioeconomic stratum to people in both groups are similar, people in the lower stratum transmit the virus to somebody in their own group 95% more than to their richer peers.

The model estimates that, at the peak of the pandemic, Bogotá's inhabitants reduced their social interactions with 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 1%.

Related literature. There is a burgeoning literature that 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 where 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. There are several papers that address similar questions. For example, Eichenbaum et al. (2021), Hur (2020), and Kaplan et al. (2020). In addition to several modelling 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 socio-economic group. However, as we do not compute the social planner's allocation our approach does not take into account the externalities associated with vaccines as in Garriga et al. (2020) and Boppart 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, and conclusions in section 6.

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. (2021), 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 are 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.[3] 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 comprised of the lower three and the top three SES. The characteristics of these two groups are

[3]Gran Encuesta Integrada de los Hogares (GEIH), D.A.N.E.

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 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 comes from The Multipurpose Survey 2017 (*Encuesta Multipropósito* - DANE).

described in table 1.[4] [5]

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 that in 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 Bogota's population, the prevalence in the low-SES population was 58%, twice the one of 29% in the higher SES population.[6]

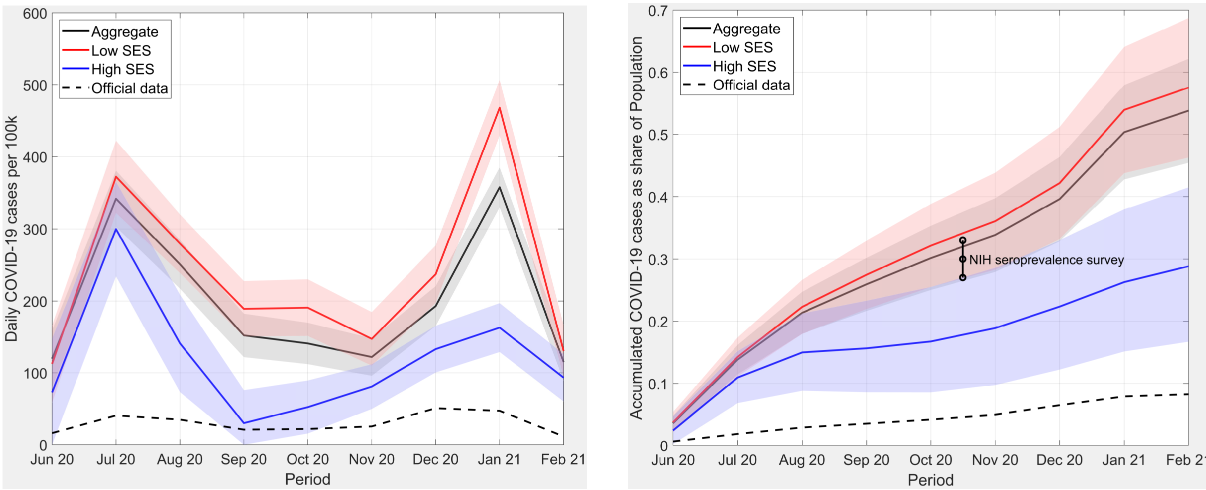
The CoVida prevalence rates reported above contrast with official counts of covid-19 cases of only 8% of the population by the end of February 2021. The official detection rate varies significantly across social groups as well: while the official detection rate in the highest socioeconomic stratum is one in six, in the lowest stratum it is one in ten (Laajaj

[4] See Marcela Eslava-Mejía and Miguel Juan Révolo-Acevedo and Rutty Paola Ortiz-Jara (2021) for a further discussion of the classification of households in socioeconomic strata and the potential missclassification, including non-vulnerable households in the lower strata, and vulnerable ones in the higher ones under the current system.

[5] Table 7 in section A describes the characteristics at a more disaggregated level.

[6] Laajaj et al. (2021) documents with more detail SARS-CoV-2 infection inequalities.

Figure 1: Epidemiological Dynamics: CoVida and Official Estimates



(a) New Cases

(b) Cumulative Cases

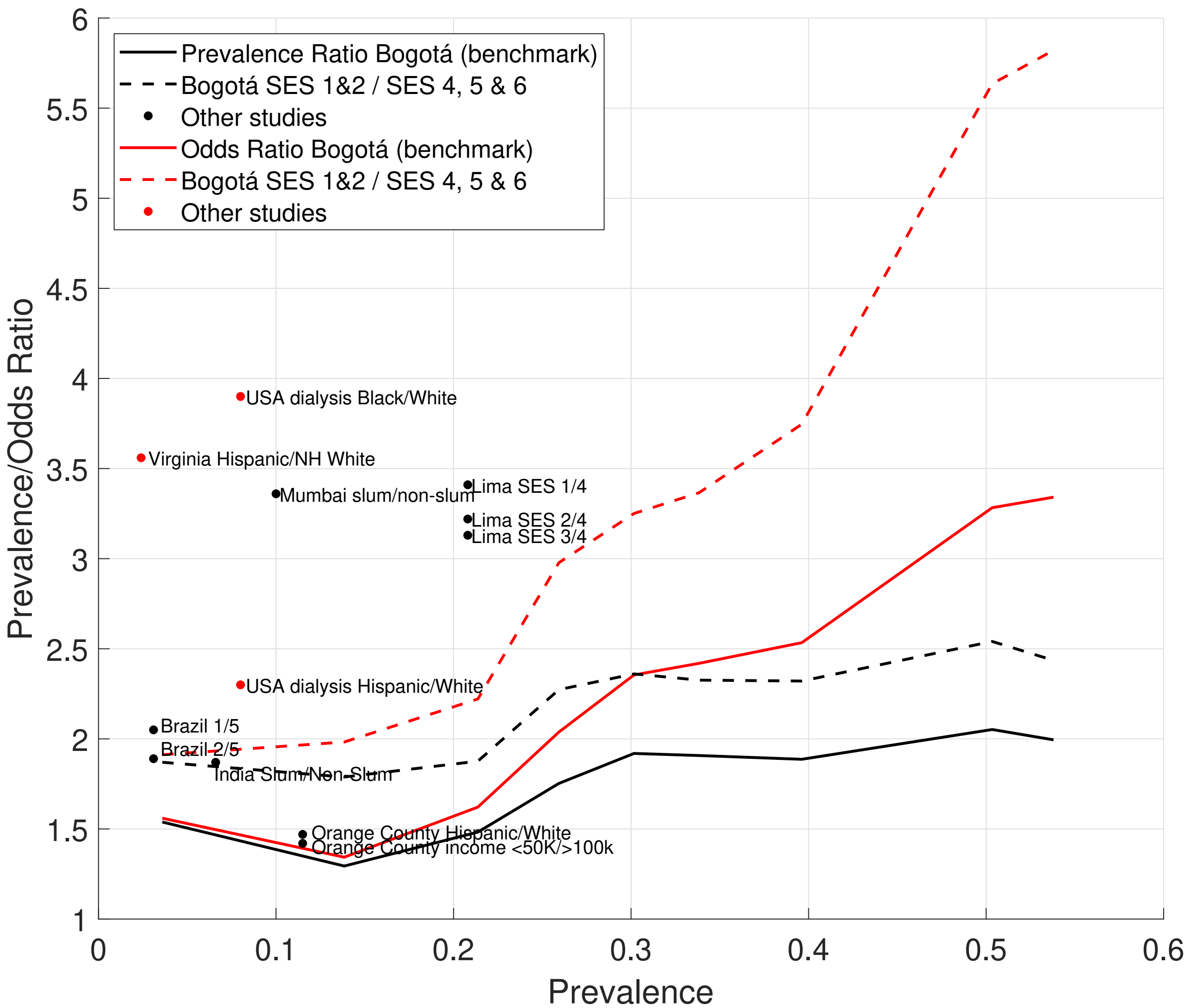
Notes: Shaded areas are 95% confidence intervals. Estimates based on the restricted CoVida sample (excludes symptomatic and close contacts of infected). Confidence intervals are computed with standard errors of seemingly unrelated regressions following the methodology in Laajaj et al. (2021)
Source: Laajaj et al. (2021) and Instituto Nacional de Salud (2020).

et al., 2021). The CoVida project's results have an external validation from a seroprevalence survey conducted by Colombia's government between October 26th and November 17th, 2020. The serosurvey estimates a prevalence rate of 30% [27-33] of the population while CoVida's data yields 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

Figure 2: Epidemiological disparities across socioeconomic strata



Note: The benchmark prevalence ratio at each t is the ratio of the prevalence up to t in the low-SES to the one in the high-SES. Analogously, the benchmark odds ratio at t is $\frac{\text{Infected}\in\text{Low-SES}}{\text{Not Infected}\in\text{Low-SES}} / \frac{\text{Infected}\in\text{High-SES}}{\text{Not Infected}\in\text{High-SES}}$ computed with the cumulative number of infections up to t. The dashed lines are the ratios computed comparing individuals in the lowest two SES with those in the benchmark high-SES. Confidence intervals are very tight so we omit them. Black/red dots represent point estimates of prevalence/odds ratios from serological studies reported in table 8 in section A.2 for the places and across the social groups in the text next to the dots. Lower numbers represent groups of less advantaged individuals.
Sources: Covida (Laajaj et al., 2021) and references in section A.2.

project in Bogotá are relatively small.[7]

We estimate an 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. Covida positive cases in adults over sixty years are 14% in the low-SES and 18% in the high-SES.[8]

Table 2: Infection Fatality Rate

	Aggregate	Low-SES	High-SES	L/H ratio
Fatality Rates (100k)				
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 (%)	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/covid related hospitalizations) are based on Eslava et al. (2020).

2.2 The Impact of covid-19 on Economic Activity and Disparities.

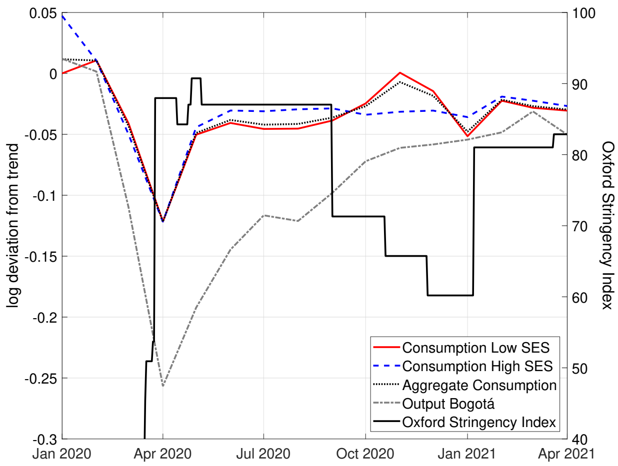
In this section, we describe the evolution of economic activity, consumption, and labor hours in Bogotá, which are depicted in figure 3, together with the national Oxford Policy Stringency

[7] See section A.2

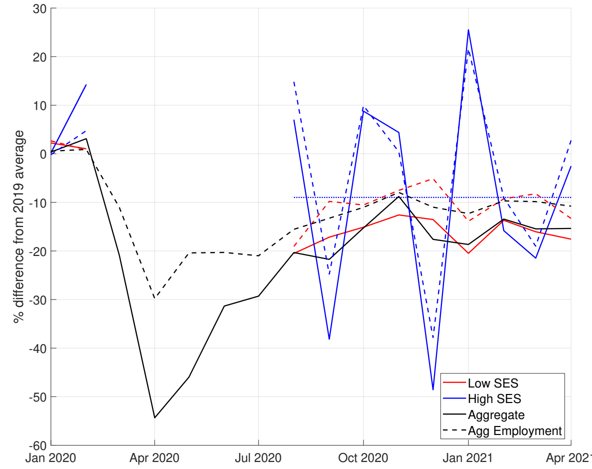
[8] The demographic structure of the population, the CoVida sample, and the CoVida positive cases by age is reported in table 10 in section A.2

Index.[9]

Figure 3: The Impact Of covid-19 on Economic Activity and Disparities



(a) Economic Activity and Consumption



(b) Labor hours

Notes: Economic data in panel (a) are log deviations from the pre-pandemic (2017-19) linear trend. Labor hours are the % 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 if 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).

Colombia imposed a strict lockdown on March 26$^{\text{th}}$, 2020 that lasted until the end of August. Most restrictions on economic activity where lifted at that time and some where reimposed for a brief period on January 7$^{\text{th}}$, 2021 at the peak of the second wave.[10]

Economic activity in Bogotá fell 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 prepandemic linear trend. Aggregate consumptions 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 recover 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 includes expenditures in used consumer durable goods, which

[9]The National Stringency Index aggregates the values of its components using the maximum value among sub-national jurisdictions.
[10]See Laajaj et al. (2021) Supplementary Table 4.

the National Income Accounts do not. RADDAR's consumption 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.[11]

The dynamics of employment during the pandemic are shown in figure 3b. The introduction of the strict lockdown in late March induced hours worked to fall by 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 that 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 is inadequate to draw conclusions on the disparities in hours worked (or employment) during the lockdown because, between March and July, DANE conducted an abridged survey in which it did not ask respondents for their SES.[12] Moreover, the data for individuals in higher SES (10% of the labor force) is very noisy. With these caveats, we observe that after the lockdown labor hours are on average slightly higher for the high-SES group than for the low-SES.

