Inequality in Life and Death*

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Abstract

The Covid epidemic disproportionately affected the economic well-being and health of poor people. To disentangle the forces that generated this outcome, we construct a model that is consistent with the heterogeneous impact of the Covid recession on low- and high-income people. According to our model, two thirds of the inequality in Covid deaths reflect pre-existing inequality in comorbidity rates and access to quality health care. The remaining third, stems from the fact that low-income people work in occupations where the risk of infection is high. Our model also implies that the rise in income inequality generated by the Covid epidemic reflects the nature of the goods that low-income people produce. Finally, we assess the health-income trade-offs associated with fiscal transfers to the poor and mandatory containment policies.

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1 Introduction

The Covid epidemic disproportionately affected the economic well being and health of poor people. In effect, it created more inequality in life and death. This paper analyses the mechanisms by which the Covid epidemic and inequality are related. In addition, we discuss how containment measures and fiscal transfers impacted income and health inequality.

We begin by documenting a striking fact: higher pre-epidemic income inequality is associated with higher Covid mortality rates. This fact holds across countries as well as across U.S. states. It is robust to controlling for other factors such as level of income. While variables like real GDP per capita, share of population 65 and older and physicians per 1,000 people are a priori relevant, they do not emerge as significant in our statistical analysis.

In principle, the link between inequality and death could result from two forces. The first, is pre-existing inequality in comorbidity rates and access to quality health care. The second, is that low-income people work in occupations where the risk of infection is high.

To disentangle these forces and understand how the recession affected inequality in life, we construct a simple quantitative model. Our model implies that about two thirds of the inequality in Covid deaths reflect the first force discussed above. The remaining third reflects the second force. Our model also implies that the rise in income inequality generated by the Covid epidemic reflects the nature of the goods that low-income people produce. Those goods are associated with higher infection risk than the goods produced by high-income people. So, employment of low-income people was disproportionately affected by Covid, fueling a rise in income inequality.

We then turn to the question: how was inequality in life and death affected by containment policies and government transfers to low-income people? According to our model, containment disproportionately reduced the employment and income of low-income workers, magnifying income disparities. Containment also dramatically reduced mortality rates for all income groups. Evidently, containment policies involve sharp trade-offs between health and income inequality.

Turning to fiscal policy, we find that government transfers increased employment and income of low-income workers, reducing income inequality. But it did not substantially increase the death toll from the epidemic. So, in the context of the Covid epidemic, government transfers do not involve sharp trade-offs between health and income inequality.

In constructing our model, we are motivated by four intriguing facts documented by

Chetty et al. (2020) for the U.S. First, consumption expenditures of high-income people fell by *more*, in percentage terms, than consumption expenditures of low-income people. Second, employment of high-income people fell by *less*, in percentage terms, than employment of low-income people. Other things equal, this finding implies that Covid increased income inequality. Third, consumption expenditures of low-income people recover more quickly than those of high-income people. Fourth, consumption expenditures of high-income people fell proportionally by more than their employment. So, income of high-income people was smoother than their consumption. The spending patterns documented by Chetty et al (2020) have been corroborated by other authors using data for the U.S. (Cox et al. (2020)), the U.K. (Hacioglu, et al. (2020)), Spain (Carvalho et al. (2020)), and Portugal (Eichenbaum et al. (2020)), respectively.

After reviewing these facts, we turn to the task of constructing a model that is consistent with them. This task is challenging because conventional business cycle models generally embody strong consumption smoothing motives, at least for high-income agents.[1]

Our model has the following key features. The economy produces tradable and non-tradable goods. Tradable goods are less infectious in consumption and production than nontradable goods. Workers are specialized and can work only in one sector. There is a relatively large supply of workers who can produce the nontradable good. As a result, wages are much higher in the tradable-goods sector than in the nontradable goods sector. Taken together, these assumptions are consistent with the evidence discussed in Section 3 that low-income people work in occupations that are more contact intensive than those of high-income people. Consistent with evidence in Drefahl et al. (2020), we assume that the poor are more likely to die from a Covid infection than the rich.

For tractability, we consider a small-open-economy model in which both the government and high-income people can borrow and lend in international capital markets at a fixed real interest rate. In the spirit of the heterogeneous agent new-Keynesian literature, we assume that low-income people are "hand-to-mouth" consumers (see Auclert (2019) and Kaplan, Moll and Violante (2018)). Finally, we assume that wages in the nontradable sector are sticky. This assumption allows the model to produce large fall in employment without inducing counterfactual movements in relative prices.

Having established the ability of our model to account for the Chetty et al. (2020) facts,

[1]A potentially important exception are business cycle models with wealthy hand-to-mouth consumers of the type emphasized by Kaplan, Violante, and Weidner (2014).

we use it to assess the health-income trade-offs associated with fiscal transfers to the poor and mandatory containment policies.

To focus our analysis, we abstract from three important issues that have received extensive attention in the literature. The first is the impact of ethnicity and racial background per se on Covid infections and death (see e.g. Benitez, Courtemanche, and Yelowitz (2020), Desmet and Wacziarg (2020) and McLaren (2020)). The second is the impact of the Covid recession on gender equality (see e.g. Alon, Doepke, Olmstead-Rumsey, and Tertilt (2020), Jin et al. (2020)). The third is the differential impact of Covid on young and old (see e.g. Acemoglu, Chernozhukov, Werning, and Whinston (2020), Brotherhood, Kircher, Santos, and Tertilt (2020), Eichenbaum, Godinho de Matos, Lima, Rebelo, and Trabandt (2020), Giagheddu and Papetti (2020), and Glover, Heathcote, Krueger, and Ríos-Rull (2020)).

The paper is organized as follows. Section 2 briefly reviews the economics literature on the impact of the epidemic in models with heterogeneity. Section 3 contains the empirical evidence we use as the background for our analysis. Section 4 describes the model. Section 5 discusses the quantitative properties of our model and its implications for the impact of containment measures and fiscal transfers. Section 6 concludes.

