RESEARCH ARTICLE

The Unequal Impact of COVID-19 Across Countries

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ABSTRACT

We evaluate the effects of COVID-19 across countries. Where income is low, fewer jobs can be performed from home, hospital capacity is lower, and enduring long periods with no income is harder. On the other hand, these countries have younger populations, making death less likely. To study the overall effect, we extend the SIR model in 1, with a subsistence level of consumption, work-at-home possibilities, hospital capacity, and a death rate that depends on the age distribution. A 1% lower income increases infections by 326 people per million, and increases the fall of consumption by 0.03%, with no effects on death. Using Google data, we confirm that traffic around workplaces has fallen more in rich countries. Social distancing policies do not affect infections inequality. A better strategy would consist of loans to finance imports. Loans reduce infections and recessions across the board, with greater impact on low-income countries. Optimal loans are much cheaper in low-income countries, ranging from a present value of $84 per capita in Ecuador to almost $5,000 in Ireland.

Keywords: COVID-19; Coronavirus; Social Distancing; Low-income countries; Inequality. JEL Codes: E1, H0, I1

Introduction

As COVID-19 spreads, governments are asking their citizens to socially distance them- selves, at least until we find a better solution. In many cases, where jobs cannot be performed from home, this leads to workers not receiving income for an uncertain amount of time. This is a problem for relatively poor households that cannot endure these income-less periods, making the crisis worse in poor countries. In this paper, we compare the impact of COVID-19 in countries with different levels of income.

We build on 1 (henceforth ERT), who combine the SIR epidemiological model by 2 with a standard macroeconomic model. Individuals can be susceptible to contracting the disease, infected, recovered, or dead. Recovered individuals cannot get re-infected.[11] Rates of contagion depend on the actions of individuals: an increase in labor participation or in consumption increases the spread of the disease. In equilibrium, susceptible individuals endogenously substitute consumption for leisure to minimize the risk of contagion.

The problem is that in low-income countries, consumption is not easily substituted for leisure. To model this, we modify ERT by introducing a subsistence level of consumption. Being close to the subsistence level increases the marginal utility of consumption. As a result, hours worked react less to the risk of infection or to social distancing policies.

An additional problem in low-income countries is that there are fewer jobs that can be performed at home. 3 find a positive relationship between GDP per capita and the share of jobs that can be performed from home. To address this, we assume that a fraction of individuals can work in each country without increasing their risk of contagion. A third problem, related to the transition from infection to death, is that the number of hospital beds per capita is decreasing in income, as evidenced by 4. Counteracting these effects, the fact that populations are relatively younger in lower income countries reduces the probability of death.

We find that without government intervention, there is less self isolation in countries with lower income per capita, increasing the peak of infections more where income is low. Quantitatively, a 1% increase in income per capita reduces the peak of infections by 326 people per million. This does not translate into a lower death rate. While the point estimate suggests that a 1% increase in income lowers the death rate by 2 people per million, this is not statistically significant. Macroeconomic effects are milder in poor countries: a 1% increase in income increases the drop in consumption relative to steady state by 0.03%.

We next introduce social distancing as in ERT. This involves a tax on consumption that is rebated back to consumers. It makes consumption expensive relative to leisure, so consumers work and consume less, which effectively amounts to social distancing. This tax is determined by maximizing the present value of the utility of individuals. While the levels of infections and deaths drop following this policy, their effect is larger in richer economies, having almost no impact on inequality. The inequality in recessions increases to almost 0.05% larger recession per percentage point increase in GDP per capita. This stems from taxes being higher in high income economies.

Almost half of the inequality in infections is due to the possibilities to work from home. Ignoring the level of subsistence consumption would lead to the false conclusion that inequal- ity in infections is 10% lower than what it actually is. The fact that there is no inequality in deaths is a combination of more people infected in low-income countries, and them being younger, and therefore more likely

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[1] We work with that assumption, even if this is not the case. The reason is that re-infections tend to be less harmful than initial infections.

to survive. In fact, using the age distribution of the U.S. in all countries greatly increases the inequality in deaths rates. In this case, an increase in GDP per capita of 1% increases the death rate by over 15 people per million, significant at the 1% level.

To verify whether the model implications have any empirical validity, we turn to Google mobility data, which tracks GPS cellphone usage at various locations including the work- place. Mobility around the workplace dropped significantly more in high income countries, especially when compared to the drop in other locations, such as grocery stores and transit

stations. Relative to the drop in the other locations included in the Google database, an increase in income of 1% reduces traffic around workplaces by 7%. These results are in line with 5, who finds that lockdown policies were highly effective in rich neighborhoods in Santiago, Chile, but had no significant effects on lower income neighborhoods.

This begs the question: is there a better policy to implement in developing countries? The first policy to encourage would be to allow workers to work from home, but this would be too hard to enforce and would probably involve deep re-structurings that take time. Alternatively, a loan, paired with imports, addresses the problem of subsistence consumption. In practice, a country like China could lend money to Mexico, which Mexico would in turn use to finance imports from China. This would help both Mexico and China. It would provide a boost to income in Mexico, so individuals would reduce hours worked without sacrificing consumption. It would help China by boosting demand, which is particularly relevant in a world where China seems to be recovering faster than other countries. The potential gains by the lender are beyond the scope of this paper.

Loans are more powerful in improving both epidemiological and macroeconomic outcomes than the optimal social distancing policy. Loans reduce the peak of infections, deaths, and recession for all countries. Loans also reduce the unequal effects of COVID-19: the reduction in infections are decreasing in income, and the reduction in the peak of the recession are increasing in income. Finally, the cost of these loans is much smaller in low-income countries. The present value of the optimal loan would be of $84 per person in Ecuador, versus $4,959 in Ireland. In the U.S. the present value of this loan is equal to $4,371, considerably larger than the stimulus of roughly $1,000 per person. However, this comparison is not straightforward, since we are abstracting from other policies contained within the CARES act, such as unemployment insurance (see 6, 7 for an analysis of the effects of unemployment insurance). The closest paper to ours is 4, who explore the different effects we should expect among countries of different income. The main difference with them is that we calibrate the economy to many individual countries, while they compare a representative developed country with a representative developing country, with similar conclusions in terms of infections being higher in the developing country, and recessions milder. My conclusions, on the other hand, stem from comparing all countries we have information for. The different exercises also lead to several modeling assumptions. In particular, 4 feature a greater level of heterogeneity across populations, with a share of individuals that consume "hand to mouth". Doing so in this paper would be impractical, since it would add an extra layer of complications that would be very hard to calibrate, since this share is not available for the countries in my sample. Another area where we depart from them (and from 8), is in the way to incorporate the additional risk introduced by older populations. They introduce a new set of older individuals, with their own discount, contagion and death probabilities, while we directly incorporate it in the probability of becoming critically ill. It makes sense for them to introduce them the way they model the economy, with heterogeneous agents that have exogenous income processes. With homogeneous agents and deterministic incomes, introducing a new type of older individuals would not change the results.

This paper is related to a number of recent papers incorporating the SIR model to macroeconomics. 9 introduces the model and discusses a number of applications. 10 and 11 use versions of this model to infer an optimal lockdown and testing policies. While we abstract from lockdown policies, these are very effective, especially when combined with testing, as several papers have recently found (see 12–14 among others). A proper analysis of these containment policies across countries would greatly complement this paper.

15 extend it to incorporate skilled and unskilled workers to explore the containment policy in India. 16 adapt the model to study how different sectors react, finding that sectors with lower rate of contagion in consumption expand at the expense of sectors with higher rates. This substitutability reduces the economic and epidemiologic effects of the pandemic. The fact that we abstract from this possibility implies that my effects are larger than the actual ones. However, the relative effects across countries should be similar. 17 find that the pandemic increases the probability of default in

low-income countries, which matters in
my case given that the alternative policy suggested includes a loan. However, their findings concern existing loans, and, similar to my findings, they show that low-income countries can greatly benefit from fresh loans.

This paper is organized as follows. Section 2 presents the observations that motivate the differences across countries. Section 3 introduces the model and characterizes the equi- librium. Section 4 calibrates it. Section 5 presents the main results. Section 6 provides a measure of empirical validation to my results. Section 7 introduces a loan, and section 8 concludes.

1   Data

This paper models how differences in subsistence consumption, opportunities to work from home, healthcare systems, and the age of a population influence the effects of COVID- 19 across countries. To that end, this section shows how these characteristics vary across countries.

Figure 1 shows the cost of living in different countries, as estimated by The Economist Intelligence Unit (EIU). GDP per capita is from the Groningen Growth and Development Centre (GGDC). Clearly, richer countries have higher living costs. The slope of a fitted line across countries implies that an increase in GDP per capita of 1% increases the cost of living by about a quarter of a percent. Thus, relative to income, the cost of living is larger in poorer countries, putting additional pressure on these when hit by COVID-19. 18 and 19 describe this dataset in detail.