The functional distribution of income is 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.

Transfer Policies

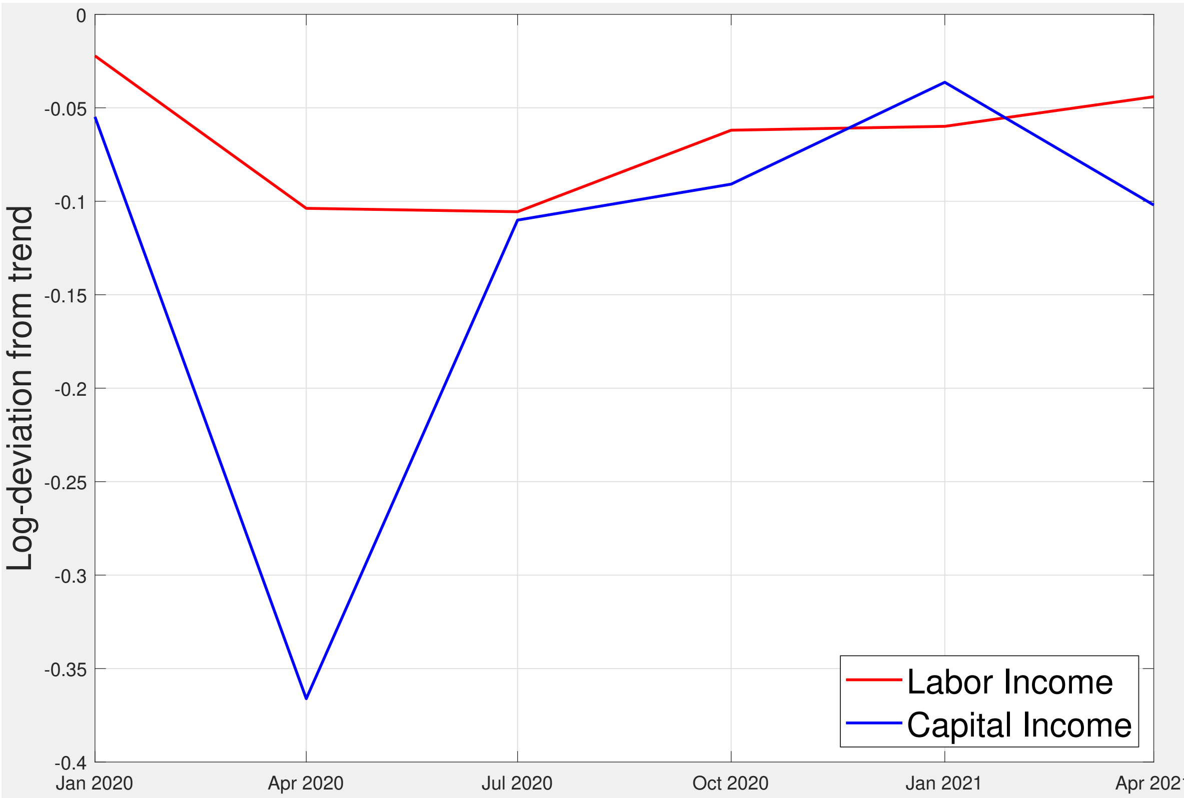
During 2020-1, Colombia's government set in motion a battery of new social programs and enhanced existing ones (Lustig et al., 2021), which add up to 4.6% of average pre-pandemic labor income per person for individuals in the low-SES group (SES 1, 2, and 3).[13] If we assume these payments are targeted at the lowest two SES they amount to 8.3% of per

[11]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.

[12]DANE has a project to recover the missing data in 2020 and is expected to publish the results by the end of 2021

[13]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.

Figure 4: Functional Distribution of Income



Note: Nominal income figures are deflated with the implicit price deflator. Mixed income is assigned 2/3 to labor and 1/3 to capital. Trend is the 2018-19 linear trend.
Source: D.A.N.E

person pre-pandemic labor income.[14]

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 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

[14] 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.

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 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 $\{S_{H,t}, S_{L,t}\}$; the persons that are infectious, denoted by $\{I_{H,t}, I_{L,t}\}$; and the persons that are removed from the pandemic either because they acquired immunity, $\{R_{H,t}, R_{L,t}\}$, or because they died, $\{D_{H,t}, D_{L,t}\}$. Let $\{\Gamma^S_{j,t}, \Gamma^I_{j,t}\}$ 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:

$$S_{j,t+1} - S_{j,t} = -\left(\tilde{\beta}^{j,H}(\Gamma^S_{j,t}, \Gamma^I_{H,t}) I_{H,t} + \tilde{\beta}^{j,L}(\Gamma^S_{j,t}, \Gamma^I_{L,t}) I_{L,t}\right) S_{j,t}, \tag{1a}$$

$$I_{j,t+1} - I_{j,t} = \left(\tilde{\beta}^{j,H}(\Gamma^S_{j,t}, \Gamma^I_{H,t}) I_{H,t} + \tilde{\beta}^{j,L}(\Gamma^S_{j,t}, \Gamma^I_{L,t}) I_{L,t}\right) S_{j,t} - \left(\pi^R + \pi^D\right) I_{j,t}, \tag{1b}$$

$$R_{j,t+1} - R_{j,t} = \pi^R I_{j,t}, \tag{1c}$$

$$D_{j,t+1} - D_{j,t} = \pi^D I_{j,t}, \tag{1d}$$

where π^R is the rate at which infected individuals recover and π^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*:

$$\tilde{\beta}^{j,i}(\Gamma^S_{j,t}, \Gamma^I_{i,t}) = \beta^{j,i}_C(\Gamma^S_{j,t}, \Gamma^I_{i,t}) + \beta^{j,i}_N(\Gamma^S_{j,t}, \Gamma^I_{i,t}) + \beta^{j,i}_A(\Gamma^S_{j,t}, \Gamma^I_{i,t}). \tag{2}$$

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 re-interpretation 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 $\tilde{\beta}^{j,i}(\Gamma^S_{j,t}, \Gamma^I_{i,t})$ 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 less ability to shop online and stock-up goods, are more likely to work in contact-intensive industries, have less possibilities 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.

Transition probabilities, individual choices and health dynamics

When agents make choices, they take into account how these 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 $\pi^I_j\left(\gamma_t, \Gamma^I_{H,t}, \Gamma^I_{L,t}\right)$ to denote probability that a susceptible agent of type j, with individual choices γ_t becomes infected next period given aggregate choices $\Gamma^I_{H,t}$ and $\Gamma^I_{L,t}$. Aggregation requires:

$$\pi^I_j\left(\gamma_t, \Gamma^I_{H,t}, \Gamma^I_{L,t}\right) = \tilde{\beta}^{j,H}(\gamma_t, \Gamma^I_{H,t}) I_{H,t} + \tilde{\beta}^{j,L}(\gamma_t, \Gamma^I_{L,t}) I_{L,t}. \tag{3}$$

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

$$S^j_{t+1} = \left(1 - \pi^I_{j,t}(\Gamma^S_{j,t}, \Gamma^I_{H,t}, \Gamma^I_{L,t})\right) S^j_t, \tag{4a}$$

$$I^j_{t+1} = \left(1 - \pi^R - \pi^D\right) I^j_t + \pi^I_{j,t}(\Gamma^S_{j,t}, \Gamma^I_{H,t}, \Gamma^I_{L,t}) S^j_t, \tag{4b}$$

$$R^j_{t+1} = R^j_t + \pi^R I^j_t, \tag{4c}$$

$$D^j_{t+1} = D^j_t + \pi^D I^j_t. \tag{4d}$$

The first equation describes the dynamics of susceptible households. The share of susceptible households of type j next period, S^j_{t+1}, is simply the fraction of them that do not get infected in the current period, $(1-\pi^I_{j,t})S^j_t$. Likewise, the share of infected households of type j next period equals those that did not recover or die, plus the susceptible 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 $\{\xi_t, \tau_t\}_{t=0}^{\infty}$, where $0 < \xi_t \leq 1$ represent limits on firm production and $\tau_t \geq 0$ represent lump sum transfers to λ 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

$$y_t = Z k_t^{\alpha} n_t^{1-\alpha}, \tag{5}$$

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.[15] First order conditions imply that factor prices must satisfy

$$w_t = (1-\varphi_t)(1-\alpha) Z k_t^{\alpha} n_t^{-\alpha}, \tag{8a}$$

$$v_t = (1-\varphi_t)\alpha k_t^{\alpha-1} n_t^{1-\alpha}, \tag{8b}$$

[15] 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.

where φ_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 $\sigma \in \{\mathfrak{s}, \mathfrak{i}, \mathfrak{r}\}$ 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. Section D sketches the details of this insurance arrangement.

To set up the consumer's problem recursively, we use Σ_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

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

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 σ_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

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

High-SES consumers

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

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

where w_t is the wage rate, v_t is the return to capital, and $r(b_t^H)$ is the interest rate schedule faced by each agent,[16] and $\mathcal{T}_t^j$ are insurance transfers that break the link between the health status and wealth described in section D. A borrowing limit that bounds consumption completes the constraint set of high-SES agents.

Individual's welfare at period t satisfies the following recursive expression:

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

where the optimization problem in 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 in the right-hand side of (12) is taken with respect to the next period health status and it 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 and thus we have

$$\mathbb{E}\left[V_t^H(\sigma, k, b; \Sigma) \mid \mathfrak{r}\right] = V^H(\mathfrak{r}, k, b; \Sigma).$$

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

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

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

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

[16] 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 $\partial r(b)/\partial b$ is a small positive number that induces consumption and asset holdings to be stationary following Schmitt-Grohe and Uribe (2003).

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.

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

$$c_t + x_t = w_t n_t + v_t k_t + \tau_t + \mathcal{T}_t^L(\sigma_t, \Sigma_t) \tag{13}$$

where the parameter $\omega \leq 1$ captures the fact that low-SES 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

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

for all t, where the problem in 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 it was the case for the high-SES agent, the continuation value in the right-hand side depends on the health status of the decision maker, and so 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 $\sigma \in \{\mathfrak{s}, \mathfrak{i}, \mathfrak{r}\}$ is representative of her group. This means that at every period t we must have

$$C_{j,t}^{\sigma} = c_{j,t}^{\sigma}, \qquad N_{j,t}^{\sigma} = n_{j,t}^{\sigma}, \qquad A_{j,t}^{\sigma} = a_{j,t}^{\sigma}, \qquad X_{j,t}^{\sigma} = x_{j,t}^{\sigma}, \qquad K_{j,t+1}^{\sigma} = k_{j,t+1}^{\sigma}, \tag{15}$$

for all j and σ, and

$$B_{H,t+1}^{\sigma} = b_{H,t+1}^{\sigma}, \tag{16}$$

for all σ. Aggregate consumption, investment, capital, labor, and social interaction are computed as follows:

$$
\begin{aligned}
C_t &= C^{\mathfrak{s}}_{H,t}S_{H,t} + C^{\mathfrak{i}}_{H,t}I_{H,t} + C^{\mathfrak{r}}_{H,t}R_{H,t} + C^{\mathfrak{s}}_{L,t}S_{L,t} + C^{\mathfrak{i}}_{L,t}I_{L,t} + C^{\mathfrak{r}}_{L,t}R_{L,t}, &\text{(17a)}\\
N_t &= N^{\mathfrak{s}}_{H,t}S_{H,t} + N^{\mathfrak{i}}_{H,t}I_{H,t} + N^{\mathfrak{r}}_{H,t}R_{H,t} + N^{\mathfrak{s}}_{L,t}S_{L,t} + N^{\mathfrak{i}}_{L,t}I_{L,t} + N^{\mathfrak{r}}_{L,t}R_{L,t}, &\text{(17b)}\\
A_t &= A^{\mathfrak{s}}_{H,t}S_{H,t} + A^{\mathfrak{i}}_{H,t}I_{H,t} + A^{\mathfrak{r}}_{H,t}R_{H,t} + A^{\mathfrak{s}}_{L,t}S_{L,t} + A^{\mathfrak{i}}_{L,t}I_{L,t} + A^{\mathfrak{r}}_{L,t}R_{L,t}, &\text{(17c)}\\
X_t &= X^{\mathfrak{s}}_{H,t}S_{H,t} + X^{\mathfrak{i}}_{H,t}I_{H,t} + X^{\mathfrak{r}}_{H,t}R_{H,t} + X^{\mathfrak{s}}_{L,t}S_{L,t} + X^{\mathfrak{i}}_{L,t}I_{L,t} + X^{\mathfrak{r}}_{L,t}R_{L,t}, &\text{(17d)}\\
K_t &= K^{\mathfrak{s}}_{H,t}S_{H,t} + K^{\mathfrak{i}}_{H,t}I_{H,t} + K^{\mathfrak{r}}_{H,t}R_{H,t} + K^{\mathfrak{s}}_{L,t}S_{L,t} + K^{\mathfrak{i}}_{L,t}I_{L,t} + K^{\mathfrak{r}}_{L,t}R_{L,t}. &\text{(17e)}
\end{aligned}
$$

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

$$
B_t = B^{\mathfrak{s}}_{H,t}S_{H,t} + B^{\mathfrak{i}}_{H,t}I_{H,t} + B^{\mathfrak{r}}_{H,t}R_{H,t}. \qquad \text{(18a)}
$$

3.6 An Epidemiological and Economic Equilibrium

Given a government policy $\{\xi_t, \tau_t\}$, an interest rate r^*, initial epidemiological conditions $\{S_{j,0}, I_{j,0}, R_{j,0}, D_{j,0}\}_{j\in\{L,H\}}$, and initial stocks of government debt, capital stock and bond holdings $\{B_0, K_0^j\}_{j\in\{L,H\}}$, an equilibrium for this economy is a collection of sequences for factor prices $\{w_t, v_t\}_{t=0}^{\infty}$; value functions $\{V_t^H, V_t^L\}_{t=0}^{\infty}$; 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 $\{S_{j,t}, I_{j,t}, R_{j,t}, D_{j,t}\}_{t=0}^{\infty}$ 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.