2 Related literature

There is by now a large literature on the macroeconomic impact of epidemics. Examples include Acemoglu, et al. (2020), Alvarez, Argente, and Lippi (2020), Brotherhood, et al. (2020), Buera, et al. (2020), Faria-e-Castro (2020), Farboodi, Jarosch, and Shimer (2020), Glover, Gonzalez-Eiras and Niepelt (2020), Krueger, Uhlig, and Xie (2020), Jones, Philippon, and Venkateswaran (2020), Krueger, Uhlig, and Xie (2020), Guerrieri, Lorenzoni, Straub, and Werning (2020), Piguillem and Shi (2020), and Toxvaerd (2020). We do not attempt to survey this literature here. Instead, we discuss the papers most closely related to ours.

In this paper, we build on our prior work which features an explicit two-way interaction between epidemic and economic dynamics (Eichenbaum, Rebelo and Trabandt (2020)). The epidemic creates a recession because people cut back on their economic activities to reduce the probability of being infected. At the same time, the recession reduces the rate at which the virus spreads throughout the population.

Our model is closely related to the work of Kaplan, Moll and Violante (2020). These authors study epidemics in a model where people are heterogeneous along a variety of dimensions. Two key forms of heterogeneity in their environment are differences in the probability of becoming infected at work and the extent to which liquidity constraints are binding. We view our results as complementary to theirs. Our contribution is twofold. First, we emphasize the importance of pre-existing inequality in case fatality rates between high- and low-income people. Second, we highlight in a simple setting the key forces that generate the observed unequal health and economic consequences of the epidemic.

Glover, et al. (2020) analyze a two-sector model (essential and luxury) with young workers and retirees. The epidemic creates important distributional effects because the luxury sector contracts by more than the essential sector. In addition, containment measures redistribute welfare from the young to the old. The old benefit from the reduced risk of infection produced by containment, while the young suffer the adverse employment consequences. Carnap, et al. (2020) explore how optimal containment policy varies across countries, depending on demographic factors, the prevalence of comorbidities, and the strength of the health-care system. Rubini (2020) studies a model with a subsistence level of consumption and heterogenous work-at-home possibilities. These elements generate substantial heterogeneity in the impact of the epidemic across countries. Crucini and O'Flaherty (2020) emphasize the importance of regional heterogeneity in epidemic dynamics. In their model, each location initially experiences an idiosyncratic virus shock. The virus then spreads within locations, through both consumption and employment activities. It also spreads across locations through travel. Finally, Engler, Pouokam, Guzman, and Yakadina (2020) analyze the interactions between inequality and the epidemic in an open economy context.

3 Empirical evidence

In this section, we provide the empirical background for our analysis. First, we discuss our data. Second, we present cross-section evidence on the relation between pre-existing income inequality and Covid deaths. Third, we display the time-series for consumption expenditures and employment by income groups in the U.S. using data provided by Chetty et al. (2020).

3.1 Data

In this subsection, we discuss our data sources. Consider first the variables used in the cross-section regressions. The number of Covid deaths per million, as of September 27, 2020, is from the University of Oxford "Our World in Data" website. The Gini index is from the

United Nations University World Institute for Development Economics. To measure income inequality before the epidemic, we use the most recent measure of the Gini index before 2016, the last date for which the data is available. For robustness, we also consider alternative measures of the Gini index obtained from Solt's (2020) Standardized World Income Inequality Database (version 8) and the World Economic Forum's Inclusive Development Index 2018. Our measure of real per capita GDP is from the University of Oxford's "Our World in Data" website. For robustness, we also consider the measures of real per capita GDP from the International Monetary Fund's World Economic Outlook data set. Our data on the fraction of the population aged 65 or older is from the University of Oxford's "Our World in Data" website. The share of the population in urban areas in 2018 is from the United Nations' Department of Economics and Social Affairs. We refer to this variable as the "urban share." The number of physicians per one thousand people is from the World Bank database.

The sources of the data used in the U.S. cross-state regressions are as follows. The number of Covid deaths per million, as of September 27 2020, is from the Centers for Disease Control and Prevention. The Gini Index is from the 2019 Census Bureau's American Community Survey. Data on real personal income per capita (purchasing-power-parity adjusted) is from the Bureau of Economic Analysis for 2019, quarter 4. Data on the fraction of the population aged 65 or older is from the 2019 Census Bureau's American Community Survey. Data on the share of the population in urban areas is from the 2010 Census. Data on the number of physicians per one thousand people is from the American Association of Medical Colleges.

The following sources were used to obtain the data used in our robustness analysis. Data on purchasing-power-parity-adjusted, per capita Health Expenditures in 2017 and measures of comorbidity (the probability of dying between ages 30 and 70 from cardiovascular disease, cancer, diabetes, or chronic respiratory disease) is from the World Health Organization. Average temperature in January-March of 2011, 2012 and 2013 (the most recent available date) is obtained from the Berkeley Earth Database.

3.2 Cross-sectional correlations

Table 1 reports the average level of the variables used in our empirical analysis. Relative to the world or OECD average, the U.S. has both substantially more Covid deaths per million and much higher income inequality.

Table 2 reports the cross-sectional standard deviation of the logarithm of the variables used in our analysis. There is a great deal of cross-sectional variability in Covid deaths

Table 1: *Data: Summary Statistics, Means and relative S.E.*

	World		OECD		US States	
	mean	s.e.	mean	s.e.	mean	s.e.
Total Deaths per million	212.3	28.8	241.2	41.6	507.0	51.6
Gini Index	37.8	1.1	32.2	1.1	46.3	0.3
Real GDP per capita (PPP adjusted)	32,349.5	2,475.6	44,522.3	2,933.6		
Real Income per capita (PPP adjusted)					50,387.7	770.1
65 or older, share of pop	13.4	0.7	17.2	0.7	16.9	0.3
Urban share	71.9	1.9	78.5	1.8	73.8	2.1
Physicians per 1000	2.8	0.2	3.6	0.2	2.8	0.1
Obs	71		37		50	

Note: Means pertain to the level of the variables. Data sources are discussed in the main text.

per million across countries and U.S. states. For example, the standard deviation of the logarithm of deaths per million is roughly 177, 143 and 74 percent, respectively. To interpret these numbers, consider the following illustrative calculation for the U.S. A one standard deviation log-percentage change in U.S. total deaths per million relative to the mean (507) translates into an additional 556 deaths per million.