2 estimate the fraction of jobs that can be done from home, finding a positive association with income. Figure 2 shows this.
Figure 3 shows the number of beds per 10,000 people across countries. The World Health Organization (WHO) provides the number of hospital beds, not intensive care units (ICU) beds. We assume that ICU beds are proportional to hospital beds, in the same proportion as in the U.S., where there are ICU beds to cover 0.042 percent of the population, as in 8. The figure shows that richer countries have more hospital beds per person.
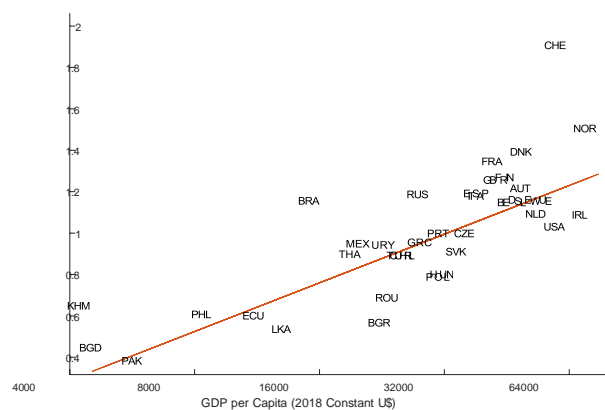
Figure 1: Cost of Living Across countries (EIU).

The last statistic in this section is the fraction of the population older than 64, shown in Figure 4. Data comes from the World Development Indicators (WDI). Richer populations are also relatively older. This relaxes the effects of COVID-19 in poor countries.

These data suggest that there are reasons for which this disease may be worse in low-income countries because of higher living costs relative to income, less jobs that can be done from home, and lower hospital capacity. On the other hand, the fact that these countries are relatively younger implies milder consequences. To explore the importance of each effect, the next section develops a model incorporating all these features.

3   The Model

The model mixes a macroeconomic model with an epidemiological model. We start describing the

former and then introduce the epidemiological aspects. While there are many countries in the analysis, each country is a closed economy. Thus, we do not differentiate across countries and clarify which parameters change across countries in section 4.
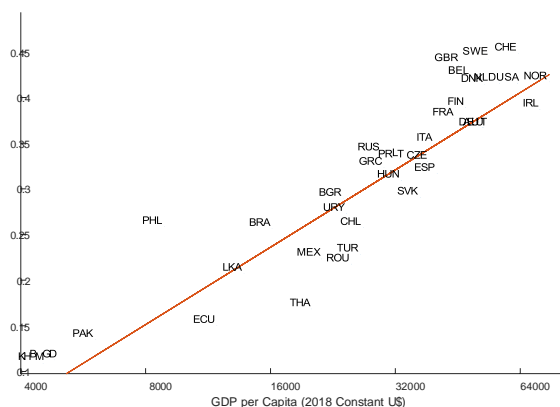
Figure 2: Percentage of jobs that can be done from home (3).

3.1   The Macroeconomic Model

Time runs $t = 0, 1, 2, ..., \infty$. There is a continuum of agents at time 0 with measure 1, with preferences

$$U = \sum_{t=0}^{\infty} \beta^t u(c_t, n_t)$$

where $\beta \in (0, 1)$ is the discount factor, $c_t \geq 0$ is consumption in period t and $0 \leq n_t \leq \bar{n}$ is hours worked. One of the main departures from ERT is in the definition of the within period utility function. This is

$$u(c_t, n_t) = \ln(c_t - \bar{c}) - \frac{\theta}{2} n_t^2$$

In ERT, $\bar{c} = 0$. This represents a minimum level of consumption needed for subsistence. It is a way to model low-income countries needing to maintain a relatively high level of con- sumption. High income countries behave as if $\bar{c} = 0$. Low-income countries have equilibrium levels of c_t relatively close to $\bar{c}$, which implies a high marginal utility of consumption and less ability to substitute consumption for leisure.
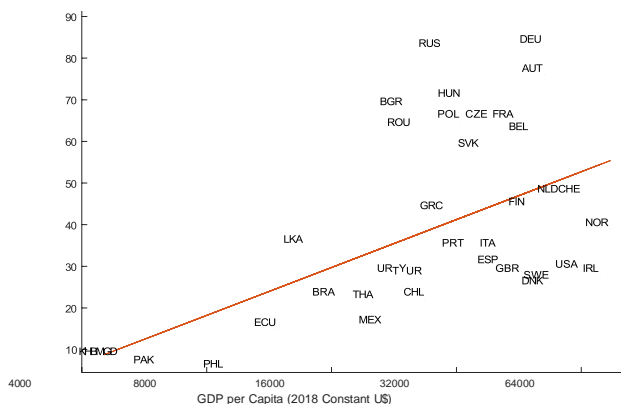
Figure 3: Hospital beds per 10,000 people (WHO).

Individuals cannot borrow or save. This greatly simplifies the analysis, and it is unlikely that relaxing this assumption would bring additional realism. In any case, the ability to save is lower in low-income countries, so adding savings would likely amplify the differences across countries.

There is a representative firm with technology $C_t = AN_t$, where $C_t \geq 0$ is output in period t, $A \geq 0$ is productivity, and $N_t \geq 0$ is labor demand. This stand-in firm operates under perfect competition. While this seems a reasonable assumption, 20 show that, when investment is added to the model, an industrial organization with monopolists works better in accounting for the behavior of investment. Since this work abstracts from investment, we maintain the assumption of perfect competition. Lastly, feasibility implies $c_t = C_t$ and $n_t = N_t$.

3.2   The Epidemiological Model

The epidemiological side is based on 2. The population is divided into four groups: susceptible (not yet exposed to the disease), infected (contracted the disease), recovered (survived the disease and acquired immunity), and deceased (died from the disease). The fractions of people in these four groups are denoted by S_t, I_t, R_t and D_t, respectively. The labor productivity is 1 for S and R individuals, $\phi < 1$ for I individuals, and 0 for D individuals. The productivity of I individuals is lower than 1 to reflect the fact that a fraction of individuals are symptomatic and cannot work, making their productivity 0 and reducing the aggregate productivity of the group.
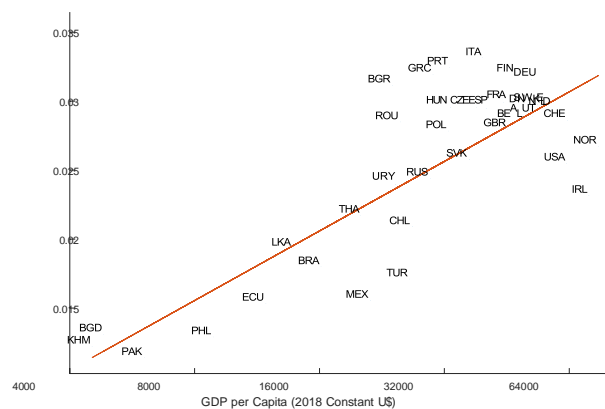

Figure 4: Fraction of the population over 65 (WDI).

Every period, I individuals can become critically ill with probability η, in which case they can die, recover, go back to being infected but not critical, or remain critical. Technically, becoming critically ill is an i.i.d. shock to the pool of infected individuals. It proxies for how exposed a population is. Given that COVID-19 is more likely to kill relatively older people, countries with older populations have higher η. Critically ill do not work or consume,[2] and their utility is normalized to u_c.[3]

Susceptible individuals can become infected in three ways. First, they can meet people while purchasing consumption goods and services with probability $\dfrac{\pi_{sc} C_{st}}{C_{rss} \left(\frac{(1-\eta)C_{it}}{c_{rss}} \right)}$.

This depends on a constant π_{sc}, the measure of infected, non-critical individuals $(1 - \eta)I_t$, how much they consume C_{it} relative to the steady state C_{rss}, and how much susceptible individuals consume C_{st} relative to the steady state. We depart from ERT in assuming that consumption *relative to steady state* matters in determining this probability, while they assume that

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[2] This is not the group that lowers the productivity of I individuals. Some individuals can be symptomatic but not critical, as in ERT, and this is the group that lowers the productivity of I individuals.

[3] Hospitals take care of critically ill individuals' needs, which is outside of the scope of this paper.

only consumption matters. None of their results would be affected by this as- sumption: only the value of π_{sc} would change. When dealing with several countries with different levels of consumption, consumption relative to steady state should be used. In- tuitively, in low-income countries, individuals might have smaller cars or may go to the supermarket on foot, which results in them making fewer purchases per trip, so by normal- izing consumption to the steady state level, we are capturing the number of trips to the supermarket more precisely, and therefore the number of interactions while shopping.

A second way to contract the disease is by working. The more the hours worked, the more likely a susceptible individual contracts the disease. However, some jobs can be easily performed at home, so not all increases in hours worked increase the probability of contagion. Let $0 \leq \chi \leq 1$ denote the fraction of jobs that can be performed from home. Then the probability of contracting the disease at work is $\pi_{sn}N_{st}((1-\eta)I_t N_{it})(1-\chi)$, where N_{st} is hours worked by a susceptible individual and N_{it} by an infected one. ERT do not incorporate χ into the analysis.