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:

$$\tilde{u}^{H}_{\mathbf{x},t}\left(c,n,a,k',b'\right) = u_{\mathbf{x}}\left(c,n,a\right) + \frac{\partial \pi^{I}_{H,t}(c,n,a)}{\partial \mathbf{x}}\left[\frac{V^{H}_{t+1}\left(\mathfrak{i},k',b';\Sigma\right) - V^{H}_{t+1}\left(\mathfrak{s},k',b';\Sigma\right)}{1+\rho}\right], \tag{19a}$$

$$\tilde{u}^{L}_{\mathbf{x},t}\left(c,n,a,k'\right) = u_{\mathbf{x}}\left(c,n,a\right) + \frac{\partial \pi^{I}_{L,t}(c,n,a)}{\partial \mathbf{x}}\left[\frac{V^{L}_{t+1}\left(\mathfrak{i},k';\Sigma\right) - V^{L}_{t+1}\left(\mathfrak{s},k';\Sigma\right)}{1+\rho}\right] \tag{19b}$$

for $\mathbf{x} \in \{c,n,a\}$. The term between square brackets in 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), entail the following intratemporal first order conditions

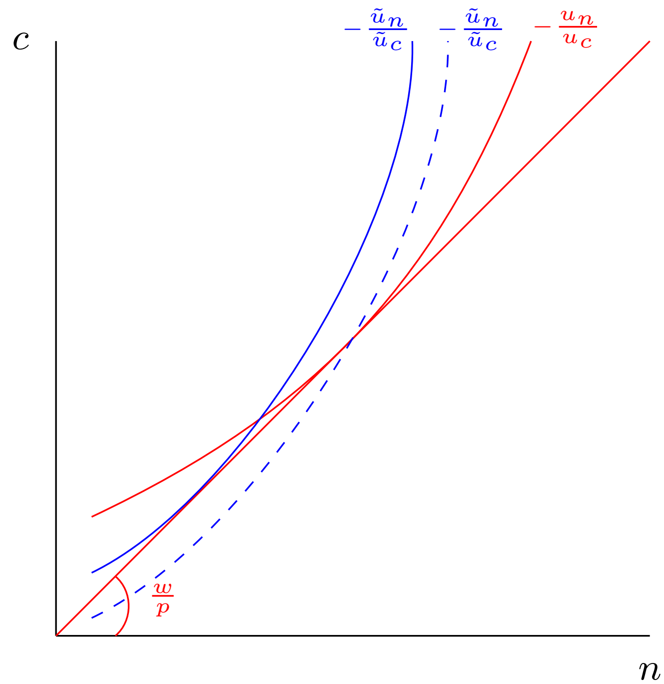
$$-\frac{\tilde{u}_{n,t}\left(\mathfrak{s}\right)}{\tilde{u}_{c,t}\left(\mathfrak{s}\right)} = \omega w_t, \tag{20a}$$

$$\tilde{u}_{a,t}\left(\mathfrak{s}\right) = 0, \tag{20b}$$

for all t, where we introduced the shorthand notation $\tilde{u}_{\mathbf{x},t}(\mathfrak{s})$ to denote the holistic marginal utility in activity $\mathbf{x}$ and omitted the arguments and the group identity for convenience and the fact that the wage of the low SES agents is ωw_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., $-\tilde{u}_{n,t}\left(\mathfrak{s}\right) < -u_{n,t}\left(\mathfrak{s}\right)$), and decreases the marginal utility of consumption (e.g., $\tilde{u}_{c,t}\left(\mathfrak{s}\right) < u_{c,t}\left(\mathfrak{s}\right)$).[17] 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

[17] This logic presumes that the probability of infection is increasing in every argument.

Figure 5: Economic Activity and the Risk of Infection



Note: the graph shows that as at any point indifference curves between consumption and work are steeper for the holistic preferences that the normal marginal rate of substitution, susceptible agents will restrict their economic activity reducing c and n.

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 $\tilde{u}_{a,t}(\mathfrak{s}) < u_{a,t}(\mathfrak{s})$ for all a and $u_{a,t} = 0 \Rightarrow \tilde{u}_{a,t} < 0$.

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 ϵ of consumers become infected. The dynamics of the pandemic unfold from period 1 onwards. 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.

4.1 Functional forms

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 $i, j \in \{\text{L,H}\}$ in our model is

$$\tilde{\beta}^{j,i}(\Gamma^S_{j,t}, \Gamma^I_{i,t}) = \beta^{j,i}_N \frac{N^S_{j,t}}{\overline{N}^S_j} \frac{N^I_{i,t}}{\overline{N}^I_i} + \left(\beta^{j,i}_C \frac{C^S_{j,t}}{\overline{C}^S_j} \frac{C^I_{i,t}}{\overline{C}^I_i} + \beta^{j,i}_A \frac{A^S_{j,t}}{\overline{A}^S_j} \frac{A^I_{i,t}}{\overline{A}^I_i} \right) \frac{1 - N^S_{j,t}}{1 - \overline{N}^S_j} \frac{1 - N^I_{i,t}}{1 - \overline{N}^I_i}, \tag{21}$$

where the variables with 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 $\tilde{\beta}^{j,i}(\Gamma^S_{j,t}, \Gamma^I_{i,t}) = \beta^{j,i}_N + \beta^{j,i}_C + \beta^{j,i}_A$

Instantaneous preferences

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

$$u(c, n, a) = \log(c) + \nu_j^{1/\zeta} \frac{(\bar{n} - n)^{1-1/\zeta}}{1 - 1/\zeta} + \kappa \left[\log(a) - a + 1\right] + \bar{u} \tag{22}$$

for $j \in \{L, H\}$. The term $\bar{u}$ 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 $\{\nu_L, \nu_H, \kappa, \zeta, \bar{u}\}$, and the only source of heterogeneity in preferences comes from ν_j.

Capital adjustment costs

The functional form of adjustment costs is

$$\Phi(k, k') = \frac{\phi}{2} \left(\frac{k' - k}{k} \right)^2 k, \tag{23}$$

which is standard in the literature. To set the investment adjustment cost parameter ϕ, 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 ϕ is chosen so that the standard deviation of investment relative to the standard deviation of GDP equals 3.75.[18]

Interest rate schedule

The interest rate schedule is

$$r(b) = r^* + \chi \left(\exp\left(\frac{\overline{B} - b}{\bar{y}} \right) - 1 \right), \tag{24}$$

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

4.2 Parameters

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

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 π^D and π^R.

In order 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 η_1, by imposing that

$$\beta_{\mathbf{x}}^{L,L} = \eta_1 \beta_{\mathbf{x}}^{L,H}, \tag{25a}$$

$$\beta_{\mathbf{x}}^{H,H} = \eta_1 \beta_{\mathbf{x}}^{H,L}, \tag{25b}$$

for $\mathbf{x} \in \{C, N, A\}$. In addition, we consider the possibility of *asymmetric interaction*, which

[18] García-Schmidt and García-Cicco (2020), García et al. (2019)

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 η_2, through the following condition

$$\beta_{\mathbf{x}}^{H,L} \quad = \quad \eta_2 \beta_{\mathbf{x}}^{L,H}, \tag{26}$$

for $\mathbf{x} \in \{C, N, A\}$. Equations (25) and (26) imply that $\beta_{\mathbf{x}}^{H,H} = \eta_1 \eta_2 \beta_{\mathbf{x}}^{L,H}$ so all the parameters $\beta_{\mathbf{x}}^{j,i}$ can be expressed in terms of $\beta_{\mathbf{x}}^{L,H}$.[19]

To calibrate $\beta_{\mathbf{x}}^{L,H}$ in each activity, we follow Eichenbaum et al. (2020) in assuming that, at the onset of the pandemic, 1/6 of the infections stem from contacts in consumption venues and workplaces, whereas 2/3 come from contacts at spaces of social interaction. We will write each $\beta_{\mathbf{x}}^{L,H}$ as a function of R_0.

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

$$R_0^i = \frac{\sum_x \beta_x^{L,i} \lambda + \beta_x^{H,i}(1-\lambda)}{\pi^R + \pi^D}.$$

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 λ $(1-\lambda)$, the basic reproduction number is

$$R_0 = \lambda R_0^L + (1-\lambda) R_0^H. \tag{27}$$

The transmission rates $\beta_{\mathbf{x}}^{L,H}$ then can be written as

$$\beta_C^{L,H} \quad = \quad \frac{1}{6} \frac{(\pi^R + \pi^D)}{\lambda^2 \eta_1 + \lambda(1-\lambda)(1+\eta_2) + (1-\lambda)^2 \eta_1 \eta_2} R_0, \tag{28a}$$

$$\beta_N^{L,H} \quad = \quad \frac{2}{3} \frac{(\pi^R + \pi^D)}{\lambda^2 \eta_1 + \lambda(1-\lambda)(1+\eta_2) + (1-\lambda)^2 \eta_1 \eta_2} R_0, \text{ and} \tag{28b}$$

$$\beta_A^{L,H} \quad = \quad \frac{1}{6} \frac{(\pi^R + \pi^D)}{\lambda^2 \eta_1 + \lambda(1-\lambda)(1+\eta_2) + (1-\lambda)^2 \eta_1 \eta_2} R_0. \tag{28c}$$

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

[19] Notice that, while any η_2 different from one would indicate asymmetric interaction, segmentation requires η_1 to be strictly greater than one.

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, $\{\nu_H, \nu_L, \zeta\}$, are set to match a Frisch elasticity of 1.5 and to guarantee that both types of consumer use 20% of total available time to work.[20]

To calibrate $\overline{u}$, we use an estimate of the Statistical Value of Life (SVL) lost due to covid-19 of six times consumption following Hall et al. (2020). Hence, in our model we must have

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

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 is derived from the steady state Euler equation for bond holdings is $(1+\rho)^{52} = (1+r^*)^{52} - \chi\, \frac{b}{\bar{y}}$ so weekly ρ is equal to $\rho = \left((1+r^*)^{52} - \chi\, \frac{b}{\bar{y}}\right)^{\frac{1}{52}} - 1$.

The initial capital stock for low-SES consumers is set to 1/2 of the aggregate capital stock. 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%, which is in line with the evidence reported in Smith et al. (2021) for the U.S.[21] Under these assumptions a representative high SES agent owns eight times more capital than a low SES individual.

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). This fact and the government budget constraint set the values for $\{\tau_t\}_{t=0}^{\infty}$.

We parameterize the path of output limits during the pandemic as a piece-wise linear function, for which we fix the values at 4 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

[20] Considering an employment to population ratio of 0.6 and that agents use 1/3 of their time to work delivers 20%.

[21] Smith et al. (2021)report that the top 1% of the wealth distribution holds as much capital as the following 90-99% and the bottom 90%. Thus, ignoring the top 1%, the ratio of aggregate capital in hands of the remaining two groups is equal to one.

Table 3: **Calibrated parameters**

Parameter	Description	Value	Source/Comment
ρ	Rate of time preference	0.0003	$\left((1+r^*)^{52} - \chi\frac{b}{\bar{y}}\right)^{\frac{1}{52}} - 1$
r^*	Interest rate (annualized)	0.015	
χ	Elasticity credit supply	0.0001	
λ	Share of low-SES	0.89	See Table 1
ω	Efficiency units for low-SES	0.22	
$\begin{bmatrix}\nu_L \\ \nu_H\end{bmatrix}$	Labor preference parameter	$\begin{bmatrix}2.76 \\ 2.07\end{bmatrix}$	Hrs worked/Total hrs Bogotá
ψ	Frisch elasticity = 1.5	0.38	García et al. (2019)
ϕ	Investment adjustment cost		St dev of Investment
δ	Weekly dep. rate (4% p.a.)	$1 - 0.96^{\frac{1}{52}}$	García et al. (2019)
$K_{H,0}/K_{L,0}$	90/10 capital stock ratio	1	Smith et al. (2021)
$\bar{u}$	Joy of life	8.26	SVL= $6C$ in Hall et al. (2020)
$\begin{bmatrix}\bar{\xi}_1 \\ \bar{\xi}_2 \\ \bar{\xi}_3 \\ \bar{\xi}_4\end{bmatrix}$	Output limits	$\begin{bmatrix}0.25 \\ 0.12 \\ 0.04 \\ 0.02\end{bmatrix}$	
κ	Social Preference parameter	0.053	See Section 4.3
$\begin{bmatrix}\eta_1 \\ \eta_2\end{bmatrix}$	Transmission rate parameters	$\begin{bmatrix}1.38 \\ 0.71\end{bmatrix}$	
R_0	Basic Reproduction number	2.36	
ϵ	Fraction of initial infected	0.05%	

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 (simulated method of moments)

We use the simulated method of moments to calibrate the vector $\{\bar{\xi}_1, \bar{\xi}_2, \bar{\xi}_3, \bar{\xi}_4, \kappa, \eta_1, \eta_2, R_0, \epsilon\}$. 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 (4 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.