Table 3 presents our main empirical results. In all cases, the independent variables are measured prior to the onset of the Covid epidemic. Since these variables are predetermined, we interpret the regression results as being causal in the sense that variations in the right-hand-side variables induce, through unspecified mechanisms, variations in Covid deaths.

Columns (1), (3) and (5) present the results from regressing the logarithm of Covid deaths per million on the logarithm of the Gini index, the urban share, and a constant for the world, the OECD, and the U.S., respectively. Columns (2), (4) and (6) add the logarithms of GDP per capita, the share of the population older than 65, and the number of physicians per capita as independent variables.

Three results are worth noting. First, for the world and the OECD, the coefficient on the Gini index is statistically significant at a five percent significance level regardless of whether we include additional controls or not. For the U.S., this coefficient is significant only at the ten percent level when we don't include the extra controls, but is significant at

Table 2: *Data: Summary Statistics, Sample Standard Deviations*

	World	OECD	U.S. States
Total Deaths per million	177	143	74
Gini Index	25	19	4
Real GDP per capita (PPP adjusted)	74	39	
Real Income per capita (PPP adjusted)			11
65 or older, share of pop	60	30	13
Urban share	27	15	22
Physicians per 1000	71	28	25
Obs	71	37	50

Note: Standard Deviations pertain to the log of the variables. Numbers refer to percentage points. Data sources are discussed in the main text.

the one percent level when we do. Second, the coefficient on the urban share is statistically significant for the world and the U.S. The precise significance level depends on whether extra controls are included or not. For the OECD, the coefficient on the urban share is statistically insignificant. This result might reflect the low variability of that variable across OECD countries (see Table 2). Third, with the exception of per capita GDP in the OECD case, the additional variables included in the regressions of Table 2 are not statistically different from zero at a five percent significance level. While variables like real GDP per capita, share of population 65 and older and physicians per 1000 people are a priori relevant, they do not emerge as significant in our statistical analysis.

The key takeaway from Table 3 is that pre-epidemic income inequality is a robust explanatory variable for Covid deaths. We now display the association between these two variables in our three data sets. Figure 1 is a scatter diagram of the logarithm of the Gini index and the logarithm of Covid deaths per million. The raw correlation between these variables is 0.09, 0.32 and 0.53 for the world, the OECD, and the U.S., respectively. Figure 2 shows the partial correlation between the Gini index and Covid deaths per million based on the controls included in column 6 of Table 3. The high partial correlation for the U.S. is consistent with the relatively high R^2 in columns (5) and (6) in Table 3.

We now interpret the magnitude of the coefficients on the Gini index reported in columns