A third way in which individuals can contract the disease is randomly. This probability is $\pi_{sr}(1-\eta)I_t$. The total mass of new infections in period t is

$$T_t = S_t I_t (1-\eta)\left[\pi_{sc}\left(\frac{C_{st}}{C_{rss}}\right)\left(\frac{C_{it}}{C_{rss}}\right) + \pi_{sn}N_{st}N_{it}(1-\chi) + \pi_{sr}\right]$$

The law of motion for susceptible individuals is $S_{t+1} = S_t - T_t$. Infected individuals can recover with probability π_r. The probability of death depends on the number of ICU beds available. If this exceeds the number of critically ill, a patient dies with probability π_d. If the number of beds available is lower than the number of critically infected, the beds are randomly allocated among the critically ill, as in 4. Not having assigned a bed increases the death probability to $\tau\pi_d$, where $\tau > 1$. Denote the probability of death by $\tilde{\pi}_d(I)$ and the number of beds by B, then

$$\tilde{\pi}_d = \begin{cases} \pi_d \text{ if } \eta I < B \\ \dfrac{\pi_{dB} + \tau\pi_d(\eta I - B)}{I} \text{ otherwise} \end{cases}$$

This implies that the law of motion for infected people is $I_{t+1} = I_t + T_t - (\pi_r + \tilde{\pi}_d(I_t))I_t$, the law of motion for recoveries is $R_{t+1} = R_t + \pi_r I_t$, and the law of motion for deaths is $D_{t+1} = D_t + \pi_d \min\{\eta I_t, B\} + \max\{\tau\pi_d(\eta I_t - B), 0\}$. Population evolves as $L_{t+1} = L_0 - D_{t+1}$.

3.3 The Social Distancing Policy

We follow ERT in introducing a consumption tax μ_t to proxy for social distancing, re- bating the proceeds back to consumers. This makes consumption relatively more expensive, so individuals substitute away from consumption and into leisure. The budget constraint of individuals is

$$(1 + \mu_t)c_t = w_t \phi_t n_t + \Gamma_t,$$

where $\Gamma_t = \mu_t(S_t C_{st} + I_t(1-\eta)C_{it} + R_t C_{rt})$ (implying a zero fiscal deficit each period) and the price of the consumption good is normalized to 1. The wage rate per efficiency unit is w_t, and ϕ is the number of efficiency units per hour worked.

3.4 Equilibrium

At time 0, there is a measure $I_0 = \varepsilon > 0$ of infected individuals. This implies $S_0 = 1 - \varepsilon$, $R_0 = 0$ and $D_0 = 0$. The laws of motion depend on the behavior of each type of individual.
Susceptibles. The maximization problem of susceptible individuals is

$$U_{st} = max_{n,c,p} u(c,n) + \beta[(1-p)U_{s,t+1} + pU_{i,t+1}]$$

$$s.t.\, p = (1-\eta)I_t\left[\pi_{sc}\frac{c}{C_{rss}}\frac{C_{it}}{C_{rss}} + \pi_{sn}n\,N_{it}(1-\chi) + \pi_{sr}\right]$$

$$(1+\mu_t) = w_t n + \Gamma_t$$

Note that susceptible people determine their probability of contagion p_t. Working more, or consuming more, increases this probability. They take this into account when optimizing.

Infected. Infected individuals can be critical or non-critical. If critical, their consump- tion is exogenous, and uses up resources normalized to 0. Since the probability of being critical is η, their maximization problem is $U_{i,t} = \eta U^c_{i,t} + (1-\eta)U^{nc}_{i,t}$, where

$$U^c_{i,t} = u_c + \beta[(1-\pi_r - \mathit{ff}_d(I_{t+1}))U_{i,t+1} + \pi_r U_{r,t+1}], \text{ and}$$

$$U^{nc} = \max u(c,n) + \beta[(1-\pi_r - \mathit{ff}_d(I_{t+1}))U_{i,t+1} + \pi_r U_{r,t+1}]\, s.t.\, (1+\mu_t)c = w_t\phi n + \Gamma_{t.i,tc,n}$$

and u_c is the value of the utility of a hospitalized individual. Notice here that $U_{d,t+1} = 0$, so that the cost of death is foregone utility of life. Through some algebra, this value function becomes

$$U_{i,t} = \max \eta u_c + (1-\eta)u(c,n) + \beta[(1-\pi_r - \eta\, \mathit{ff}_d(I_{t+1}))U_{i,t+1} + \pi_r U_{r,t+1}]c,n$$

$$s.t.\, (1+\mu_t)c = w_t\phi n + \Gamma_t.$$

This specification makes it clear that the actual rate of death for an infected individual is $\eta\,\mathit{ff}_d(I_{t+1})$. The behavior of this group produces the externality: since they are already infected, they are more likely to go to work and consume, increasing the rate of contagion. The social distancing policy μ corrects for this. The next proposition shows how this works:

Proposition 1 *The effect of the social distancing policy μ is decreasing in the ratio $\bar{c}/A$.*

Proof See Appendix A.

The proposition shows that the ratio $\bar{c}/A$ is key to determine the effect of the social distancing policy μ on hours worked. The higher this ratio, the lower the response. This implies that ignoring subsistence consumption would amplify the effect of the social distancing policy, predicting a success of the policy that is not likely to take place.

Recovered. The maximization problem of recovered individuals is

$$U_{r,t} = \max u(c,n) + \beta U_{r,t+1}\quad s.t.\quad (1+\mu_t)c = w_t n + \Gamma_t.c,n$$

Market clearing. The labor and consumption markets clear. This implies

$$N_t = S_t N_{st} + (1-\eta)I_t N_{it} + R_t N_{rt},\; AN_t = S_t C_{st} + (1-\eta)I_t C_{it} + R_t C_{rt}.$$

3.5 Equilibrium Characterization

Before moving on to the quantitative results, it is worth describing the qualitative prop- erties of the equilibrium. Figure 5 shows how the crisis unfolds.[4] The scenarios portrayed are the decentralized equilibrium and the optimal social distancing policy. The top panels focus on the epidemiological consequences. In this example, without any explicit policy, the rate of infections peak at about 6.67% of the population in week 32, and the total death rate is 0.35%. Adding the optimal policy reduces the peak of infections to 6.34% in week 32 and the death rate to 0.35%. The bottom panel shows the economic effects. At maximum impact absent any government policy, consumption by susceptible individuals falls by 11% relative to its steady state level, and

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[4] The parameter values are those for the U.S., described in section 4.

that of those infected by 16%. This is mainly driven by the reduction in hours worked by susceptible people, in an effort to prevent contagion. Infected people increase their labor supply by 4.5%. This has two main reasons. The first is that these individuals are already infected, so the preventative motive no longer applies. The second is a wealth effect: the reduction in productivity lowers their income, which drives them to work more. Notice that there is also a substitution effect that goes the other way: the reduction in wages makes leisure relatively cheaper. Along similar lines, recovered individuals, who cannot contract the disease at work, do not change their behavior relative to the steady state.