Table 4: **Model Performance**

Targeted Moments	**Model**	**Data**
Output (relative to SS)		
Last week of Mar-20	0.77	0.77
Last week of Aug-20	0.88	0.89
First week of Jan-21	0.96	0.96
Last week of Feb-21	0.99	0.99
Prevalence rate		
First week of Aug-20	0.21	0.21
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

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 η_1 and η_2 reported in table 3 together with equations (25)-(26) imply that the transmission matrix from each source of exposure (x) is proportional to

$$\begin{pmatrix} \beta_x^{LL} & \beta_x^{LH} \\ \beta_x^{HL} & \beta_x^{HH} \end{pmatrix} \propto \begin{pmatrix} 1.38 & 1 \\ 0.71 & 0.98 \end{pmatrix} \tag{29}$$

The estimated transmission rates have several implications. (i) Low SES individuals are 40% more vulnerable to the virus. This is a consequence of the fact that the ratio $\left(\beta_x^{LL} + \beta_x^{LH}\right) / \left(\beta_x^{HL} + \beta_x^{HH}\right) = 1.4$ captures the difference in the vulnerability to infection across SES. (ii) The number of infections induced by one individual is independent of their SES. This is a consequence of the fact that the ratio $\left(\beta_x^{LL} + \beta_x^{HL}\right) / \left(\beta_x^{LH} + \beta_x^{HH}\right) = 1.06$ 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 $\beta_x^{LL}/\beta_x^{HL} = 1.95$ and $\beta_x^{LH}/\beta_x^{HH} = 1.02$ capture the heterogeneity in vulnerability to an infectious person in the low- and high-SES, 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 show first the behavior of aggregate variables, then individual behavior and we close with the model's implications on the cost of social distancing and the private value of a vaccine.

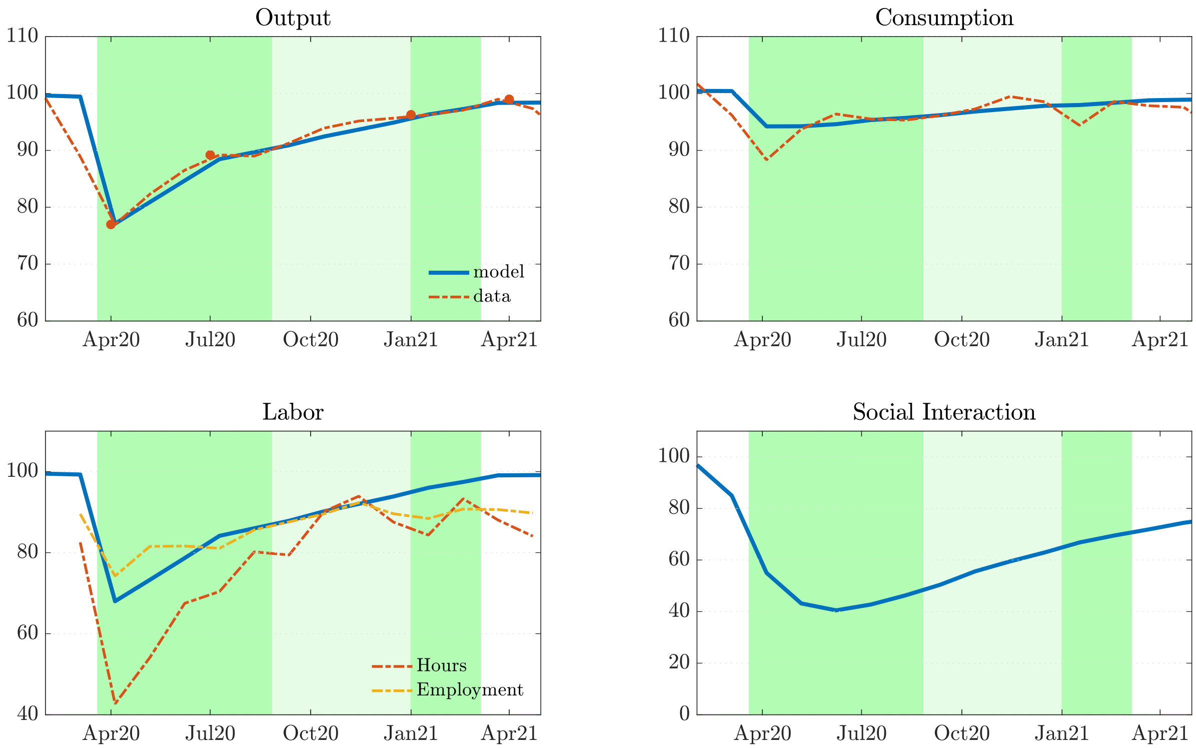
Aggregate variables

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 counterpart 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 due to 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 at 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, like measures of mobility from mobile telephones[22], 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 working less. This adjustment in behaviour 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

[22] e.g. Google Mobility, Safe Graph, Facebook, etc.

Figure 6: Aggregate Results (monthly).



Note: Shaded bars identify the shutdown periods. Light shades identify the interim period in which some restrictions were lifted. In the top-left panel, red dots represent calibration targets.

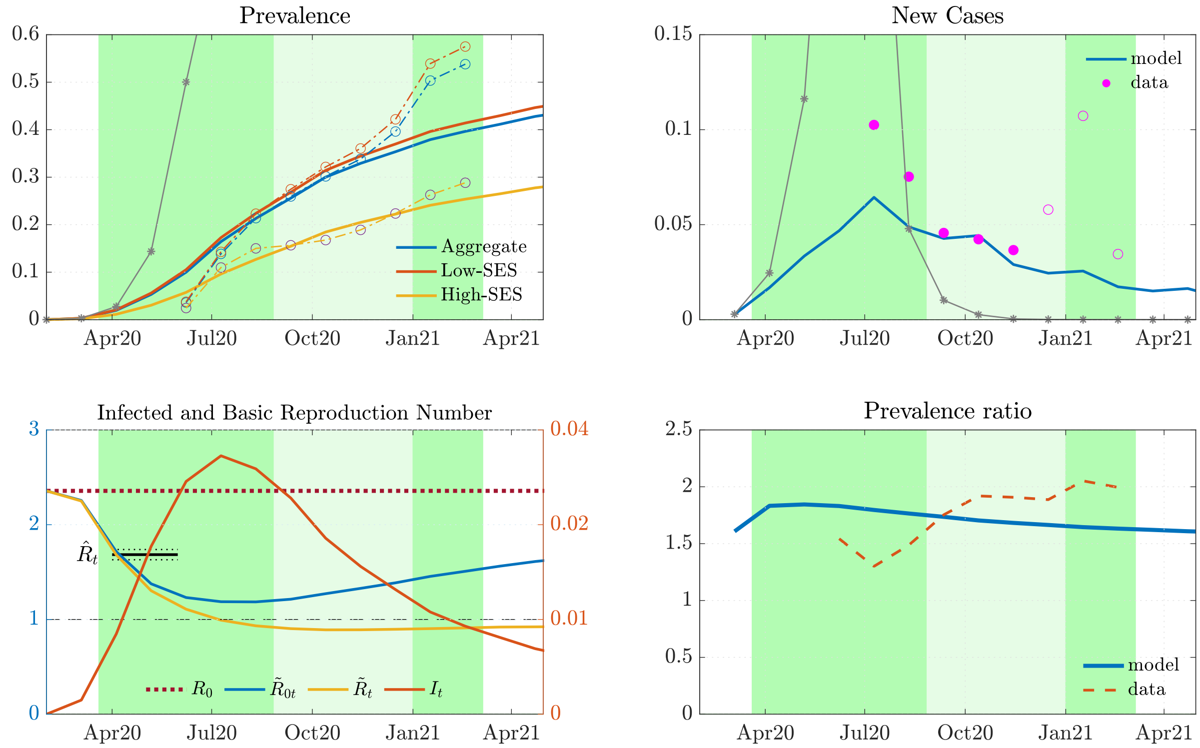
increases very sharply at the peak of the pandemic, a feature that the model does not capture. The epidemiological dynamics in the non-behavioral SIRD model, depicted in grey, in the top two graphs go off-scale in overpredicting the speed of infections as they do not take into account the endogenous mitigating behavior.

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

$$\tilde{R}_{0,t} = \frac{\frac{I_t^L}{I_t}\left(\sum_x \tilde{\beta}_x^{L,L}\frac{S_t^L}{S_t} + \tilde{\beta}_x^{H,L}\frac{S_t^H}{S_t}\right) + \frac{I_t^H}{I_t}\left(\sum_x \tilde{\beta}_x^{L,H}\frac{S_t^L}{S_t} + \tilde{\beta}_x^{H,H}\frac{S_t^H}{S_t}\right)}{\pi^R + \pi^D}. \tag{30}$$

In contrast to the basic reproduction number, the behavioral reproduction number $\tilde{R}_{0,t}$ 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 $\tilde{R}_{0,t} = \left(\sum_x \tilde{\beta}_x\right) / \left(\pi^R + \pi^D\right)$. Estimates of R_0 based on observational data like the rate of growth of cases estimate $\tilde{R}_{0,t}$, not R_0. The effective reproductive number is $\tilde{R}_t = \tilde{R}_{0,t}S_t$. It represents the number of new cases per each infected individual.

Figure 7: Epidemiological Dynamics (monthly).



Note: Shaded bars identify the shutdown periods. Light shades identify the interim period in which some restrictions were lifted. In the first two figures, red dots represent data points. In the bottom right figure, the target is the average prevalence ratio in the data. In the bottom left panel, R_0 is the estimated non-behavioral basic reproductive number defined in equation (27), $\tilde{R}_{0,t}$ is the behavioral reproduction number defined in equation (30), and $\tilde{R}_t = \tilde{R}_{0,t} S_t$ is the behavioral effective reproduction number. $\hat{R}_t$ is the estimated reproduction number based on Laajaj et al. (2021)'s estimates of Bogotá's daily rate of growth of cases and the dotted lines are 95% confidence intervals (see footnote 24 for more details). The top two panels report prevalence and new cases in the non-behavioral single group SIRD model with $R_0 = 2.36$ as a reference.

The lower left panel in figure 7 depicts the basic reproduction number R_0, the behavioral reproductive number $\tilde{R}_{0,t}$, and the effective behavioral reproduction number $\tilde{R}_t$. 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.[23] 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, $\hat{R}_0 = 1.68$, estimated in Laajaj et al. (2021).[24] As the number of active cases, I_t, increases, the behavioral adjustment deepens.

[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).

[24] Laajaj et al. (2021) estimate the average daily rate of growth of new cases in Bogotá, g, from April 1st, 2020 to May 31s, 2020 at 0.038. The rate of growth of deaths for that period is similar. The SIR model

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 $\tilde{R}_{0,t}$ 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, $\tilde{R}_{0,t}S_t$, falls below one after five months and stays just under one 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 in top-left panel shows.[25] 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.[26] The prevalence ratio in the model is humped shaped because the disease progresses faster in the low-SES, but at some point there are relatively fewer susceptible low-SES and thus the disease spreads faster among high-SES agents.

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 to their 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.