Figure 1: Gini coefficient and Covid deaths

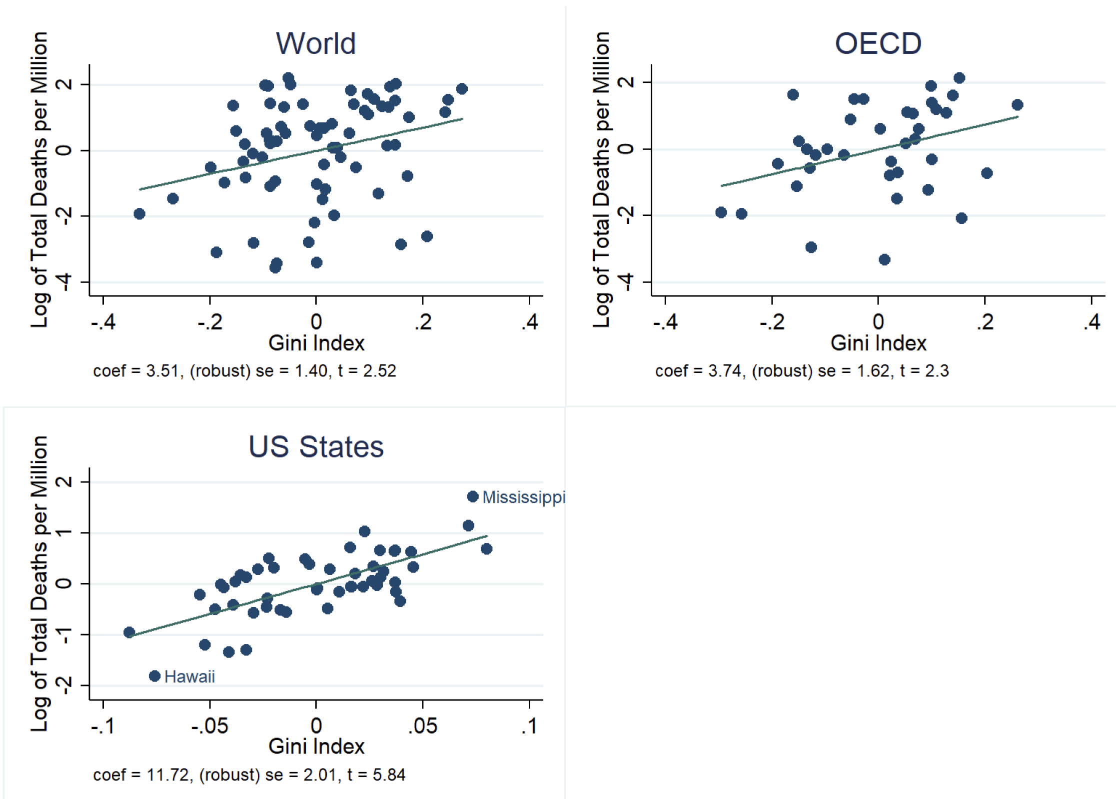


Table 3: *Baseline Regressions for World, OECD and US panels*

	(1) World	(2) World	(3) OECD	(4) OECD	(5) US States	(6) US States
Gini Index	1.26**	3.51**	2.16**	3.74**	6.91*	11.72***
	(0.63)	(1.40)	(0.82)	(1.62)	(3.60)	(2.01)
GDP per capita		0.54		1.26***		
		(0.43)		(0.46)		
Income per capita						0.99
						(1.04)
65 or older pop share		0.98		0.07		1.01*
		(1.09)		(1.44)		(0.57)
Urban share	3.32***	2.33*	1.79	0.70	1.07**	1.32***
	(1.10)	(1.37)	(1.46)	(1.51)	(0.40)	(0.41)
Physicians per 1000		-0.24		-0.14		-0.46
		(0.73)		(1.10)		(0.36)
Constant	-14.18**	-25.77**	-10.53*	-24.67**	-25.14*	-57.71***
	(5.53)	(9.98)	(6.14)	(10.48)	(13.55)	(13.06)
Observations	69	69	37	37	51	50
R-squared	0.17	0.21	0.14	0.20	0.38	0.62

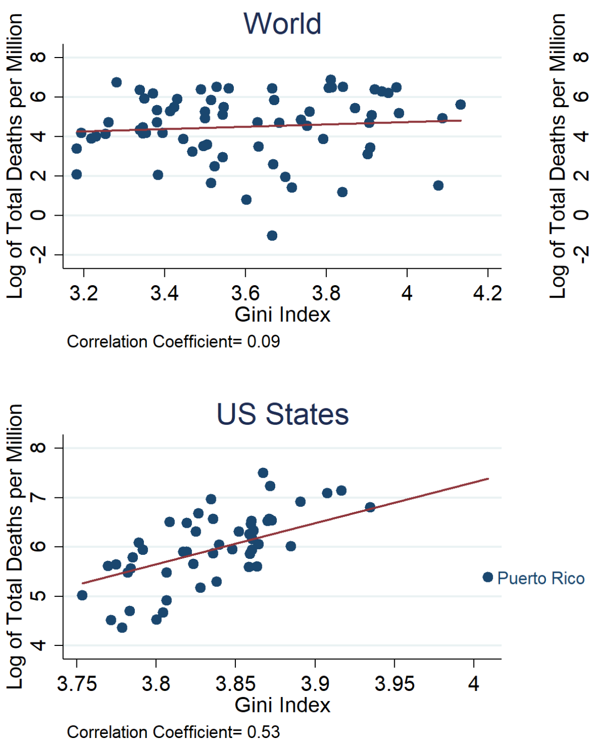
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All variables included in the regression are in logs. Sources are outlined in the main text. Summary Statistics are provided in Table 2. Robust Standard Errors are reported in parenthesis.

(1), (3) and (5) of Table 3. For the world, the OECD and the U.S., a one standard deviation increase in the Gini index increases the number of Covid deaths per million by 32, 41, and 28 percent, respectively.

In the appendix (Tables 4 and 5), we show that our results for the world and the OECD are robust to including the following additional control variables: Purchasing-power-parity-adjusted Health Expenditures per capita in 2017, average temperature, and a measure of comorbidity prevalence. The coefficients on these variables either have the wrong sign or are not statistically significantly. The coefficient on the Gini index remains statistically significant. We also show in the appendix (Tables 6 and 7) that our results are robust to using alternative measures of the Gini index.

Figure 2: Gini coefficient and Covid deaths, partial correlations



3.3 Health outcomes and pre-existing income inequality

Taken at face value, our results suggest that inequality has a very large impact on the incidence of Covid deaths. To be clear, the data at our disposal is not sufficiently rich to be dispositive about the transmission mechanism by which inequality leads to more deaths from Covid. But there is a literature that suggests different mechanisms by which inequality and Covid deaths are related.

First, there is strong evidence that the Covid case fatality rate is substantially higher for poor people. Chen and Krieger (2020) and Krieger, Waterman, and Chen (2020) find that, in the U.S., case fatality rates are higher in lower-income counties and zip codes. While useful, those studies do not link individual incomes to health outcomes. Drefahl et al. (2020) overcome this limitation. These authors use data that link all recorded Covid deaths in Sweden to highly-accurate individual-level administrative data. They find a sharp, negative correlation between case fatality rates and income levels.

Second, the probability of dying from Covid is highly correlated with comorbidity conditions and lack of access to high-quality health care. The Center for Disease Control and Prevention (2020) provides a thorough review of the comorbidities that increase the risk of severe illness and death from Covid. There is substantial evidence that the relevant comorbidities are negatively related to income, see for example Hosseinpoor et al. (2012), Price-Haywood et al. (2020), Raifman and Raifman (2020), and Williamson, et al. (2020).

Third, the probability of being infected with Covid is correlated with the use of public transportation which is disproportionately used by low-income people. Carvalho et al. (2020) show that spending on urban transportation is a leading indicator of future Covid deaths. Zhao et al. (2020) find a strong, significant association between the number of train passengers and the number of Covid cases in China. Harris (2020) finds that New York subway lines with the largest drop in ridership during the second and third weeks of March had the lowest subsequent rates of infection in the zip codes traversed by their routes.

Fourth, the probability of being infected with Covid is correlated with crowded living conditions, a situation clearly related to low income. According to the World Health Organization, inadequate shelter and overcrowding are major factors in the transmission of acute respiratory infections. Consistent with this view, Mejia and Cha (2020) find that California counties with a higher percentage of essential workers in overcrowded homes have a higher incidence of Covid deaths. Using data for California's Mission district, Fernandez and Weiler

(2020) find that out of 89 percent of the residents who tested positive, most live in households comprised of three to five people (60 percent) or more (29 percent).