The optimal policy amplifies the recession, with a maximum drop in consumption by susceptibles of 15%, and their hours at work dropping by 16%. The infected drop their consumption by 21% and hours worked by 2.7%, both at their peak contraction. By making consumption more expensive, the hours worked by all individuals drops, even those infected, reducing labor supply and hence output.
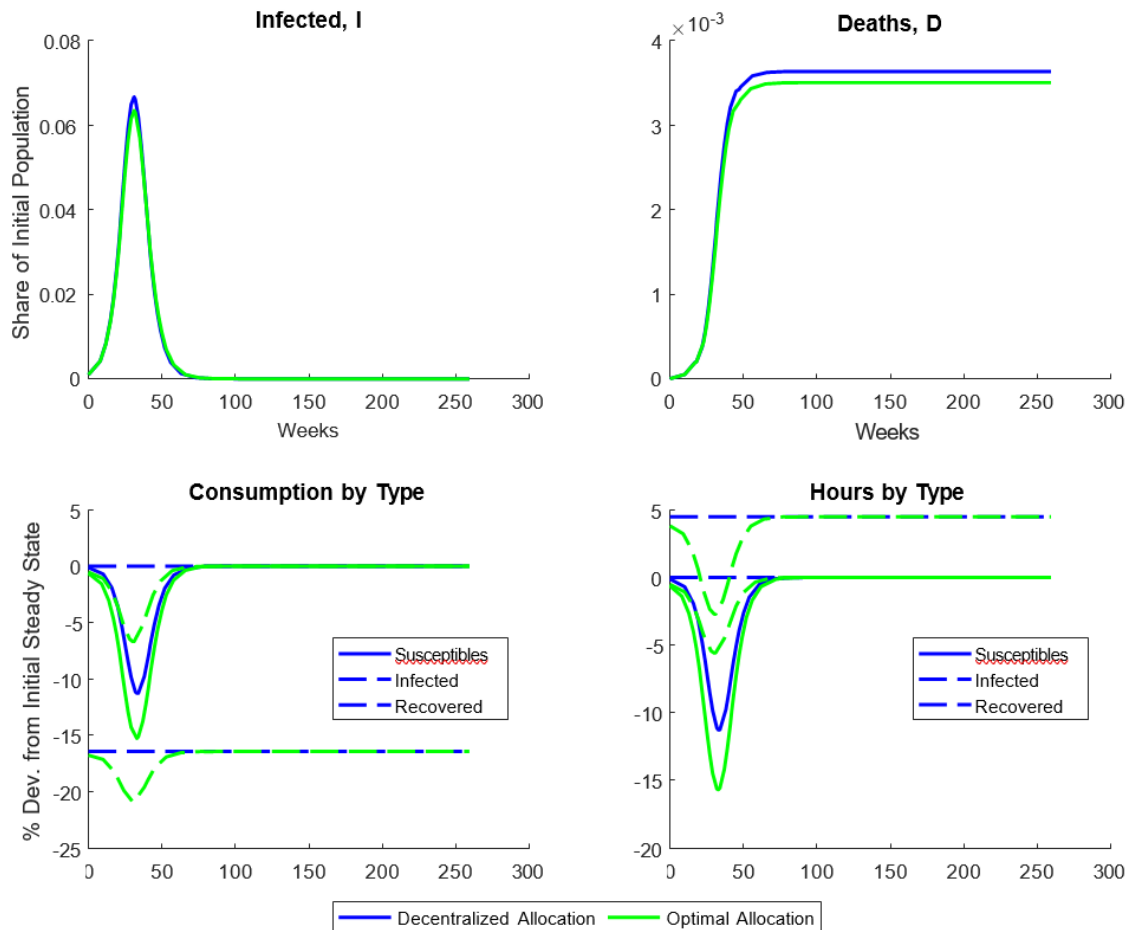
Figure 5: Equilibrium with and without optimal social distancing

Figure 6 shows the optimal policy. It involves very large tax rates at the onset of the disease, of up to 17% by week 30, and then a slow convergence to 0. The strong initial response is similar to what 21 find when solving for an optimal policy of a planner that minimizes the number of deaths subject to costs associated to output loss.
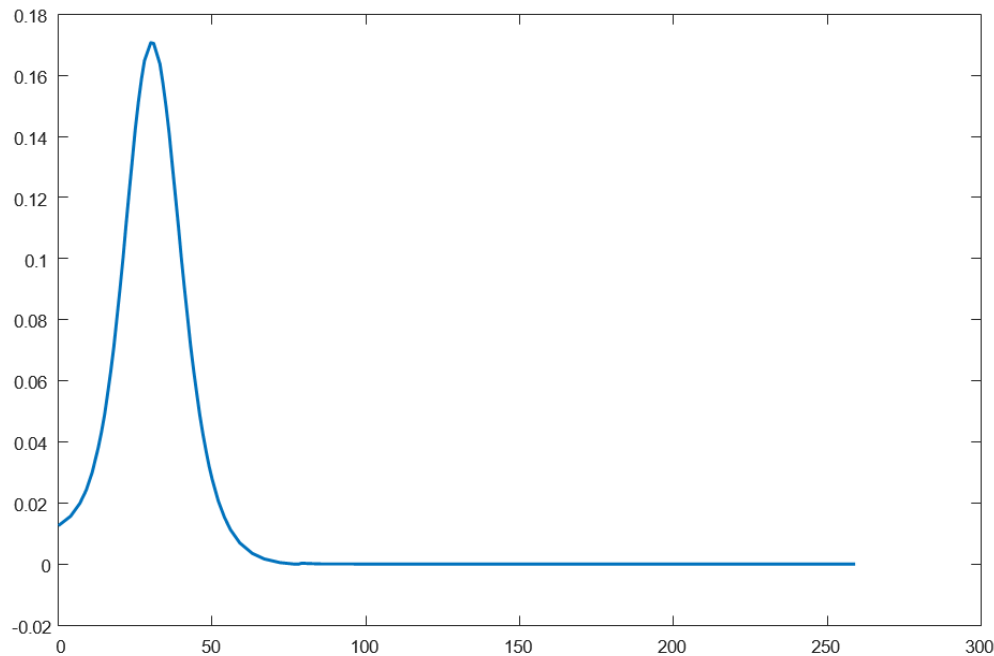
Figure 6: Optimal Policy

4   Calibration

We follow ERT in the calibration, except for the additional parameters we introduce. We start by describing the data sets used. Next, we describe how we calibrate the parameters that are common to all countries, which, with the exception of the share of infected house- holds with critical conditions, replicates the strategy in ERT, and we finally describe the country specific parameters. Appendix Appendix B lists the countries in the sample.

4.1   Parameters Common to all Countries

One period is a week. The mortality rate π_d comes from the South Korean Ministry of Health and Welfare from March 16, 2020. These estimates are reliable because, as of late March, South Korea had the world's highest per capita test rates for COVID-19 (22). Excluding people aged 70 and over, because their labor-force participation rates is very low, the average mortality rate is 0.4 percent. Excluding people aged 75 and over, the mortality rate is 0.7 percent. Based on these estimates, we target a mortality rate equal to 0.5 percent. As in Atkeson (2020), it takes on average 18 days to either recover or die from the infection. Recall that the recovery probability is π_r, and the death rate is $\eta\pi_d$. The calibration for η is described in section 4.2. Given this value, and since the model is weekly, set $\pi_r + \eta\pi_d = 7/18$. A 0.5 percent mortality rate for infected people implies $\eta\pi_d = 7/18 \times 0.005$.[5] The parameters π_{sc}, π_{sn} and π_{sr} come from contagion rates in other respiratory diseases. In the case of influenza, 23 argue that 30 percent of transmissions occur in the household, 33 percent in the general community, and 37 percent in school or the workplace.

Using data from the Bureau of Labor Statistics 2018 Time Use Survey, ERT estimate that 48 percent of time spent on general community activities relates to consumption. Thus, 16 percent (= 0.33 × 0.48) of infections come from consumption. Related to work, ERT estimate that 46 percent of transmissions come from the workplace. Since 37 percent of transmissions occur in schools and workplaces, 17 percent of transmissions are related to work (0.37 × 0.46).

This implies the following equations must hold:

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[5] This holds when the hospital capacity does not bind. We make this assumption because it amplifies the calibration. Incorporating the dates when hospital capacity binds barely change any calibration estimate.

$$\frac{\pi_{sc}}{\pi_{sc} + \pi_{sn}N^2 + \pi_{sr}} = 0.16, \frac{\pi_{sn}N^2}{\pi_{sc} + \pi_{sn}N^2 + \pi_{sr}} = 0.17$$

where N is hours worked in steady state. In addition, 60 percent of the population either recovers or dies from the infection. This follows an article that cites Angela Merkel's estimates.[6] The resulting values are $\pi_{sc} = 8.7 \times 10^{-8}$, $\pi_{sn} = 1 \times 10^{-4}$ and $\pi_{sr} = 0.51$.

The measure of individuals initially infected is $\varepsilon = 0.001$. We set $\beta = 0.96^{1/52}$ so that the value of life is \$9.5 million in 2018 Dollars (see ERT). We set $\phi = 0.8$ as in ERT, to reflect the fact that 80% of COVID-19 carriers are asymptomatic according to the China Center for Disease Control and Prevention. We set τ, the probability of dying if not assigned an ICU bed, to 2, as in 4. We normalize the within period utility of being critically ill to $u_c = 0$.[7]

4.2   Parameters Specific to Each Country

The parameters that are calibrated individually for each country are A, ϑ, $\bar{c}$, χ, η, and B. We set these to match the GDP per capita in each country, the weekly hours worked, the relative cost of living, the fraction of jobs that can be performed from home, the fraction of the population younger than 15 and older than 65 and their death rates, and the number of hospital beds available. GDP per capita and weekly hours worked come from the Total Economy Database produced by the GGDC. We use 2018 data. Relative cost of living is from the EIU. The fraction of jobs that can be performed from home is from 3. The composition of the population by age comes from the WDI. Hospital beds come from the WHO.

We set the subsistence level of consumption in the U.S. equal to 30% of income, following the rule of thumb for how much a household should spend on rent. This is conservative in the sense that rent is not the only subsistence consumption item, so this is a lower bound.