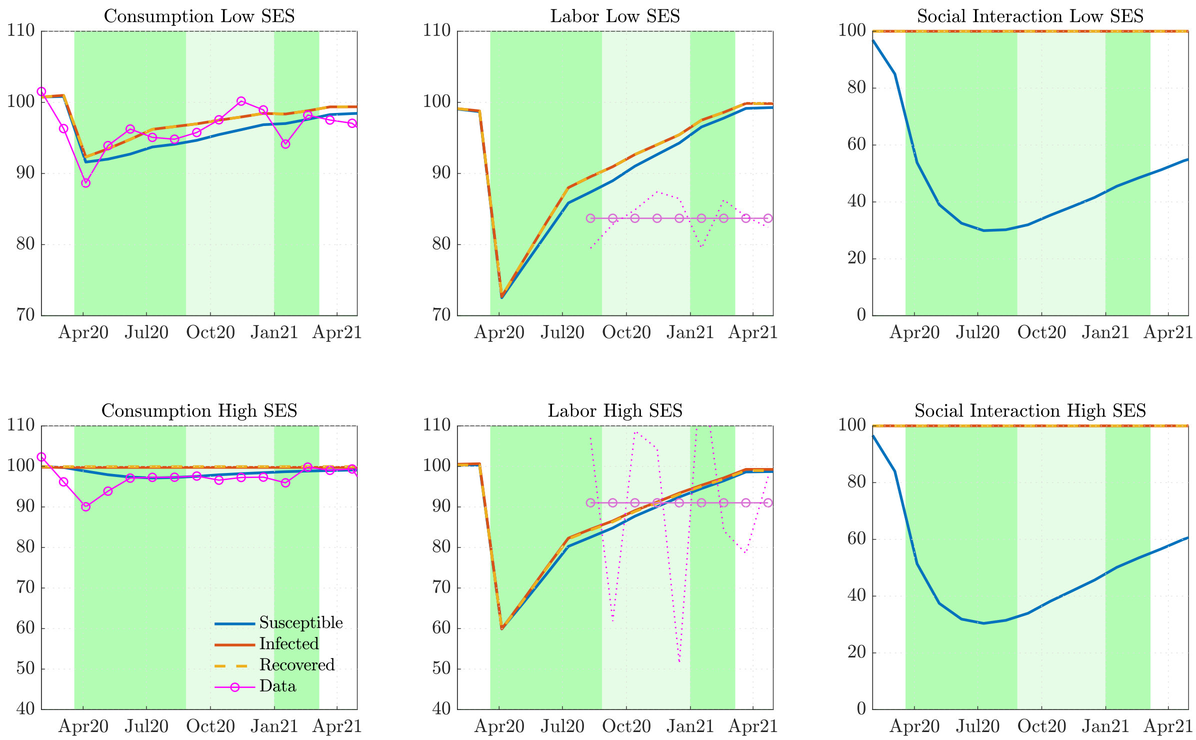
Susceptible agents. Susceptible low-SES consumers mitigate the risk of contagion by reducing all three activities that contribute to disease transmission as shown in the top row of figure 8. While social activities voluntarily drop sharply and remain low throughout the epidemic outbreak, the adjustment of consumption and the labor supply is less persistent and is largely driven by the shutdown, as it 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 due to the shutdown (see figure 9). The model's prediction for low-SES consumption is well aligned with the data, but recovers

implies that $R_0 = 1 + \frac{g}{\gamma} = 1 + 0.038 \times 18 = 1.68$

[25] The model could incorporate waning immunity and shifts in β'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).

Figure 8: Microeconomic choices (monthly).



Note: Shaded bars identify the shutdown period. Light shades 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 is available.

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 the 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 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 behaviour of the infected and the recovered highlights the role played in this model by the health externality, health immunity after infection, the financial exclusion of people in 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

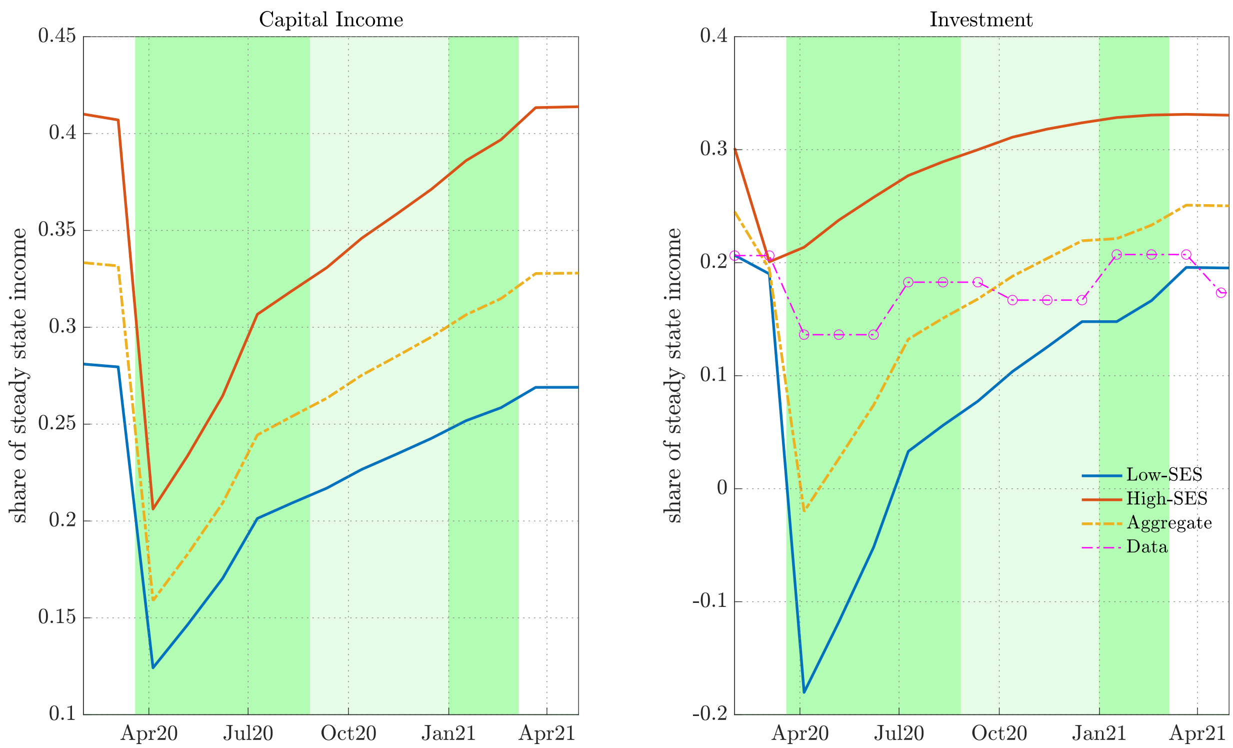
[27]See Buera et al. (2020) for an analysis of the speed of recovery from shutdowns.

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 behaviour of the recovered and the 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.

Figure 9: Capital income and investment (monthly).



Note: The left panel depicts capital income net of adjustment costs, e.g. $v_t k_t - \Phi(k_t, k_{t+1})$. The right figure depicts investment, e.g. $k_{t+1} - (1-\delta)k_t$. In both cases, values are expressed as a share of steady state income of each group. The data line is the national gross fixed capital formation in constant prices and deseasonalized published with the NIPA by D.A.N.E. The data on investment is divided by the linear trend in GDP extrapolated from the Q102018-Q42019 linear trend.

The role of capital is interesting as it simultaneously amplifies and dampens the economic effect of the shutdown. This is 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 in April frees up to 35% of prepandemic 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.

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 the infected individuals can be used to measure the private value of a vaccine and the parameter κ can be used to price social distancing in terms of consumption.

5.1.0.1 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, $V_t^i(\mathfrak{r}, \cdot; \Sigma) - V_t^i(\mathfrak{s}, \cdot; \Sigma)$ and transform this variation into steady state consumption units, $\left(\exp\left(\frac{\rho}{1+\rho}\left(V_t^i(\mathfrak{r}, \cdot; \Sigma) - V_t^i(\mathfrak{s}, \cdot; \Sigma)\right)\right) - 1\right)$ 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:

$$\mathcal{V}_t^i = \frac{1+\rho}{\rho}\left(\exp\left(\frac{\rho}{1+\rho}\left(V_t^i(\mathfrak{r}, \cdot; \Sigma) - V_t^i(\mathfrak{s}, \cdot; \Sigma)\right)\right) - 1\right)\bar{C}^i,$$

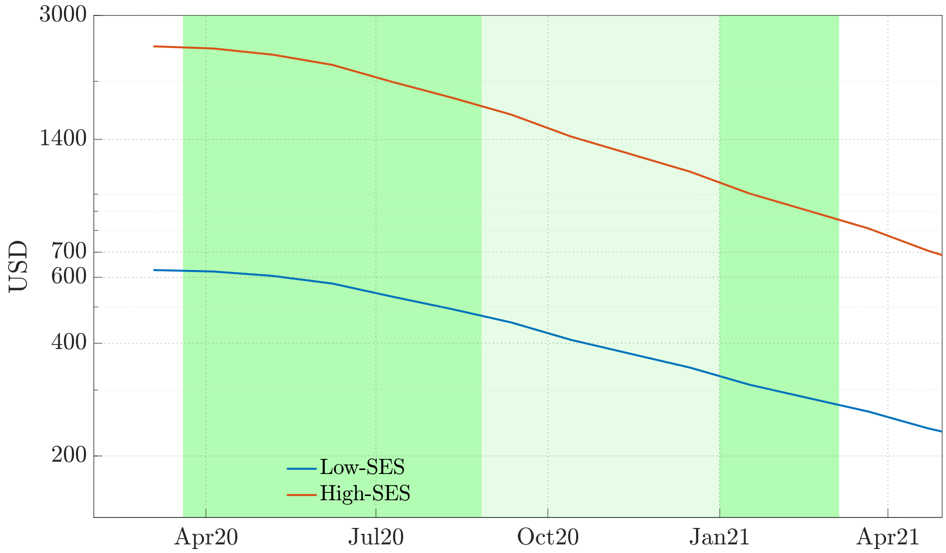
where $\bar{C}^i$ denotes the steady state consumption.

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 USD627 and USD2,481, respectively, at the onset of the pandemic in February 2020, whereas only USD344 and USD1,149 when vaccines became available at the end of December, in the 48^{th} 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 it is immediately distributed. If people anticipate the arrival of the vaccine they will change their behavior and this will have an effect on the epidemiological dynamics and on the value

[28] The **social value** of the vaccine measures the change in welfare from the effect of the vaccine on the aggregate health state Σ.

Figure 10: The Private Value of a Vaccine



Note: At each period, we first compute the fraction of consumption that a recovered agent would be willing to forego for not becoming susceptible. We then compute the USD value of steady state consumption for each type of consumer considering an aggregate consumption value of 115 USD. The value of the vaccine is the perpetuity value of the product of the CE variation computed in the first step, and the steady state consumption computed in the second step.

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.

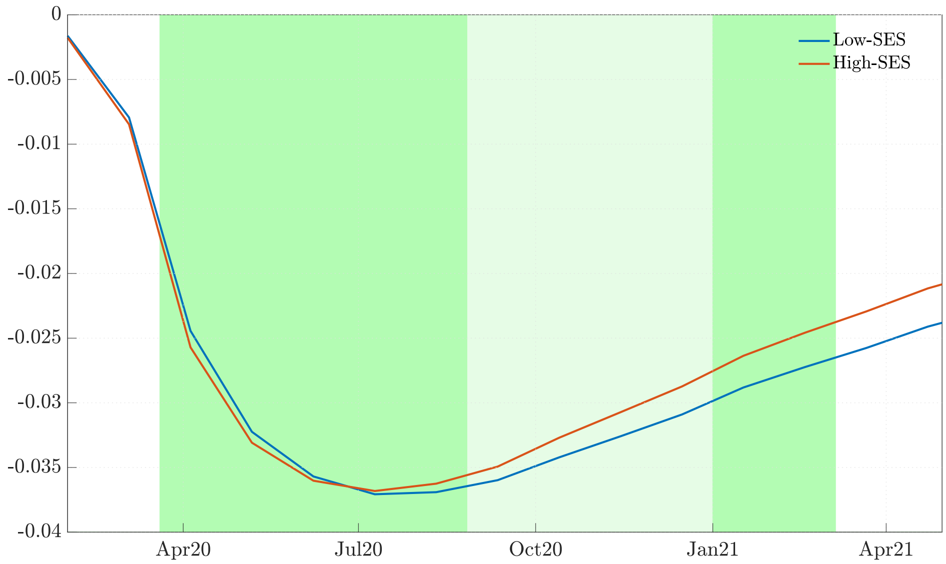
5.1.0.2 The cost of social distancing

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

$$\left.\frac{dc}{da}\right|_{du=0} \frac{a}{c} = -\kappa \left(\frac{1}{a} - 1\right) a. \tag{31}$$

In August, at the epidemic's peak, the value of a is approximately $a^H = 0.31$ and $a^L = 0.30$, whereas $\kappa = 0.053$ in the calibration. This implies that persons in the low-SES would give up 3.7% of weekly consumption or 3 USD to increase a by 1% for a week, while people in the high-SES would pay 3.6% of weekly consumption or 14 USD. The evolution of this cost, expressed in terms of the fraction of weekly consumption foregone, is displayed in figure 11.

Figure 11: Cost of social distancing.



Note: Shaded bars identify the shutdown period. Light shades identify the interim period in which some restrictions were lifted. The cost of social distancing for each group is computed as indicated in equation (31).

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:

$$\frac{\partial\tilde{\beta}^{j,i}(\Gamma^S_{j,t},\Gamma^I_{i,t})}{\partial N^S_{j,t}} = \beta^{j,i}_N \frac{1}{\overline{N}^S_j}\frac{N^I_{i,t}}{\overline{N}^I_i} - \left(\beta^{j,i}_C \frac{C^S_{j,t}}{\overline{C}^S_j}\frac{C^I_{i,t}}{\overline{C}^I_i} + \beta^{j,i}_A \frac{A^S_{j,t}}{\overline{A}^S_j}\frac{A^I_{i,t}}{\overline{A}^I_i}\right)\frac{1}{1-\overline{N}^S_j}\frac{1-N^I_{i,t}}{1-\overline{N}^I_i}, \tag{32}$$

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 in the right-hand side. This direct effect is moderated by the second term that captures the fact that the time not spent working is allocated to consumption and social activities.[29] 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). The two effects that changing hours worked by a susceptible individual have on the probability of infection of each consumer type are depicted in figure 14. It shows that this derivative flips signs and it 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 while in the case without a shutdown there are moderate increases in wages due to 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 shutdown has a moderate impact on epidemiological outcomes "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 $\tilde{R}_{0t}$ and, as a result, the prevalence rate and the peak in new cases is is 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.