Fifth, several studies show that the probability of being infected at work is higher for high-contact industries. For example, Barbieri, Basso, and Scicchitano (2020) use Italian data to show that the degree of physical proximity in the workplace is highly correlated with exposure to disease. A study by the Washington State Department of Health (2020) uses the Bureau of Labor Economics' Occupational Information Network survey (O*NET) to show that contact-intensity measures correlate with actual infections.[2] This study finds that infection rates are disproportionately high in high-contact industries (e.g. health care, social assistance, traditional manufacturing and food-processing facilities) and disproportionately low in low-contact industries (e.g. real estate, finance and insurance, and public administration).[3] Using UK data, Mutambudzi et al. (2020) show that the risk of Covid infection is higher for high-contact occupations such as health care professionals and social care workers.

Sixth, there is substantial evidence that high-contact industries disproportionately employ low-skill, low-wage workers. Other studies provide evidence that high-contact industries disproportionately employ low-skill, low-wage workers. For example, Leibovici, Santacreu and Famiglietti (2020) combine individual-level data from the 2017 American Community Survey with the O*NET index of occupational contact-intensity. These authors show that the workers in high-contact occupations have on average lower incomes. The fact that infections through work are much more likely for low-income than for high-income people is consistent with evidence in Dingel and Neiman (2020). Finally, Kaplan, Moll and Violante (2020) provide micro evidence that low-income people work in occupations that are more contact intensive than those of high-income people.

3.4 U.S. employment and consumption expenditures during the Covid recession

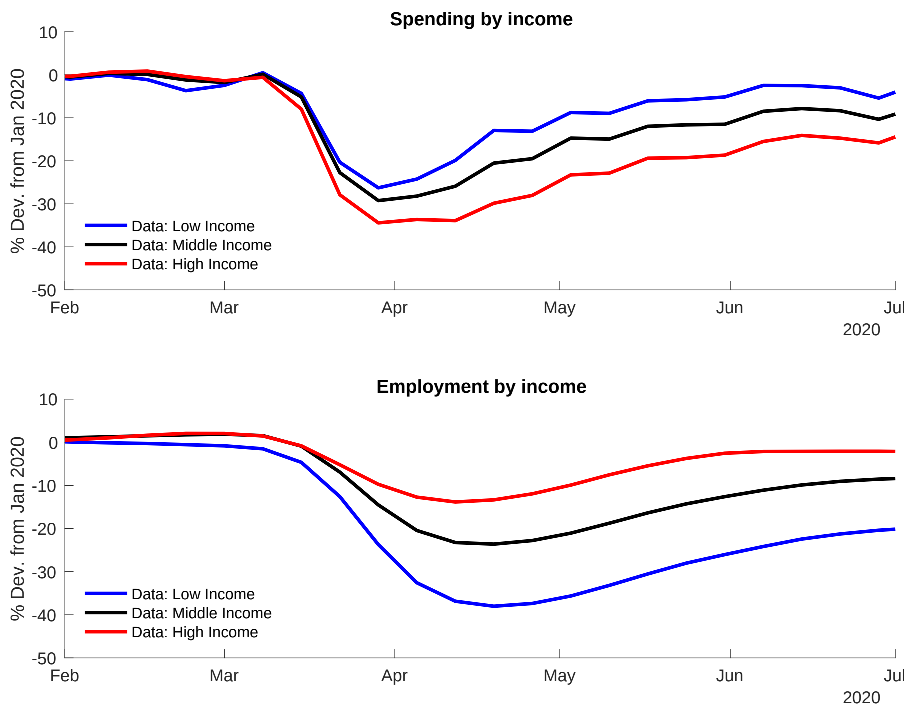
In this subsection, we review three important findings documented by Chetty et al. (2020). Along with mortality rates, these findings play a central role in our quantitative analysis.

Figure 3 displays weekly U.S. employment and consumption expenditures, relative to Jan-

[2]The O*NET survey measures the extent to which performing a job requires close physical proximity to other people.

[3]An interesting anecdote about the relation between contact intensity and risk of infection is provided by The City (July 30, 2020): train operators and conductors have recorded the highest number of Covid infections among subway workers in New York City.

Figure 3: Spending and Employment by Income



uary 4-31, 2020, for three income groups. Panel A displays employment levels for workers with low (bottom quartile) median (two middle quartiles), and high income (top quartile). Panel B displays consumption expenditures for people in ZIP codes with low (bottom quartile) median (two middle quartiles), and high income (top quartile). Our sample period is January 14 to June 28, 2020. The data are aggregated to a weekly frequency from daily data provided by Chetty et al. (2020).

Five features emerge from Figure 3. First, employment and consumption expenditures fell for all groups in the beginning of the crisis and then recovered during the summer. Second, employment fell the most for workers in the bottom quartile of the income distribution, with a peak-to-trough decline of roughly 28 percent. The analogue decline for workers in the top-income quartile was only 14 percent. Third, consumption expenditures fell the most for people in high-income ZIP codes, with a peak-to-trough decline of 34 percent. The analogue decline for consumers in low-income ZIP codes is only 28 percent. Fourth, consumption expenditures of low-income people recover more quickly than those of high-income people. Five, the percentage decline in employment for high-income workers was much smaller than the percentage decline in consumption expenditures. So, for this group income was smoother than consumption.

4 Model

To study the economic impact of the Covid epidemic, we consider a small open economy that produces a nontradable and a tradable good. People are specialized in the type of goods that they can produce. There is a relatively large supply of people who can produce the nontradable good. As a result, wages are much higher in the tradable goods sector than in the nontradable goods sector. For convenience, we refer to people who work in the tradables and nontradables sector as high- and low-income people, respectively.

The nontradable good is associated with greater infection risk than the tradable good, both in production and consumption. The government and high-income people can borrow and lend in international capital markets at a fixed real interest rate. Low-income people are “hand-to-mouth” consumers.