For the remaining countries, we set $\bar{c} = P \times \bar{c}_{US}$, where P is an index of the cost of living in each country, and $\bar{c}_{US}$ is the subsistence consumption level in the U.S. We set η to reflect the higher death probability of old people, and the different rates of old people in different countries. To represent the different age distribution across countries, we use the share of population younger than 15 and older than 65 reported by the WDI. To impute the different death rates of older populations, we rely on 24, who compute the death rate by age group of critically ill patients, along with the rate of symptomatic patients that need hospitalization. Specifically, the WDI reports the share of people older than 65, and younger than 15. Ferguson reports the share of symptomatic patients that get hospitalized, the share of those that are critical, and the share that die, in the U.S., in age groups of 10 years, that is, from 0 to 9, 10 to 19,..., 70 to 79, and more than 80. To determine the value of η, we first compute the simple average death rate for individuals between 0 and 14, 15 to 64. The death rate for those under 15 is the average of the death rate of those between 0-9, and 10-19. The rate for those between 15 and 64 is the average death rate of those between 10-19, 20-29,..., 60-69. The rate for those older than 64 averages the rates for the groups 50-69, 70-79, and 80 and older. The resulting rates are 0.01%, 1.06%, and 11.47%, respectively. Next, we use the fraction of the population in each group as weights to compute a weighted average of these death rates.

To compute the number of ICU beds in each country, we rely on data by the WHO. The problem with these data is that they do not distinguish between a normal hospital bed and an ICU bed. To work around this, we follow 4 and assume that the number of ICU beds is proportional to the number of beds. We set the number of ICU beds in the U.S. as in 8 to 0.042 percent of the population, and the number of ICU beds in each country as $B_i = 0.00042 \times \tilde{B}_i / \tilde{B}_{US}$ for each country i, where $\tilde{B}_i$ is the number of total hospital beds in country i.

Table 1 shows the parameters that are common to all countries, and Table 2 shows the parameters for each country.

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[6] "Merkel Gives Germans a Hard Truth About the Corona Virus," New York Times, March 11, 2020.
[7] Changing this so that critically ill have the same utility level as non-critically ill infected individuals as very minimal effects on the optimal policy or the optimal loans in section 7.

Parameter	Value
π_r	0.3869
π_d	0.0763
π_{sc}	9e-08
π_{si}	0.0001
π_{sr}	0.5225
β	0.9992
ϕ	0.8000
τ	2.0000
ϵ	0.0010
u_c	0.0000

Table 1: Parameter values common to all countries.

5   Results

This section presents the main results. The decentralized equilibrium has $\mu_t = 0$, and the optimal social distancing policy computes the sequence of μ_t that maximizes the sum of the welfare of all individuals, that is,

$$\max_{\{\mu_t\}} S_0 U_{s0} + I_0 U_{i0} + R_0 U_{r0}$$

Country	A	$\theta \times 1,000$	$\bar{c}$	$\eta \times 100$	$\chi \times 100$
AUT	32.23	1.81	431.39	2.89	36.69
BEL	31.14	1.99	405.9	2.86	42.34
BGR	14.56	1.74	195.24	3.12	28.9
CHE	39.92	2.43	682.79	2.86	44.86
CHL	13.71	1.8	312.62	2.09	25.74
CZE	21.32	1.61	352.51	2.95	32.99
DEU	37.95	2.47	413.58	3.16	36.73
DNK	37.83	2.76	495.44	2.96	41.42
ECU	7.3	10.85	207.04	1.53	15.02
ESP	23.77	2.06	422.59	2.95	31.69
FIN	28.73	1.97	449.23	3.19	38.92
FRA	29.29	2.65	477.87	2.99	37.74
GBR	27.35	1.99	445.47	2.8	43.5
GRC	14.65	1.54	335.97	3.2	32.34
HUN	19.32	1.64	280.15	2.96	30.92
IRL	39.82	1.17	384.33	2.32	38.71
ITA	22.99	2	415.44	3.31	34.99
LKA	7.19	2.37	183.58	1.93	20.74
MEX	9.37	2.88	333.09	1.55	22.32
NLD	39.69	2.03	386.38	2.93	41.55
NOR	53.02	2.13	536.5	2.67	41.72
POL	16.36	1.19	272.7	2.78	33.35
PRT	17.49	1.72	351.73	3.25	33.16
ROU	13.84	1.64	239	2.85	21.76
RUS	14.95	2.65	420.87	2.44	33.92
SVK	21.62	1.7	316.54	2.58	29.04
SWE	33.33	1.72	411.21	2.97	44.2
THA	9.12	2.94	314.08	2.17	16.84
TUR	14.39	2.1	312.9	1.71	22.84
URY	15.93	3.83	328.29	2.4	27.29
USA	35.38	1.21	364.19	2.55	41.57

Table 2: Country-specific calibrated parameter values.

5.1 The Decentralized Equilibrium

To represent the problem of the spread of the virus, we focus on the rate of infections at its peak. This is more meaningful than the total number of infections, because infections are worse when they are concentrated in time. They make the externality problem worse, and they put more pressure on hospital capacity. Figure 7 shows the peak of the infections rate across countries, along with a fitted line using least squares. The slope of the line fitting the data has a coefficient of −0.0326, suggesting that an increase in GDP per capita of 1% reduces the infections peak by 326 infections per million people. This is significant at the 1% level.
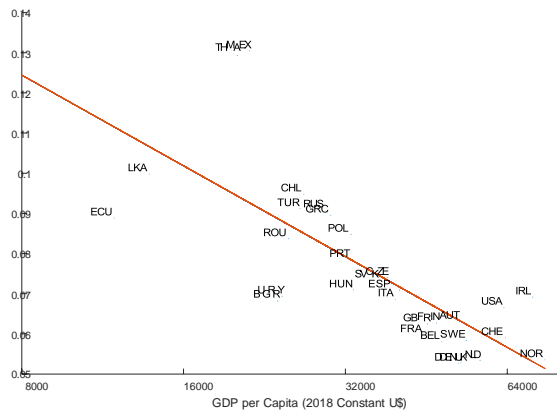

Figure 7: Peak of Infections

In the case of deaths, we focus on total (accumulated) deaths. The slope of the OLS fit is −0.000226, suggesting that an increase in GDP per capita of 1% reduces the number of deaths per million people by 2. However, the estimate is not significant. This is in line with death rates not being higher in low-income countries. 25 document that, until May 2020, only 21% of COVID related deaths came from low-income countries, when these countries hold 85% of the world population.

A 1% increase in income increases the trough of consumption relative to steady state, meaning that richer countries suffer larger recessions. The elasticity is 0.034, so that an increase in income of 1% deepens the recession by 0.03%. These numbers are shown in the first row of Table 3.

Table 4, columns 3 to 5, shows the actual estimated number of infections at the peak, deaths, and consumption trough for each country.

5.2 Optimal Policy

The second row in Table 3 shows the inequality under the optimal social distancing policy. Introducing an optimal social distancing policy reduces the peak of infection rates in all countries, but it exacerbates the inequality to a reduction in infections of 326 people per million per percent increase in income. The reason for this is that the policy is "tougher" on countries with higher income. Figure 8 shows the relation between the sum of taxes collected in time relative to income in each country. The OLS fit has a slope of 0.79, significant at the 5% level, meaning that an increase in income of 1% increases the tax collected relative to income by 0.81 percentage points. Note that this is taxes added throughout all periods, with no discounting. Adding a discount rate equal to β does not affect these estimates.

Columns 6 to 8 shows the deaths, infections, and consumption trough across countries under the optimal social distancing policy.
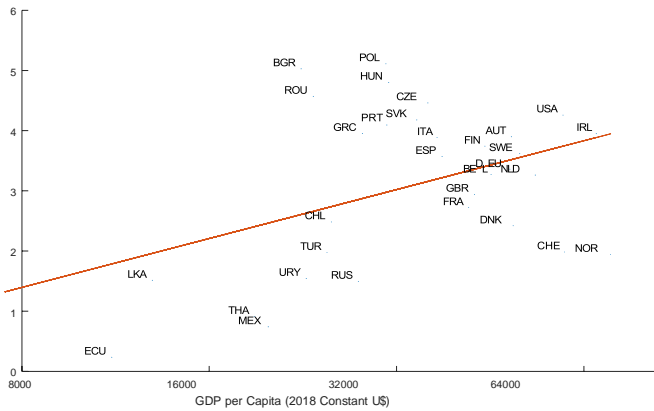
Figure 8: Sum of optimal taxes collected relative to income across time.

5.3 Decomposing the Effects

To understand the effect of each one of the features introduced in the model on inequality, this section performs counterfactuals where we change these features one at a time. This reveals what lies behind the large inequalities in infection rates, and the lack of inequality in deaths. Table 3 reports shows all the numbers.

Most of the inequality in infections stems from the ability to work at home or not. In fact, if all countries had the same possibilities as the U.S., an increase in GDP per capita of 1% would reduce the infection rates by 180 per million. Compared to the decentralized equilibrium, this is a reduction of 45%. The change in the consumption trough is very mild. Abstracting from the subsistence level of consumption would undermine the unequal effects of COVID-19. Setting $\bar{c} = 0$, one would conclude that the elasticity of infections with respect to income is of 293 per million, almost 10% lower than what it actually is. Different hospital capacities do not affect infection rates or consumption change with income. There is a reduction in the point estimate of inequality in death rates, but still this is not significant.