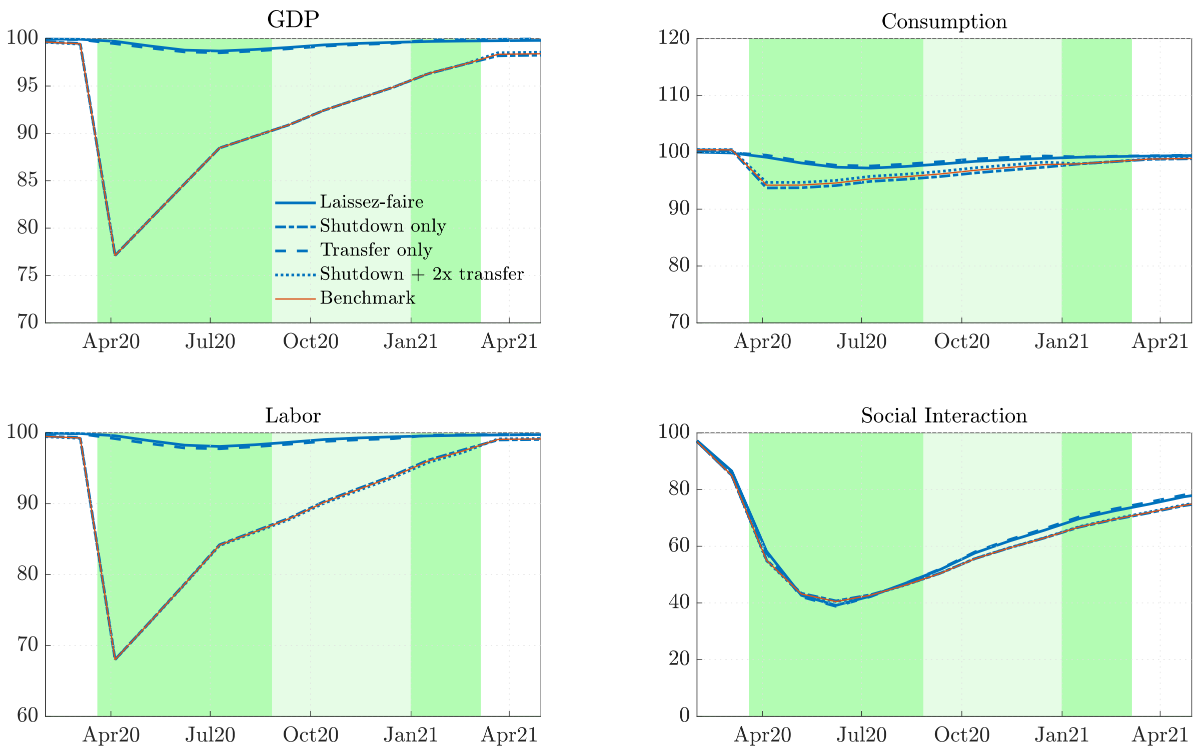
Transfer policies. We analyze the effects of redistributive transfers by comparing the laissez-faire economy with an economy with only transfers, and by comparing the shutdown-only economy with the benchmark economy (with the shutdown and transfers) and another economy with the shutdown and transfers twice as large as in the benchmark. The benchmark

[29]A 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.

transfer is 4.6% of the low-SES's labor income in the disease free steady state for ten months.

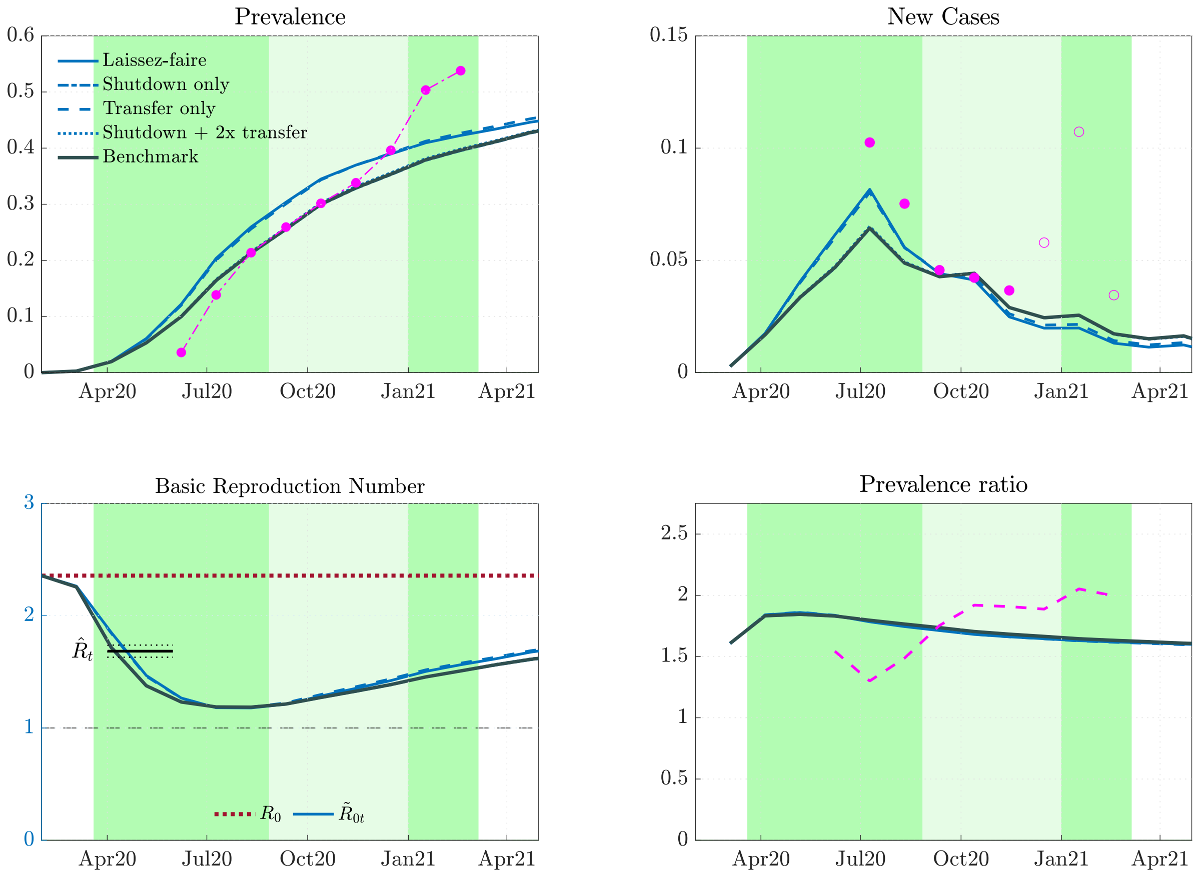
In all the cases, the redistributive transfers *reduce* aggregate labor supply and output, and increases consumption and investment. In the background, the city's current account deficit increases. The transfer induces low-SES agents to work less, invest more, and consume more. The fall in the labor 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 due to the binding constraint on output. The transfer increases investment because the low SES agents use capital as a vehicle to save the chunk 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 in table 6.

Figure 12: Counterfactuals: Aggregate Dynamics (monthly).



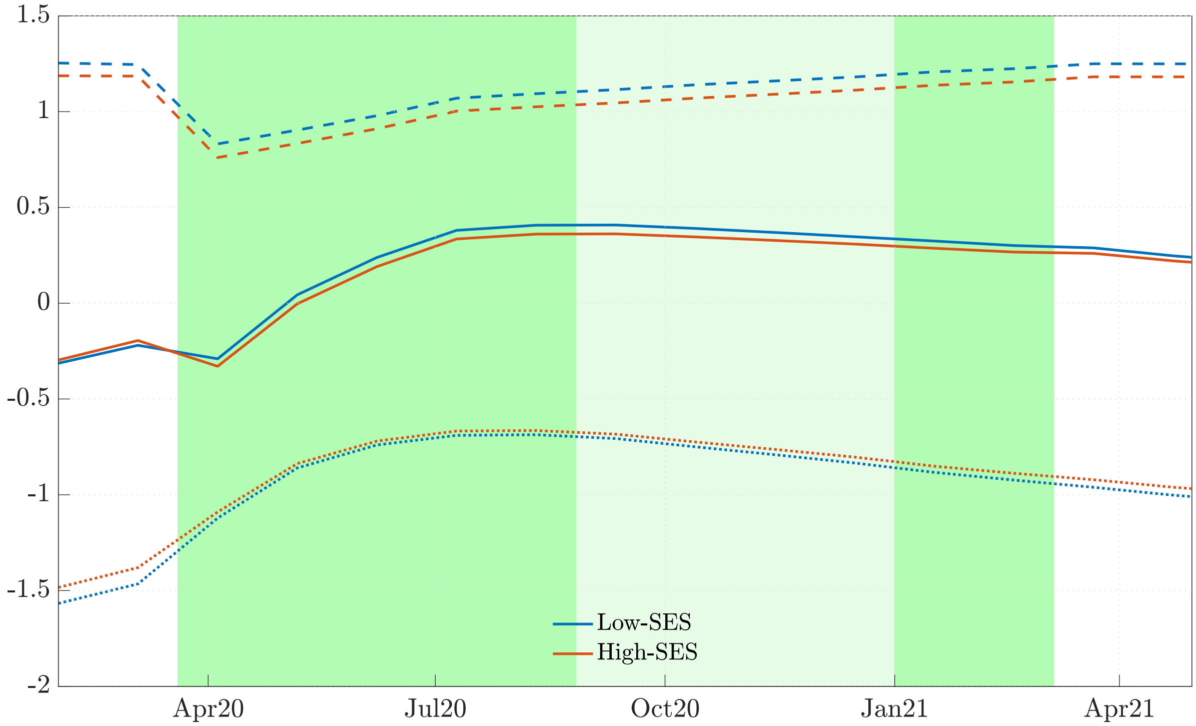
Note: Shaded bars identify the shutdown period. Light shades identify the interim period in which some restrictions were lifted.

Figure 13: Counterfactuals: Epidemiological Dynamics (monthly).



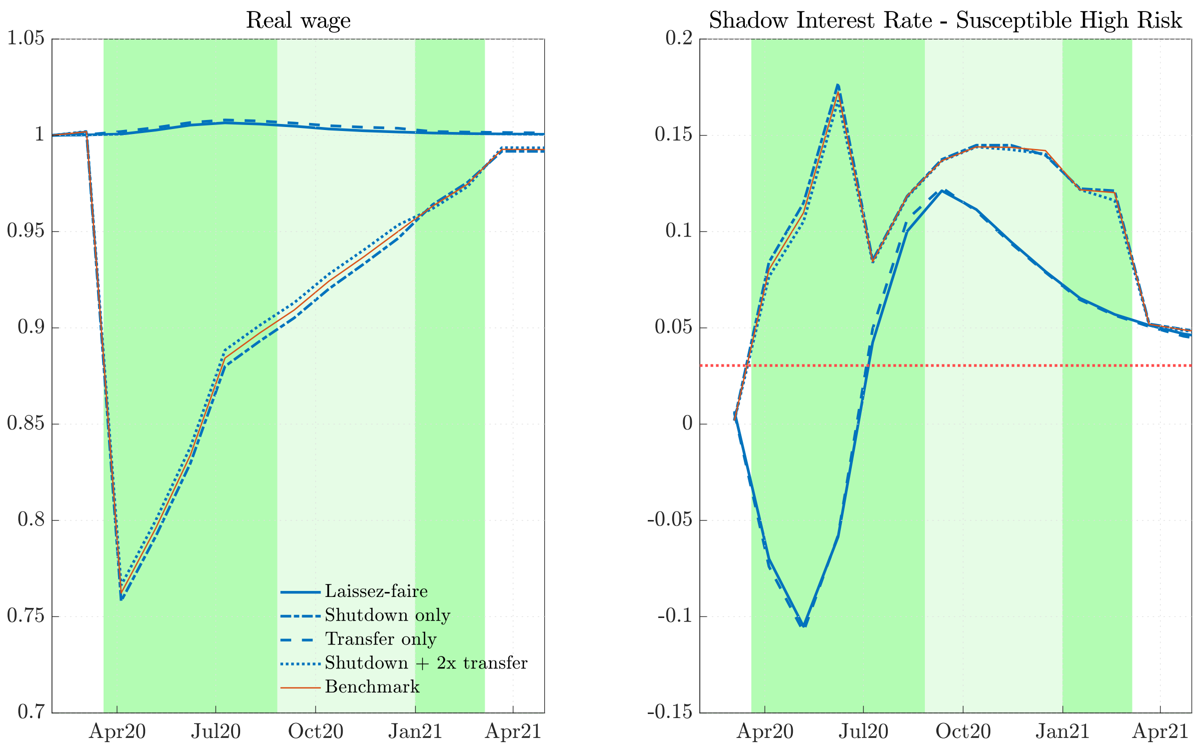
Note: Shaded bars identify the shutdown period. Light shades identify the interim period in which some restrictions were lifted.

Figure 14: Derivative of Probability of Infection (monthly).