For tractability, we assume that people are organized into high- and low-income households, each of which has a continuum of identical members. This household structure introduces limited sharing of health risks among people with the same income. Without the household structure, the asset holdings of a person would depend on how long they had a particular health status. So, as time goes by, we would have to keep track of an increasing number of types of people.

4.1 Tradable and nontradable consumption goods

The price of the nontradable good, P_{1t}, is determined in the domestic market. The price of the tradable good, P_{2t}, is determined in international markets by absolute purchasing power parity:

$$P_{2t} = X_t P_t^*.$$

Here, P_t^* is the price of the tradable good in foreign currency and X_t is the nominal exchange rate, expressed as units of domestic currency per unit of foreign currency. To simplify, we normalize X_t and P_t^* to one, so

$$P_{2t} = 1.$$

There is a measure-one continuum of competitive tradable and nontradable good firms. Production of the nontradable good (Y_{1t}) is given by:

$$Y_{1t} = AN_{lt}.$$

Production of the tradable good (Y_{2t}) is given by:

$$Y_{2t} = AN_{ht}.$$

The variables N_{lt} and N_{ht} denote the amount of labor used in the production of nontradable and tradable goods, respectively.

Firms are owned by high-income households. The profits of nontradable and tradable goods producers are

$$\begin{aligned} \psi_{1t} &= P_{1t}AN_{lt} - w_{lt}N_{lt}, \\ \psi_{2t} &= P_{2t}AN_{ht} - w_{ht}N_{ht}, \end{aligned}$$

where w_{lt} and w_{ht} are the wages of workers in the nontradable and tradable sector, respectively. Since people can only work in one sector, w_{lt} is, in general, not equal to w_{ht}.

Firms' first-order conditions are

$$w_{lt} = P_{1t}A, \tag{1}$$

$$w_{ht} = P_{2t}A. \tag{2}$$

4.2 Sticky wages

To simplify our analysis, we mimic the effects of nominal rigidities by assuming that wages are sticky and equal to their pre-epidemic levels. According to equation (1), sticky wages imply that P_{1t} is sticky. The assumption of sticky wages has no impact on the market for high-income workers because the equilibrium value of w_{ht} is constant and equal to its pre-epidemic value (see equation (2)).

The sticky-wage assumption does affect the equilibrium wages of low-income workers. As is standard in sticky-wage models (e.g. (Erceg, Henderson and Levin (2000)), we assume that employment is demand determined. So, the first-order condition for hours worked does not hold for low-income people. In contrast, the first-order conditions for hours worked by high-income workers does hold.

4.3 Epidemic dynamics

Before the onset of the epidemic, the economy is in a steady state. We normalize the size of the initial population to one. Let s_h and s_l denote the share of the initial population that has high and low income, respectively. As in the classic SIR model of Kermack and McKendrick (1927), at the onset of the epidemic the population is divided into four groups: susceptible (people who have not yet been exposed to the virus), infected (people who have been infected by the virus), recovered (people who survived the infection and acquired immunity), and deceased (people who died from the infection). We denote the fraction of the initial population in each group by S_{jt}, I_{jt}, R_{jt} and D_{jt}, respectively. The subscript j refers to high (h) or low skill (l), $j \in \{l, h\}$.

At time zero, a fraction ε of the population is infected by a virus. The initial infection is distributed across high- and low-skill workers according to the weight of these groups in the population,

$$\begin{aligned} I_{h0} &= s_h \varepsilon, \\ I_{l0} &= s_l \varepsilon. \end{aligned}$$

The rest of the population is susceptible to the virus,

$$\begin{aligned} S_{h0} &= s_h \left(1 - \varepsilon\right), \\ S_{l0} &= s_l \left(1 - \varepsilon\right). \end{aligned}$$

Social interactions occur at the beginning of the period (infected and susceptible people meet). Then, changes in health status unrelated to social interactions (recovery or death) occur. At the end of the period, the consequences of social interactions materialize and T_{jt} susceptible people of type j become infected.

As in Eichenbaum, Rebelo and Trabandt (2020), we assume that susceptible people can become infected in three ways: purchasing consumer goods, working, and through random interactions unrelated to economic activity.

The variables (c^s_{jgt}, c^i_{jgt}, c^r_{jgt}) and (n^s_{jt}, n^i_{jt}, n^r_{jt}) denote the consumption of good g and hours worked by a person of type j (high- or low-income) who is susceptible, infected and recovered, respectively.

Recall that a person of type j belongs to a household of type j. The shares of people in household type j who are susceptible (s_{jt}), infected (i_{jt}), recovered (r_{jt}), and deceased (d_{jt}) evolve according to

$$s_{jt+1} = s_{jt} - \tau_{jt}, \tag{3}$$

$$i_{jt+1} = (1 - \pi_{jr} - \pi_{jd})\, i_{jt} + \tau_{jt}, \tag{4}$$

$$r_{jt+1} = r_{jt} + \pi_{jr} i_{jt}, \tag{5}$$

$$d_{jt+1} = d_{jt} + \pi_{jd} i_{jt}. \tag{6}$$

In every period, t, τ_{jt} people who are susceptible become infected at time $t+1$ (equations (3) and (4)). A fraction π_{jr} of type-j people who are infected at time t become recovered at time $t+1$ (equations (4) and (5)). A fraction π_{jd} of type-j people who are infected at time t die at time $t+1$ (equations (4) and (6)).

The fraction of people in a low-income household who become infected at time t is

$$\begin{aligned} \tau_{lt} = {} & (1 - \epsilon^\tau_t)\, [\pi_1 s_{lt} c^s_{l1t} (I_{ht} C^I_{h1t} + I_{lt} C^I_{l1t}) + \pi_2 s_{lt} c^s_{l2t} (I_{ht} C^I_{h2t} + I_{lt} C^I_{l2t}) \\ & + \pi_{l3} s_{lt} n^s_{lt} I_{lt} N^I_{lt} + \pi_4 s_{lt} (I_{ht} + I_{lt})]. \end{aligned} \tag{7}$$

Here C^I_{j1t} and C^I_{j2t} is the total consumption by infected people type j of good 1 and 2, respectively. The variables I_{ht} and I_{lt} denote the aggregate number of high- and low-income people who are infected, respectively.