The lack of inequality in death rates is a combination of a younger population in low-income countries, pushing death rates down, and higher infection rates, pushing them up. To see this, assuming the population of the U.S. in all countries would greatly amplify the inequality in deaths, as shown in Table 3, to 15 additional deaths per million people per percentage point drop in income. This supports the conclusions in 25, who argue that the reduced death toll in low-income countries is due to a younger population. The last counterfactual exercise shows that not taking into account differences in living costs would dramatically increase the inequality to an elasticity of infections to income of 450 people per million, and the elasticity of recessions to 0.06. Inequality in deaths would become significant at the 10% level. This is because lower income countries usually have lower living costs.

Elasticity with respect to income of	Infections per Million (1)	Death per Million (2)	Consumption Trough Relative to Steady State (%) (3)
Dec. Eq.	-326.05***	-2.26	-0.0341***
	(53.73)	(3.53)	(0.01)
Opt. Policy	-325.73***	-2.38	-0.0468***
	(53.54)	(3.43)	(0.01)
Counterfactuals			
No subsistence	-293.25***	0.36	-0.0214***
	(24.91)	(1.71)	(0.00)
USA W.A.H.	-180.49***	1.46	-0.0355***
	(39.70)	(3.37)	(0.00)

USA Hosp. Cap.	-326.05***	1.52	-0.0341***
	(53.73)	(3.48)	(0.01)
USA Age Prof.	-301.63***	-15.28***	-0.0319***
	(51.02)	(3.68)	(0.01)
USA Living Cost	-449.83***	-8.18*	-0.0637***
	(64.77)	(4.38)	(0.00)

Table 3: Decomposing the effects of income on different outcomes. The dependent variable is the log of GDP per capita. The coefficient shows the increase in the peak of infections and death rates per million people in columns 1 and 2, and the increase in consumption trough relative to steady state in column 3. Standard errors in parentheses. * and *** indicates significant at the 10% and 1% level, respectively.

6   Empirical Validation

This section evaluates one key implication that can be verified empirically. The model predicts that individuals in rich countries are more likely to stay away from their workplace. To test this in the data, we turn to the Google Mobility Dataset (26) paired with GDP per capita. Appendix C lists the countries in the sample.

Google tracks and reports how traffic has changed relative to a benchmark date pre-COVID-19 in different locations, including workplaces. 27 already find that non-pharmaceutical interventions are effective in limiting mobility in all except the lowest income countries, pro- viding some evidence in favor of my predictions. In this section, we go further in the empirical analysis and test whether there is a continuous relationship between income per capita and the reduction in mobility.

To study the change in traffic around location j in country i, we regress:

$$y_{ij} = \alpha_{0j} + \alpha_{1j} \log(GDPpc_i) + \varepsilon_{ij}, \qquad\qquad (1)$$

where $GDPpc_i$ is GDP per capita in country i, and y_{ij} is percentage change in traffic in country i around location j = work, groceries and pharmacy, parks, transit stations, retail and recreational, and residential. The estimate for $y_{i,j}$ is a simple average of each $y_{i,j,t}$, where t stands for day over the period 2/15/2020 through 8/17/2020. Table 5, row 1 column 1, shows the results. Specifically, an increase in GDP per capita of 1% reduces traffic around the workplace by almost 4%. Appendix D shows the results of regressing the traffic around each location on GDP per capita. An interesting observation is that income reduces traffic around non-workplace locations by less than around workplace locations. In the case of parks and grocery stores, an increase in income increases traffic.

A valid criticism is that the error term could be correlated with GDP per capita. For example, people in lower income countries could be less obedient of government mandates. To address this, we model the error term as $\varepsilon_{ij} = \epsilon_i + v_{ij}$, which assumes that the part correlated with income is common to all locations, and then run the difference equation:

$$\Delta y_i = \zeta_0 + \zeta_1 \log(GDPpc_i) + \tilde{\varepsilon}_i, \qquad\qquad (2)$$

where $\Delta y_i = y_{ij} - y_{ij}'$, $\zeta_0 = \alpha_{0j} - \alpha_{0j}'$, $\zeta_1 = \alpha_{1j} - \alpha_{1j}'$ and $\tilde{\varepsilon}_i = v_{ij} - v_{ij}'$ for some pair $j \neq j'$. In practice, we compute the difference between traffic around workplaces (j) and the simple average of traffic around all other locations (j') except residential.[8] Row 2 in Table 5 shows the results become even stronger.

A second criticism is that the higher work mobility in low-income countries may be due to the different seasons. South America and Oceania are in the summer during the benchmark

[8]We exclude residential because an increase of traffic around these locations is expected under social distancing. Notwithstanding, we also included this with a negative sign and found ~~qualitatively identical results period,~~ which is in January, so benchmarks can be artificially low because people go on holidays. To explore this, column 2 excludes South American countries, column 3 excludes both South American and Oceanic countries, and column 4 excludes all countries south of

the Equator, which adds some African countries as well.[9] The results are similar.

One last concern is that the results are driven by the behavior of those countries in the lowest income group, as defined by 27. The authors show that these are the only countries that, absent non-pharmaceutical innovations, do not reduce their traffic around the workplace. To test whether this is the case, column 5 in Table 5 excludes these countries. The results remain qualitatively unchanged.

7   An Alternative Policy

Given the lack of success of the "laissez-faire" or the social distancing policy, this section investigates whether an alternative policy could work better. We study a loan extended to finance imports at a low interest rate. It is important to highlight that this loan would not only benefit the recipient country, but also the lending country, if it gets to export the goods. We do not model these benefits, but one can understand that a country like China, by extending loans to low-income countries, could also export to these places. Since China is apparently recovering faster than other countries, this seems to be a reasonable policy.

The loan considered is a two-year loan at a 5% interest rate. Recipients can only start paying it as of month 6.[10] The loan is determined by maximizing the sum of the utility of individuals in each country, in the same way the optimal policy is determined.

Table 6 shows the effect of loans on each country's rate of infections, deaths, and con- sumption trough. Comparing it with Table 4 one can note that loans are more effective at reducing the peak of infections, deaths, and recession for all countries. Moreover, the unequal effects of loans reduce the inequality both in infections and recession.

Table 7 shows [9]These countries are Angola, Mozambique, Tanzania, Zambia, and Zimbabwe.[10] Otherwise, countries would front-load payments, increasing working hours early on this. Row 1 shows that an increase in income of 1% reduces the number of infections by 305 people per million. This is considerably lower than the 326 in the decentralized equi- librium. The point estimate for deaths barely moves. The loan is very effective at reducing the inequality in the recession. Compared to the decentralized equilibrium, where a 1% increase in GDP per capita deepens the recession by 0.03%, with loans these differences are of 0.014%, a reduction of about 60%. The reduction with respect to the optimal taxes is even larger, of over 70%. Thus, the loan reduces overall inequality: the lower the income, the larger the reduction in infections, and the higher the income, the larger the reduction in the recession. Rows 2 and 3 reproduce the inequality under the decentralized equilibrium and the one under the optimal policy, respectively.

Figure 9 illustrates these effects for infections. The solid blue line is the fit in the decen- tralized equilibrium. The dashed red line uses the optimal social distancing policy in each country, and the dotted green line uses optimal loans. The dots represent each country under each scenario, by color. It stands out how much the line flattens for loans when compared to both the decentralized and optimal allocations. While the slopes are not significantly differ- ent from each other (probably due to the low number of observations), the flattening of the loans curve highlights how far a loan can go to reduce the unequal effects of COVID-19. It also shows how the line with the optimal policy is steeper than the decentralized equilibrium, which implies deeper inequalities. Figure 10 shows that loans are the best tool in reducing the inequality in recession. The slopes are significantly different in the case of consumption. Not only are loans relatively more effective in low-income countries, they are also cheaper.

Their present value ranges from $84 in Ecuador to $4,959 in Ireland. The slope of the line associating the size of the (log of) the loan to the (log of) income is significant and equal to 1.2, implying that when income increases by 1%, the loan requested increases by 1.2%.
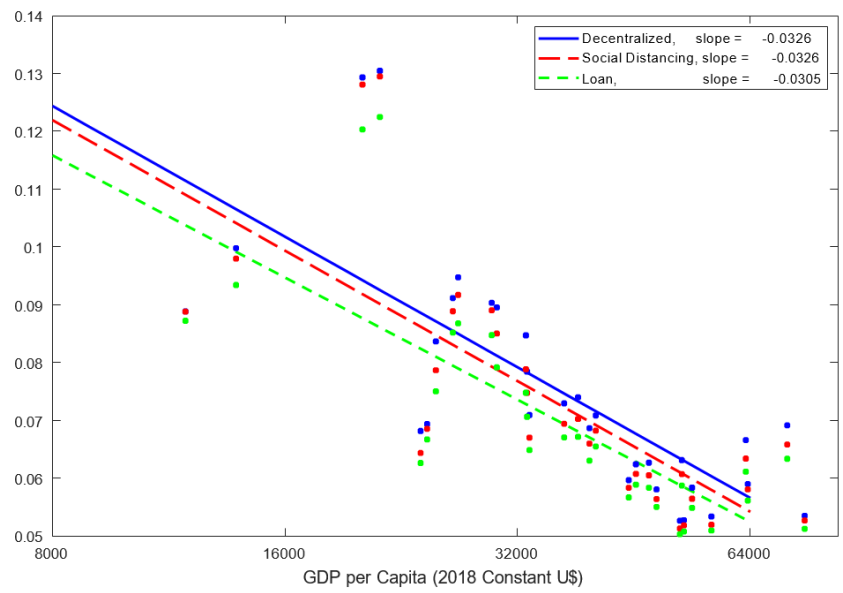
Figure 9: The success of loans in lowering the unequal effects on infections.