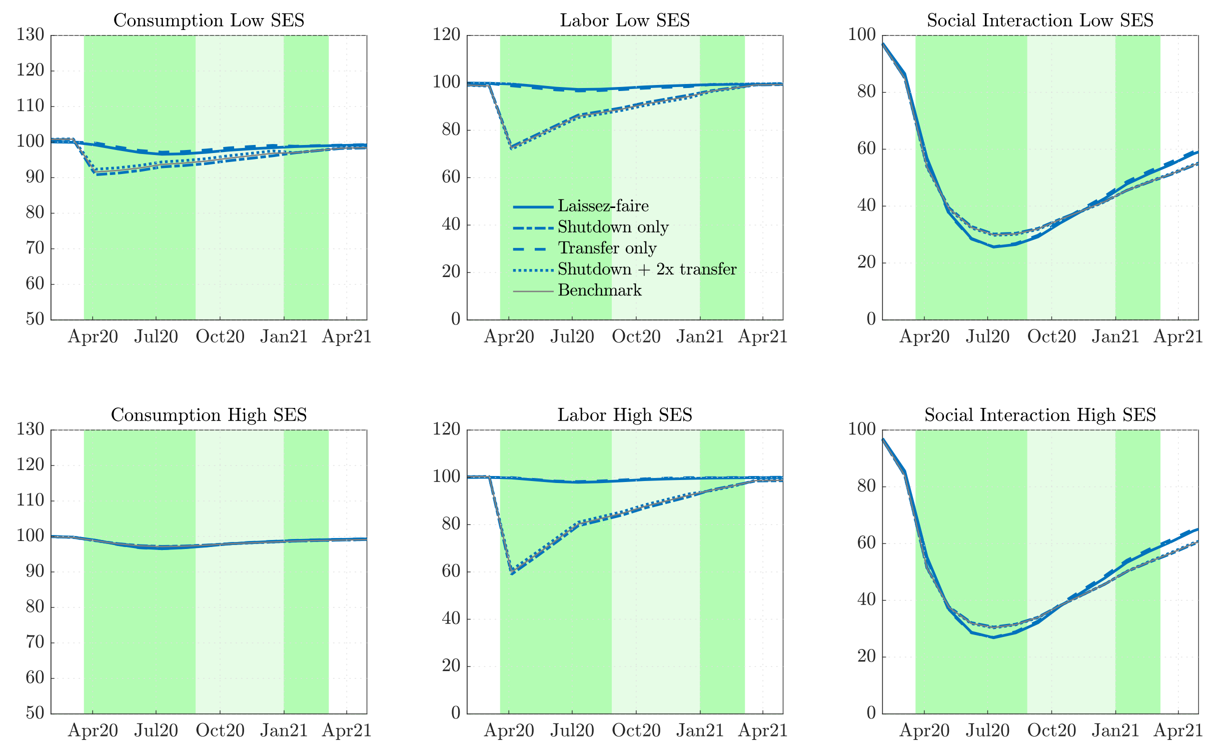
Note: Shaded bars identify the shutdown period. Light shades identify the interim period in which some restrictions were lifted. The figure depicts the numerical values of the partial derivative of the probability of infection displayed in equation (3) with respect to the choice of labor by a susceptible individual—$\frac{\partial \pi^I_{j,t}}{\partial N^S_{j,t}} = \frac{\partial \tilde{\beta}^{j,H}(\Gamma^S_{j,t},\Gamma^I_{i,t})}{\partial N^S_{j,t}} I_{H,t} + \frac{\partial \tilde{\beta}^{L,i}(\Gamma^S_{j,t},\Gamma^I_{i,t})}{\partial N^S_{j,t}} I_{L,t}$. The dashed lines take into account the direct effect of varying the labor supply, which affects the probability of infection at workplaces. The dotted lines consider the side effect of varying the labor supply, which is changing the amount of time allocated to leisure and affecting the probability of infection at consumption venues and through social interaction. These two effects have opposite signs. The solid lines capture the total effect and are simply the sum of the previous two.

Figure 15: Counterfactuals: Factor Prices (monthly).



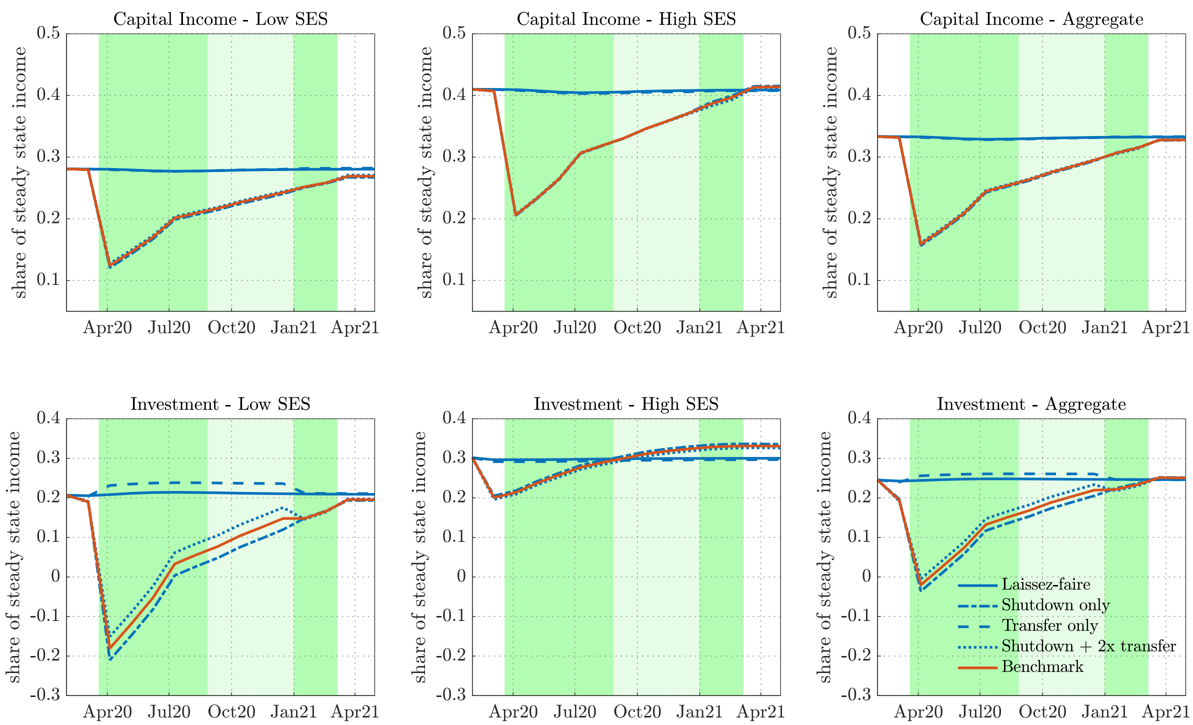
Note: Shaded bars identify the shutdown period. Light shades identify the interim period in which some restrictions were lifted.

Figure 16: Counterfactuals: Microeconomic Behavior of Susceptible (monthly).



Note: Shaded bars identify the shutdown period. Light shades identify the interim period in which some restrictions were lifted.

Figure 17: Counterfactuals: Capital income and investment (monthly).



Note: Shaded bars identify the shutdown period. Light shades identify the interim period in which some restrictions were lifted.

5.3 Welfare implications

We measure the welfare cost of the epidemic 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 an economy without the disease. It is computed by comparing the value function of a susceptible individual of either type at period $t = 1$ to her value function in a disease-free steady state, and asking how much more consumption would leave her indifferent between the two worlds. These 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 have a weight of 11% and those in the more disadvantaged group a weight of 89%.

Table 5: Welfare Cost: Permanent Consumption Equivalent

	Aggregate	Low-SES	High-SES	Ratio
Laissez-faire	0.43	0.43	0.38	1.14
Transfer only	0.36	0.34	0.55	0.62
Shutdown only	0.90	0.89	0.92	0.98
Shutdown and transfer (Benchmark)	0.82	0.79	1.08	0.73
Shutdown and 2x transfer	0.74	0.68	1.24	0.55

Note: The welfare cost is the fraction of pre-epidemic steady state consumption that would make an agent indifferent between the disease free economy and the equilibrium value function of a susceptible agent at the beginning of the outbreak. Aggregate welfare is the weighted average of the welfare cost to each agent. Shutdown of 25% of output in March 2020, 12% in September 2020, 4% in January 2021 and 2% by the end of February 2021. The transfer is 4.6% of steady state labor income for 10 months.

The welfare cost of the epidemic outbreak under laissez faire is of 0.43% of steady state consumption for the low SES individuals and of 0.38% for the high SES ones. The distributional impact of the epidemic under laissez-faire is not surprising. People in the high-SES 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 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 2.1 for the low SES agents and by 2.4 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 and giving them to the 89%

in the low-SES. Welfare is increasing in transfers for the recipients, at the cost of reducing welfare for the high SES agents that pay for them.

One could alternatively measure the welfare cost of the pandemic 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 numbers of deaths per 100K forty 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 reduce the number of deaths from 115 per 100K to 101 at week 40.

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 100K 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 (5 years). For each type of consumer, the statistic reported is calculated relative to corresponding type, not the whole population.

6 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. This is because while people in the high socioeconomic stratum are just as likely to infect people in both groups, people in the lower stratum transmit the virus to somebody in their own group 95% more than 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.

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Covid-19 in Unequal Societies

SUPPLEMENTARY MATERIAL FOR ONLINE PUBLICATION

A Data

A.1 Disaggregated descriptive statistics on socioeconomic groups

Table 7: SES descriptive statistics

	SES 1 & 2	SES 3	SES 4	SES 5 & 6
Years of Education	9.841	12.32	16	16.38
Income (USD)	285.2	444.6	1084	2204
People per room	1.785	1.541	1.336	1.385
% of population	0.5	0.4	0.07	0.04
% of population over 18	0.51	0.36	0.09	0.04
% of informality	0.47	0.42	0.27	0.28
work hours per week	45.35	43.41	40.26	41.24
hour income (USD)	1.57	2.56	6.73	13.4

Source: GEIH (DANE).

A.2 Epidemiological disparities: comparative studies

Table 8: Comparative studies of epidemiological disparities

	Weeks after First case	Prevalence (%)	Prevalence/ Odds Ratio	Group: Sub-group	Group: Criteria	Sample Size
Brazil[(a)]	14	3.1	2.05^p	Poorest	Wealth quintiles	31165
			1.89	2nd		
			Ref.	Richest		
Lima[(b)]	16	20.8	3.41^p	Low	Socioeconomic Status	3212
			3.22	Middle-Low		
			3.13	Middle		
			Ref.	High		
Mumbai[(c)]	21	10[(c1)]	3.36^p	Slum	Slum vs Non-Slum	6904
			Ref.	Non-Slum		
Virginia[(d)]	19	2.4	3.56^o	Hispanic	Ethnicity	4675
			Ref.	Non-Hispanic White		
USA Dialysis patients[(e)]	19	8.3[(e1)]	2.3^o	Hispanic	Ethnicity[(e2)]	28503
			3.9	Black		
			Ref.	Non-Hispanic White		
Orange County[(f)]	25	11.5	1.47^p	Hispanic	Ethnicity	2979
			Ref.	Other Non-Hispanic		
			1.42^p	<\$50.000	Household income p/ year	
			Ref.	$\geq$ \$100.000		
India[(g)]	29	6.6	1.87^p	Urban Slum	Area of Residence	29082
			0.57	Rural		
			Ref.	Urban Non-Slum		

Source: (a) Hallal et al. (2020), (b) Reyes-Vega et al. (2021), (c) Malani et al. (2020), (d) Rogawski McQuade et al. (2021), (e) Anand et al. (2020), (f) Bruckner et al. (2020), (g) Murhekar et al. (2021).

Notes: (c1) The value is estimated using a simulation based on the study data and the cases reported by the government. (e1) The seroprevalence is estimated over the USA Dialysis Population. (e2) The multi-nominal regressions were run in base of neighborhood aggregate values. $Value^p$ means the ratio of the seroprevalence estimations between groups and $Value^q$ is the odds ratio.