The probability of getting infected by consuming goods one and two is $\pi_1 s_{lt} c^s_{l1t} (I_{ht} C^I_{h1t} + I_{lt} C^I_{l1t})$ and $\pi_2 s_{lt} c^s_{l2t} (I_{ht} C^I_{h2t} + I_{lt} C^I_{l2t})$, respectively. The term $\pi_{l3} s_{lt} n^s_{lt} I_{lt} N^I_{lt}$ represents the probability of becoming infected at work. Equation (7) embodies the assumption that low-income people only interact with other low-income people at work. The term $\pi_4 s_{lt} (I_{ht} + I_{lt})$

represents the probability of being infected due to interactions that are unrelated to consumption or work.

The term $1 - \epsilon_t^\tau$ in equation (7) represents time variation in the probability of becoming infected. This variation comes from two sources. First, there is seasonality in rates of infection. When the weather is hot, people spend less time indoors, reducing the chances of infection. Also, it is possible that Summer conditions such as warm temperatures and abundant UV light make it harder for the virus to propagate (see e.g. Merow and Urban (2020)). Second, businesses reorganized to reduce the probability that workers and customers will get infected. This reorganization includes home delivery of food, installation of Plexiglas dividers at retail outlets, and implementation of social distancing rules and mask usage in consumption and production activities.

In a high-income household, the fraction of people who get infected at time t is

$$\begin{aligned} \tau_{ht} \quad = \quad & (1 - \epsilon_t^\tau)\left[\pi_1 s_{ht} c_{h1t}^s (I_{ht} C_{h1t} + I_{lt} C_{l1t}) + \pi_2 s_{ht} c_{h2t}^s (I_{ht} C_{h2t} + I_{lt} C_{l2t}) \right. \\ & \left. + \pi_{h3} s_{ht} n_{ht}^s I_{ht} N_{ht} + \pi_4 s_{ht} \left(I_{ht} + I_{lt}\right)\right]. \end{aligned} \tag{8}$$

The terms on the right-had side of (8) are the analogue of those on the right-hand side of (7). Equation (8) embodies the assumption that high-income people only interact with other high-income people at work.

4.4 Households

High-income people can save in international bond markets at a fixed interest rate r^*. Low-income people are "hand to mouth," i.e. their consumption and income coincide. We view the latter assumption as extreme, but it lets us model the fact that some people have a very high propensity to consume.

The nontradable good is essential in the sense that people have to consume at least $\bar{c}$ units of it. The tradable good is not essential, so there is no minimum consumption requirement.

The momentary utility function of a person with health status x is given by

$$u(c_{j1t}^x, c_{j2t}^x, n_{jt}^x) = m + (1 - \epsilon_t^c)\left[(1 - \eta)\log(c_{j1t}^x - \bar{c}) + \eta \log(c_{j2t}^x)\right] - \frac{\theta}{2}\left(n_{jt}^x\right)^2,$$

where x can take the values s, i, and r, corresponding to susceptible, infected and recovered, respectively. We use the variable ϵ_t^c to model exogenous variations in consumption demand associated with containment measures imposed by the government. We discuss the motivation for this way of modeling containment in the calibration section. As in Hall and Jones

(2007), momentary utility includes a constant m that affects the value of life. We use this constant to ensure that lifetime utility is positive so that people prefer living to dying.

Type-j households maximize their lifetime utility,

$$U_j = \sum_{t=0}^{\infty} \beta^t \left\{ s_{jt} u(c^s_{j1t}, c^s_{j2t}, n^s_{jt}) + i_{jt} u(c^i_{j1t}, c^i_{j2t}, n^i_{jt}) + r_{jt} u(c^r_{j1t}, c^r_{j2t}, n^r_{jt}) \right\}.$$

Here, s_{jt}, i_{jt}, and r_{jt} denote the measure of family members who are susceptible, infected and recovered.

The budget constraint for high-income households expressed in units of local currency is,

$$\begin{aligned} & X_t b^*_{ht+1} + P_{1t}\left(s_{ht}c^s_{h1t} + i_{ht}c^i_{h1t} + r_{ht}c^r_{h1t}\right) + P_{2t}\left(s_{ht}c^s_{h2t} + i_{ht}c^i_{h2t} + r_{ht}c^r_{h2t}\right) \\ = \ & w_{ht}\left(s_{ht}n^s_{ht} + i_{ht}n^i_{ht} + r_{ht}n^r_{ht}\right) + (1+r^*) X_t b^*_{ht} + \psi_{1t} + \psi_{2t} + \Gamma_{ht}. \end{aligned} \tag{9}$$

Here b^*_{ht} denotes the household's holdings of a foreign-currency bond and Γ_{ht} is government lump-sum transfers. Recall that X_t is the spot exchange rate which is equal to one and that ψ_{1t}, and ψ_{2t} denote the profits in the nontradable and tradable sector. There is no sign restriction on b^*_{ht}. The household is subject to the non-Ponzi scheme condition,

$$\lim_{t\to\infty} \frac{b^*_{ht+1}}{(1+r^*)^t} = 0.$$

There is no expectation operator in this expression because the household has a continuum of members, so, the law of large numbers applies.

The nominal budget constraint for low-income households is,

$$\begin{aligned} & P_{1t}\left(s_{lt}c^s_{l1t} + i_{lt}c^i_{l1t} + r_{lt}c^r_{l1t}\right) + P_{2t}(s_{lt}c^s_{l2t} + i_{lt}c^i_{l2t} + r_{lt}c^r_{l2t}) \\ = \ & w_{lt}(s_{lt}n^s_{lt} + i_{lt}n^i_{lt} + r_{lt}n^r_{lt}) + \Gamma_{lt}, \end{aligned} \tag{10}$$

where Γ_{lt} is government lump-sum transfers.