8   Conclusion

Covid-19 is currently hitting all countries, regardless of income. The best action so far to avoid infection has been to socially distance oneself. If working from home is not possible, this means enduring potentially long periods of time with no income. This is a problem in all countries, but especially in low-income ones, where citizens cannot remain under lockdowns for long periods of time. As a result, we find that infections are worse in lower income countries. The fact that populations are relatively younger in low-income countries implies that this does not translate into more deaths. Recessions are milder in lower income countries, because of the milder reaction of hours worked.

Google mobility data shows that lower income countries reduced traffic around the work- place less than high income ones, consistent with my results. It is not that low-income countries are less careful: their mobility around parks and grocery stores has been reduced by more than in high income countries. The problem is that low-income individuals cannot sustain long periods with no income.
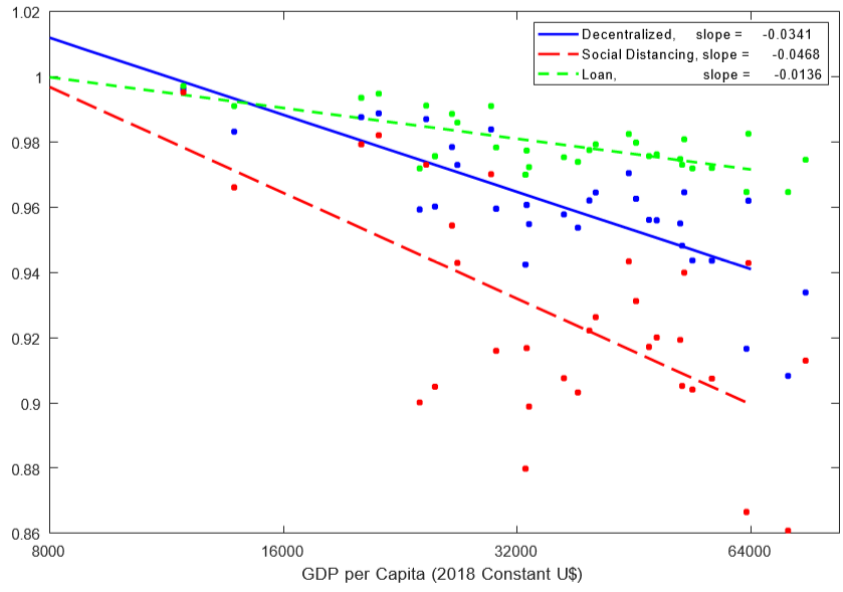
Figure 10: The success of loans in reducing the unequal effects on the recession.

An alternative policy that has larger desirable effects on low-income countries is the extension of a loan at relatively low interest rates to finance a trade deficit, to be offset in the future. Loans would be more successful at lowering the rate of infections relative to the optimal policy, particularly for low-income countries. Similarly, they are better at reducing the peak of the recession, particularly for high income countries. Since, absent any policy, infection rates are higher in low-income countries and the recession is deeper in high income ones, loans reduce the inequality in both of these dimensions.

Country	GDP per capita (2018 Dollars)	Number of deaths	Dec. Eq. Infected at peak	Consumption Trough (%)	Number of deaths	Opt. Policy Infected at peak	Consumption Trough (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AUT	52,154	22,629	569,080	94.82	21,601	546,999	90.52
BEL	48,373	29,366	669,577	95.59	28,403	649,944	92.01
BGR	23,952	22,605	478,372	95.92	21,256	451,486	90.01
CHE	63,492	26,638	514,812	96.2	26,229	506,584	94.29
CHL	26,786	73,541	1,769,099	97.29	72,110	1,711,678	94.29
CZE	38,284	35,034	786,212	95.37	33,226	746,011	90.32
DEU	51,864	192,361	4,456,301	95.5	193,499	4,339,788	91.93
DNK	52,492	23,136	309,042	96.45	22,681	303,626	93.99
ECU	11,885	47,227	1,484,700	99.62	47,200	1,483,367	99.52
ESP	40,356	216,414	3,350,305	96.45	212,425	3,223,911	92.63
FIN	47,285	21,916	348,015	95.61	21,258	335,657	91.72
FRA	44,521	181,374	4,030,681	97.04	176,723	3,940,529	94.33
GBR	45,495	268,976	4,203,427	96.26	261,685	4,088,477	93.12
GRC	30,050	56,714	946,750	95.95	54,317	898,652	91.6
HUN	33,122	29,445	693,302	95.48	27,694	654,726	89.89
IRL	71,404	16,202	338,569	90.83	15,633	322,151	86.09
ITA	39,609	305,525	4,157,871	96.2	295,048	3,996,028	92.21
LKA	13,815	68,444	2,194,242	98.31	67,518	2,153,316	96.6
MEX	21,212	444,011	16,027,336	98.88	442,361	15,903,877	98.2
NLD	56,975	49,233	926,789	94.36	47,855	901,330	90.74
NOR	75,230	14,652	287,770	93.39	14,428	283,121	91.3
POL	32,775	128,949	3,249,980	94.24	122,950	3,024,199	87.98
PRT	32,891	54,900	798,218	96.07	53,206	760,615	91.68
ROU	25,059	76,273	1,789,938	96.02	70,589	1,682,287	90.5
RUS	29,601	363,197	13,041,507	98.38	357,314	12,848,697	97.01
SVK	36,738	15,045	395,474	95.78	14,281	376,070	90.76
SWE	53,778	43,363	599,736	94.37	42,341	579,636	90.41
THA	20,138	340,020	8,758,464	98.76	338,413	8,672,670	97.92
TUR	26,362	235,093	7,808,962	97.84	228,422	7,611,839	95.44
URY	24,415	11,866	236,400	98.7	11,762	233,545	97.3
USA	63,126	1,207,015	22,162,295	91.66	1,163,794	21,085,740	86.66

Table 4: Estimates on Infections, Death, and the speed of transmission in different countries under different policies.

	Full Sample	No South America	No South America and Oceania	No South of Equator	No Low Income
	(1)	(2)	(3)	(4)	(5)
Workplace	3.97***	4.24***	4.42***	3.89***	2.79***
	(0.80)	(0.73)	(0.73)	(0.78)	(0.93)
Δ Workplace	6.66***	6.70***	7.06***	7.07***	7.25***
	(1.30)	(1.26)	(1.25)	(1.39)	(1.56)
Observations	99	90	88	82	93

Table 5: Google Mobility data across income levels. The dependent variable is average percentage drop in traffic around workplaces relative to a pre-pandemic benchmark in row 1, and the average percentage drop in traffic around workplaces minus the average percentage drop in traffic around all other locations except residential in row 2. The dependent variable is the log of GDP per capita. Standard errors in parentheses.

∗∗∗ indicates significant at the 1% level. Source: 26.

Country	GDP per Capita (2018 Dollars)	Loans per Capita (2018 Dollars)	Number of Deaths	Infected at Peak	Consumption Tough (%)
	(1)	(2)	(3)	(4)	(5)
AUT	52,154	2,958	20,753	529,197	97.3
BEL	48,373	2,326	27,580	634,316	97.62
BGR	23,952	1,442	20,635	439,264	97.19
CHE	63,492	2,484	25,362	489,695	98.25
CHL	26,786	1,059	69,212	1,619,766	98.6
CZE	38,284	2,332	31,695	713,355	97.39
DEU	51,864	2,473	196,344	4,256,815	97.48
DNK	52,492	1,999	22,327	297,412	98.08
ECU	11,885	84	46,691	1,457,220	99.72
ESP	40,356	2,026	204,480	3,094,853	97.93
FIN	47,285	2,533	20,586	323,814	97.57
FRA	44,521	1,756	170,819	3,826,956	98.25
GBR	45,495	2,035	255,504	3,963,718	97.98
GRC	30,050	1,770	51,501	836,696	97.84
HUN	33,122	2,035	26,625	633,800	97.23
IRL	71,404	4,959	15,138	310,107	96.47
ITA	39,609	2,128	285,510	3,817,088	97.76
LKA	13,815	360	64,283	2,053,142	99.1
MEX	21,212	377	428,259	15,042,739	99.48
NLD	56,975	2,903	46,813	883,833	97.2
NOR	75,230	3,487	14,026	275,469	97.46
POL	32,775	2,323	113,911	2,868,127	97
PRT	32,891	1,890	50,781	718,457	97.74
ROU	25,059	1,501	68,669	1,604,281	97.57
RUS	29,601	795	336,779	12,228,081	99.1
SVK	36,738	2,050	13,757	363,309	97.53
SWE	53,778	2,982	41,176	563,441	97.19
THA	20,138	408	326,426	8,145,775	99.36
TUR	26,362	835	221,073	7,295,428	98.86
URY	24,415	554	11,524	227,223	99.12
USA	63,126	4,371	1,131,044	20,334,906	96.47

Table 6: Infections and Death with loans.