Rogawski McQuade et al. (2021) report findings from a statewide cross-sectional surveillance study for 4675 adult outpatients presenting for health care not associated with covid-19 in Virginia between June 1 and August 14, 2020. Higher seroprevalence was associated with Hispanic ethnicity (adjusted odds ratio 3.56; 95% CI, 1.76-7.21) and residence in a multifamily unit (adjusted odds ratio, 2.55; 95% CI, 1.25-5.22). Anand et al. (2020) conducted a seroprevalence study in July, 2020, on a sample of 31,509 individuals receiving dialysis who undergo routine monthly laboratory testing. Hispanic and Black had a seroprevalence of 14.5% against the Non-hispanic white which had 4.3%, a prevalence ratio of 3.3. Residents of non-Hispanic Black and Hispanic neighbourhoods experienced higher odds of seropositivity (odds ratio 3·9 [95% CI 3.4–4.6] and 2·3 [1·9–2·6], respectively) compared with residents of predominantly non-Hispanic white neighbourhoods. Residents of neighbourhoods in the highest population density quintile experienced increased odds of seropositivity (10·3 [8·7–12·2]) compared with residents of the lowest density quintile. Between August 18 and September 20, 2020, Murhekar et al. (2021) enrolled and collected serum samples from 29,082 individuals from 15,613 households in nationwide household serosurvey in India. They found a sero-prevalence ratio between slum areas and non-slum urban areas of 1.9. From the 14th to the 21st of May 2021 and from the 4th to the 7th of June of the same year, in Hallal et al. (2020) conducted two nation wide sero-prevalence surveys in 133 cities distributed all over

Brazil. They estimated a prevalence during the second survey of 3.7 [3.1-4.3] for the poorest quantile in the population and of 1.8 [1.4-2.2] for the richest one, giving a prevalence ratio of 2.05. They did the same for the 2nd, 3rd and the 4th quartiles, estimating a prevalence of the covid-19 virus of 3.4 [2.9-4.0], 2.5 [2.0-3.0] and 2.5 [2.0-3.0] respectively. The investigators collected samples from more than 32,000 people. In Reyes-Vega et al. (2021) they enrolled 3,212 participants which were all residents of Lima between June 28th and July 9th. They collected information about the socioeconomic stratus of the individuals which allowed them to estimate the prevalence in each group. The results of the paper were estimated using a multivariate regression model and they found that the adjusted prevalence ratio of the Middle-High socioeconomic status individuals versus the high ones was of 2.24; against middle individuals, it was 3.13; Middle-Low of 3.22 and, finally, with the lowest people, that prevalence was 3.41 times higher in the latter. During June 29th and July 19th of 2020, Malani et al. (2020) interviewed and sampled 6,904 people older than 12 years. Their estimation of the prevalence of covid-19 in Mumbai slums was of 58.3% versus 17.1% in Non-slums areas, giving a prevalence ratio of 3.41. Finally, in Bruckner et al. (2020), they collected samples from 2,979 individuals that visited on of the 11 drive-through test sites from July 10th to August 16th of 2020 in Orange County, California. The researcher's discovered that house holds with annual income lower than \$50.000 had a prevalence ratio of 1.42 against those that earned more than $\$100,000$; the ratio with those that earned between $\$50,000$ and $\$100,000$ was of 1.44. They also estimated this ratio for Hispanic versus Non-Hispanic white people, obtaining a prevalence 1.47 times higher in the first group.

Table 9: Hospital Fatality Rates

SES	1	2	3	4	5	6
Deaths	72.27	43.55	25.69	16.44	11.33	8.02
Hospitalization	269.8	174.06	93.44	46	31.16	32.6
Hospital fatality rate (%)	27	25	27	36	36	25
HFR by broad SES (%)		26			33	

Notes: Deaths and hospitalizations are from Figure 2 in Eslava et al. (2020). Hospital fatality rates by broad SES are weighted Aggregate hospital fatality rates by broad SES are averages weighted by hospitalization cases

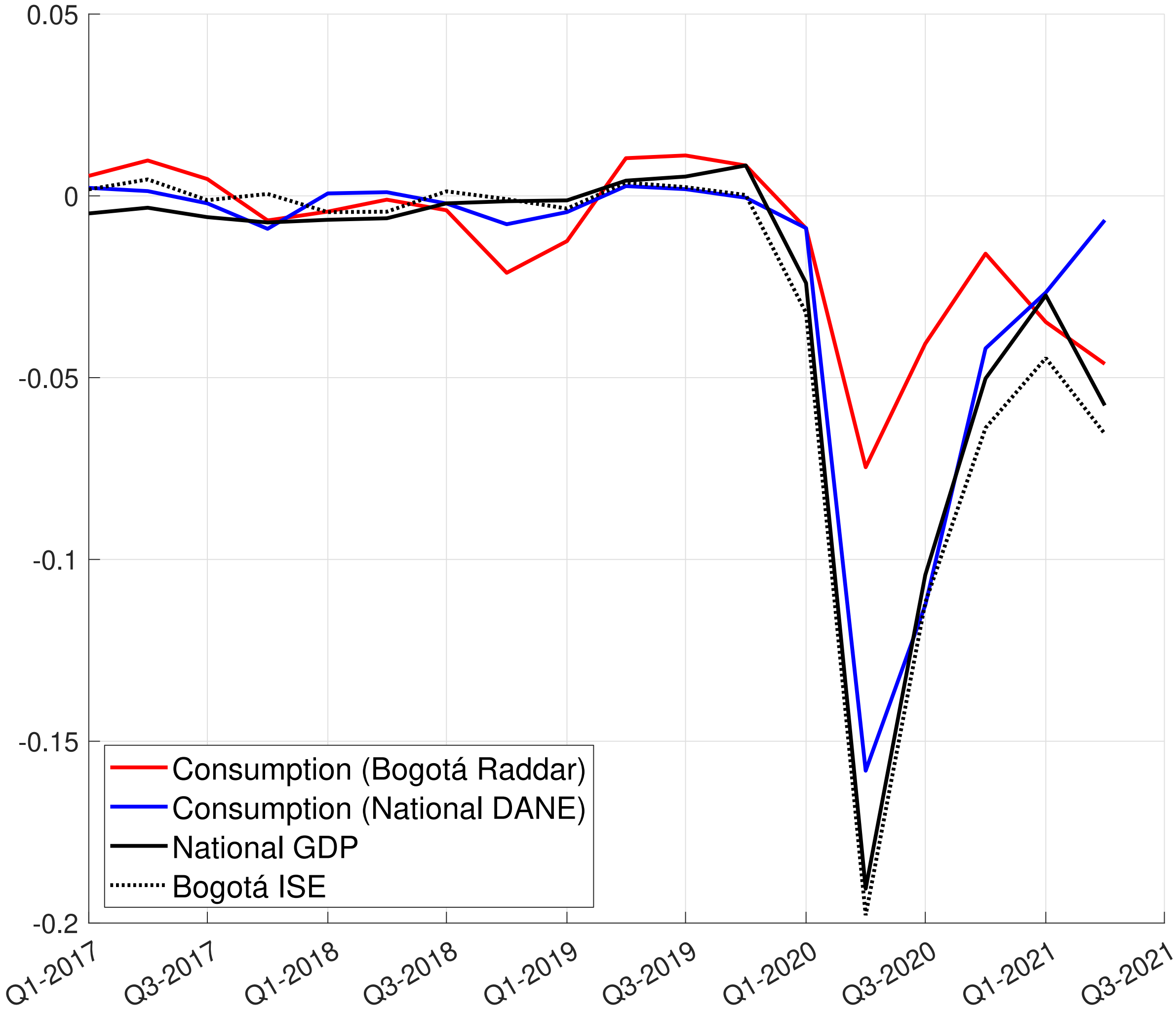
Table 10: Adult Demographic Structure by SES

	Population		CoVida Sample		CoVida positive	
Age	Low-SES	High-SES	Low-SES	High-SES	Low-SES	High-SES
18-39	0.51	0.42	0.60	0.60	0.59	0.57
40-59	0.35	0.38	0.29	0.23	0.27	0.25
60+	0.14	0.20	0.12	0.17	0.14	0.18
% population	0.87	0.13	0.67	0.33		

Note: Percentage of the different age group int the low- and high-SES groups total population. CoVida Sample excludes symptomatic and close contacts of infected persons.

A.3 Economic impact of covid-19.

Figure 18: Quarterly Economic Activity and Consumption



Notes: National consumption and GDP corresponds to real seasonally adjusted expenditures in the NIPAs published by DANE and are reported as deviations from the 2017-19 linear trend. Bogotá ISE consumption for Bogotá are the the quarterly average of monthly data reported in figure 3a

B Value of life

All household have identical preferences

$$\sum_{s=t}^{\infty}\left(\frac{1}{1+\rho}\right)^{s-t} E\left[u\left(c_s\left(\sigma_s\right),\bar{n}-n_s\left(\sigma_s\right),a_s\left(\sigma_s\right)\right)\right], \tag{1}$$

where the expectations are over the health state, c_s is consumption, n_s is hours worked, $\bar{n}$ is available time, a_s is other social activities, and ρ is a subjective discount rate.

We parametrize the utility function as

$$u_j(c,n,a) = \log(c) + \nu_j \frac{(\bar{n}-n)^{1-1/\zeta}}{1-1/\zeta} + \kappa\left[\log(a) - a + 1\right] + \bar{u}$$

for $j \in \{L, H\}$. The term $\bar{u}$ 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 $f(a)$ that has a global maximum when $a^{\star} = 1$, at which point $f(a^{\star}) = 0$.

Our objective is to find a value for $\bar{u}$ for the preferences

$$V = \sum_{t=0}^{\infty}\left(\frac{1}{1+\rho}\right)^{t} U\left(c_t, \bar{n}-n_t\right) \text{ with } U\left(c, \bar{n}-n\right) = \bar{u} + u(c) + v(\bar{n}-n),$$

where we drop the social interaction term because it has a value of zero in the pre-pandemic steady state.

Hall et al. (2020) report that the US Environmental Protection Agency recommends 7.4 million in 2006 dollars for the value of remaining life between the ages of 25 and 55. Making the same assumptions about life expectancy at 40 of 40 years, the value of life per week is about \$ 3,600 per week (7.4 mill. $/(52 \times 40)$). With weekly consumption of \$ 600 per week (\$ 31,000/52). The weekly value of life is 6 times weekly consumption. Other estimates of a year of life reported in Hall et al. (2020) range between \$ 100,000 and \$ 400,000 and would correspond to around 3 and 13 times weekly consumption.

We calibrate $\bar{u}$ assuming the value of death is zero and setting the flow utility of being alive to the statistical value of life valued at the marginal utility of consumption so that

$$U\left(c^i, \bar{n}^i - n^i\right) = 6\ c\ U_c\left(c^i, \bar{n}^i - n^i\right).$$

For the case in which $u(c) = \ln c$, this implies

$$\bar{u} = \frac{6c}{c^i} - u(c^i) - v(\bar{n}^i - n^i)$$

where consumption and leisure are set to their steady state levels. This normalization of the utility function implies that at each period t utility is equal to the value of life plus the deviation of utility from its steady state level—i.e.

$$U\left(c_t^i, \bar{n}^i - n_t^i\right) = \frac{6c}{c^i} + \left\{\left[u(c_t^i) + v(\bar{n}^i - n_t^i)\right] - \left[u(c^i) + v(\bar{n}^i - n^i)\right]\right\}$$

for the benchmark calibration.

C Computational Algorithm

In the case of the Laissez-Faire benchmark, to compute the dynamics of the pandemic we proceed as follows:

1. We compute the disease-free steady state. This is where the economy starts.
2. In the initial period, we introduce an unexpected disease outbreak: a small number of infected individuals, uniformly distributed in the population.
3. We choose an arbitrarily large terminal period $\bar{T}$, in which we assume the pandemic is over and the economy returns to the disease-free steady state (3.5 years is enough).
4. We make a guess for the path of real wages from the initial outbreak until the end of the pandemic.
5. We solve agents' problem and compute the aggregate demand for labor.
6. We use the optimal choices computed in the previous step to calculate aggregate labor supply and obtain the excess demand for labor.
7. If the excess demand for labor is sufficiently small for every period of the transition, we stop, if not, we adjust the wage sequence accordingly and iterate from step 5.

In the case of an output shutdown, we slightly adjust the algorithm because of the possibility that the epidemiological capacity constraint is binding. This means that we must also make a guess for the value of the Lagrange multiplier associated to the capacity constraint for each period in which restrictions are in place. More precisely, we modify the following steps of the algorithm:

4. We make a guess for the path of real wages and the path of Lagrange multipliers, from the initial outbreak until the end of the pandemic (multipliers are zero when restrictions are lifted).
5. We solve agents' problem and compute the aggregate demand for factors of production. We note the if the multiplier is positive, the problem of the firm pins down the demand for labor and capital; while if it is zero, firm's problem only pins down the capital to labor ratio. In the latter case, capital is determined by consumer's optimal choices.
6. We use the optimal choices computed in the previous step to calculate aggregate supply of factors of production and obtain the excess demand of them.
7. If the excess demand is sufficiently small for every period of the transition, we stop, if not, we adjust both sequences accordingly and iterate.

D Insurance markets

As noted in the text, since the individual transition across health states is stochastic, absent any insurance mechanism the model features idiosyncratic risk and heterogeneity across agents with access to financial markets. Since our objective is not to study the idiosyncratic risk implied by the pandemic within the group of high-SES agents, we simplify the model by assuming that there is a risk-neutral insurance company whereby all agents with access to financial markets can insure ex-ante at time $t = 0$ against any idiosyncratic risk induced by possibly changing health status at different dates. We want to emphasize that we impose this assumption as a numerical shortcut to avoid the additional complication of keeping track of the entire distribution of assets across agents with access to financial markets in different health status. In the rest of this appendix we sketch the insurance agreement.

In the pre-epidemic steady state, all agents with access to financial markets are identical and have the same level of capital and bonds. A perfectly competitive and risk-neutral insurance company offers the following contract to all agents with access to financial markets: at the beginning of each period, after the health status of every agent is realized, the assets of all infected agents (capital and bonds) are pooled and redistributed equally across all the infected agents with access to financial markets. Likewise, the assets of all recovered agents are pooled and redistributed equally across recovered agents with access to financial markets. We assume that there is full commitment and agents cannot walk away from the contract. The firm makes zero profits and all agents are willing to participate ex-ante in the agreement since the value functions associated with the individual Bellman equations are concave in capital and debt. With this agreement, all the idiosyncratic heterogeneity induced by the risk of infection disappears and only remains the aggregate uncertainty of being either susceptible, infected, or recovered.