Elasticity with respect to income of	Infections per Million (1)	Death per Million (2)	Consumption Trough Relative to Steady State (%) (3)
Loans	-304.88***	-2.10	-0.0136***
	(48.26)	(3.28)	(0.25)
Decentralized	-326.05***	-2.26	-0.0341***
	(53.73)	(3.53)	(0.50)
Optimal	-325.73***	-2.38	-0.0468***
	(53.54)	(3.43)	(1.03)

Table 7: Effects of Loans with changes in income and effects relative to the decentralized equilibrium. In row 1, the dependent variable is the log of GDP per capita. The coefficient shows the increase in the peak of infections and death rates per million people in columns 1 and 2, and the increase in consumption trough relative to steady state in column 3. Rows 2 and 3 replicate these elasticities for the decentralized and optimal tax cases, respectively. Standard errors in parentheses. *** indicates significant at the 1% level.

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Appendix A   **Proof of Proposition 1**

The first order conditions of the infected individuals are

$$c: \frac{1}{c - \bar{c}} = \lambda_{bit}(1 + \mu\_t) \qquad \text{(Appendix A.1)}$$

$$n: \theta n = \lambda_{ibt}\phi w_t \qquad \text{(Appendix A.2)}$$

where λ_{bit} is the Lagrange multiplier. Combining equations (Appendix A.1) and (Appendix A.2), obtain

$$n = \frac{\phi A}{\theta(\phi An - \bar{c})}\frac{1}{(1 + \mu_t)}$$

Applying the implicit function theorem,

$$\frac{\partial n}{\partial \mu_t} = -\left[\frac{\phi An - \bar{c}}{\phi A(1 + \mu_t)}\right] = -\left[\frac{n - \frac{\bar{c}}{\phi A}}{(1 + \mu_t)}\right] \qquad \text{(Appendix A.3)}$$

Since $\phi An - \bar{c} \geq 0$, this derivative is negative. Thus, the policy works as intended: an increase in μ_t reduces the labor supply by infected individuals. Moreover, this expression shows that if $\bar{c} = 0$, the response does not depend on A. Thus, in ERT, the response of the hours worked by infected people would not depend on the level of income. With $\bar{c} > 0$, the level of income becomes important. To see this, differentiate equation (Appendix A.3) with respect to $\bar{c}/A$:

$$\frac{\partial^2 n}{\partial \mu_t \partial(\bar{c}/A)} = \overline{\phi(1 + \mu_t)}$$

This expression is positive. Since the whole derivative is negative, this implies that the larger the ratio $\bar{c}/A$, the lower the reaction of hours worked to the social distancing policy. In the limit, as $\bar{c}/A \to 0$ because either A is too large or $\bar{c}$ too small, the economy behaves as if there is no subsistence consumption level. In general, in low-income countries this ratio is higher than in high income countries as we find in section 4, so the hours supplied by infected individuals are less reactive to social distancing policies.

Appendix B   **Countries included in the Analysis**

Table Appendix B.1 specifies the countries that result from the intersection of these five databases. Out of these countries, we eliminate 5 countries based on the fact that, given the targeted productivity, hours worked, and cost of living, the subsistence level of consumption is higher than the consumption when infected. These countries are Bangladesh, Brazil, Cambodia, Pakistan, and the Philippines.

Country	Abbreviation	Country	Abbreviation
Austria	AUT	Italy	ITA
Belgium	BEL	Cambodia	KHM
Bangladesh	BGD	Sri Lanka	LKA
Bulgaria	BGR	Mexico	MEX
Brazil	BRA	Netherlands	NLD
Switzerland	CHE	Norway	NOR
Chile	CHL	Pakistan	PAK
Czech Republic	CZE	Philippines	PHL
Germany	DEU	Poland	POL
Denmark	DNK	Portugal	PRT
Ecuador	ECU	Romania	ROU
Spain	ESP	Russian Federation	RUS
Finland	FIN	Slovak Republic	SVK
France	FRA	Sweden	SWE
United Kingdom	GBR	Thailand	THA
Greece	GRC	Turkey	TUR
Hungary	HUN	Uruguay	URY
Ireland	IRL	United States	USA

Table Appendix B.1: Countries in initial sample

Appendix C   **Countries in Empirical Validation**

Country Name	Country Name	Country Name	Country Name
United Arab Emirates	Estonia	South Korea	Qatar
Angola*	Egypt	Kuwait	Romania
Argentina	Spain	Kazakhstan	Serbia
Austria	Finland	Sri Lanka	Russia
Australia	France	Lithuania	Saudi Arabia
Bosnia and Herzegovina	United Kingdom	Luxembourg	Sweden
Barbados	Georgia	Latvia	Singapore
Bangladesh	Ghana	Morocco	Slovenia
Belgium	Greece	Moldova	Senegal
Burkina Faso†	Guatemala	Mali†	Thailand
Bulgaria	Hong Kong	Malta	Tajikistan
Bahrain	Croatia	Mexico	Turkey
Bolivia	Hungary	Malaysia	Trinidad and Tobago
Brazil	Indonesia	Mozambique*,†	Tanzania*,†
Belarus	Ireland	Niger†	Ukraine
Canada	Israel	Nigeria	Uganda†
Switzerland	India	Netherlands	United States
Chile	Iraq	Norway	Uruguay
Cameroon	Italy	New Zealand	Venezuela
Colombia	Jamaica	Oman	Vietnam
Costa Rica	Jordan	Peru	Yemen
Germany	Japan	Philippines	South Africa*

Denmark	Kenya	Pakistan	Zambia*
Dominican Republic	Kyrgyzstan	Poland	Zimbabwe*
Ecuador	Cambodia	Portugal	

Table Appendix C.1: Countries used for empirical validation. * African countries south of the Equator, †
low-income countries.

Appendix D   **Additional Regression Estimates from Google Mobility Data**

	Workplace	Retail and Residential	Pharma	Groceries	Parks	Transit	Stations
			Full Sample				
Log (GDP pc)	3.97***	2.13*	-1.51		-13.6***	2.26*	-0.40
	(0.80)	(1.19)	(0.97)		(3.71)	(1.14)	(0.50)
Constant	-13.1*	8.22	26.7***		130.9***	11.4	-7.60
	(7.79)	(11.5)	(9.45)		(36.0)	(11.1)	(4.88)
Observations	99	99		99	99	99	99
R^2	0.202	0.032	0.024		0.122	0.039	0.007
			No South American Countries				
Log (GDP pc)	4.24***	2.38**	-1.24		-13.5***	2.50**	-0.53
	(0.73)	(1.05)	(0.85)		(3.62)	(1.09)	(0.45)
Constant	-16.5**	3.80	22.6***		124.8***	7.58	-5.59
	(7.09)	(10.2)	(8.23)		(35.2)	(10.6)	(4.42)
Observations	90	90		90	90	90	90
R^2	0.278	0.055	0.024		0.136	0.057	0.015
			No South American or Oceanic Countries				
Log (GDP pc)	4.42***	2.45**	-1.20		-14.2***	2.43**	-0.55
	(0.73)	(1.07)	(0.86)		(3.63)	(1.11)	(0.46)
Constant	-18.0**	3.19	22.2***		131.0***	8.20	-5.46
	(7.04)	(10.3)	(8.33)		(35.2)	(10.7)	(4.49)
Observations	88	88		88	88	88	88
R^2	0.301	0.058	0.022		0.152	0.053	0.016
			No Countries South of the Equator				
Log (GDP pc)	3.89***	1.94	-1.79*		-14.9***	2.06*	-0.72
	(0.78)	(1.17)	(0.94)		(4.06)	(1.18)	(0.49)
Constant	-12.5	8.44	28.3***		137.8***	11.9	-3.57
	(7.68)	(11.4)	(9.21)		(39.8)	(11.6)	(4.80)
			No Low-income Countries				
Log (GDP pc)	2.79***	0.51	-2.83**		-16.9***	1.37	0.087
	(0.93)	(1.37)	(1.13)		(4.45)	(1.34)	(0.59)
Constant	-1.04	24.7*	40.0***		164.3***	20.4	-12.6**
	(9.11)	(13.5)	(11.1)		(43.7)	(13.1)	(5.83)
Observations	93	93		93	93	93	93
R^2	0.091	0.002	0.065		0.137	0.011	0.000

Reduction in traffic around different locations as a function of income per capita. Standard errors in parentheses. * $p <.1$, ** $p <.05$, *** $p <.01$