The household takes into account the probability of its susceptible members becoming infected when consuming or working. The household takes as given the total number of high- and low-income people infected in the economy, as well as aggregate consumption and hours worked.

The variables λ_{jst}, $\lambda_{j\tau t}$, and λ_{jit} denote the Lagrange multipliers associated with equations (3), (4), and (5). The variable λ_{bjt} denotes the Lagrange multiplier associated with the budget constraint for household type j.

The first-order conditions for the consumption of good one and two by susceptible people of type j with health status x are

$$(1-\epsilon_t^c)\,\frac{1-\eta}{c_{j1t}^x-\bar{c}} = P_{1t}\lambda_{bjt} - \lambda_{j\tau t}\,(1-\epsilon_t^\tau)\,\pi_1(I_{ht}C_{h1t}^i + I_{lt}C_{l1t}^i)\mathfrak{I}_j,$$

$$(1-\epsilon_t^c)\,\frac{\eta}{c_{j2t}^x} = P_{2t}\lambda_{bjt} - \lambda_{j\tau t}\,(1-\epsilon_t^\tau)\,\pi_2(I_{ht}C_{h2t}^i + I_{lt}C_{l2t}^i)\mathfrak{I}_j.$$

Here, the indicator function $\mathfrak{I}_j$ takes the value one if a person of type j is susceptible and zero otherwise.

The first-order condition for the labor supply of high-income susceptible people is:

$$\theta n_{ht}^s = w_{ht}\lambda_{hbt} + \lambda_{h\tau t}\pi_{j3}\,(1-\epsilon_t^\tau)\,I_{ht}N_{ht}^i\mathfrak{I}_h.$$

Recall that the first-order conditions for hours worked by low-income people do not hold because of sticky wages. Hours worked by low-income people are demand determined. We assume that all low-income people supply the same hours of work independently of their health status.

The first-order conditions with respect to s_{jt+1}, i_{jt+1}, r_{jt+1} and τ_{jt} are:

$$\begin{aligned}
&m + \left(1-\epsilon_{t+1}^c\right)(1-\eta)\log(c_{j1t+1}^s-\bar{c}) + \left(1-\epsilon_{t+1}^c\right)\eta\log(c_{j2t+1}^s)\\
&-\frac{\theta}{2}\left(n_{jt+1}^s\right)^2 + \lambda_{\tau jt+1}\left(1-\epsilon_{t+1}^\tau\right)[\pi_1 c_{j1t+1}^s(I_{jt+1}C_{j1t+1}^i + I_{jt+1}C_{j1t+1}^i)\\
&+\pi_2 c_{j2t+1}^s(I_{jt+1}C_{j2t+1}^i + I_{jt+1}C_{j2t+1}^i)\\
&+\pi_{j3}n_{jt+1}^s I_{jt+1}N_{jt+1}^i + \pi_4\left(I_{jt+1}+I_{jt+1}\right)]\\
&+\lambda_{bjt+1}\left[w_{jt+1}n_{jt+1}^s - P_{1t+1}c_{j1t+1}^s - P_{2t+1}c_{j2t+1}^s\right] - \lambda_{jt}^s/\beta + \lambda_{jt+1}^s = 0,
\end{aligned}$$

$$\begin{aligned}
&m + \left(1-\epsilon_{t+1}^c\right)(1-\eta)\log(c_{j1t+1}^i-\bar{c}) + \left(1-\epsilon_{t+1}^c\right)\eta\log(c_{j2t+1}^i)\\
&-\frac{\theta}{2}\left(n_{jt+1}^i\right)^2 + \lambda_{bjt+1}\left[w_{jt+1}n_{jt+1}^i - P_{1t+1}c_{j1t+1}^i - P_{2t+1}c_{j2t+1}^i\right]\\
&-\lambda_{jt}^i/\beta + \lambda_{jt+1}^i\left(1-\pi_{rjt+1}-\pi_{jdt+1}\right) + \lambda_{jt+1}^r\pi_{rj} = 0,
\end{aligned}$$

$$\begin{aligned}
&m + \left(1-\epsilon_{t+1}^c\right)(1-\eta)\log(c_{j1t+1}^r-\bar{c}) + \left(1-\epsilon_{t+1}^c\right)\eta\log(c_{j2t+1}^r)\\
&-\frac{\theta}{2}\left(n_{jt+1}^r\right)^2 + \lambda_{bjt+1}[w_{jt+1}n_{jt+1}^r - P_{1t+1}c_{j1t+1}^r - P_{2t+1}c_{j2t+1}^r] - \lambda_{jt}^r/\beta + \lambda_{jt+1}^r = 0,
\end{aligned}$$

$$-\lambda_{jt}^\tau - \lambda_{jt}^s + \lambda_{jt}^i = 0.$$

4.5 Government budget constraint

We model the various income-stabilization programs implemented in the U.S. and in other countries as follows. The government makes positive lump-sum transfers to low-income workers ($\Gamma_{lt} > 0$) during the epidemic. These transfers are financed by issuing government debt, b_{gt} which yields an interest rate r^*. In every period after time T, the government levies lump-sum taxes on high-income workers ($\Gamma_{ht} < 0$) to finance interest on the accumulated government debt. The flow government budget constraint is given by

$$b_{gt+1} = \Gamma_{lt} \left(S_{lt} + I_{lt} + R_{lt} \right) + \Gamma_{ht} \left(S_{ht} + I_{ht} + R_{ht} \right) + (1 + r^*) b_{gt}, \tag{11}$$

$$\Gamma_{ht} = 0 \text{ for } t < T \,, \tag{12}$$

$$\Gamma_{ht} \left(S_{ht} + I_{ht} + R_{ht} \right) = -r^* b_{gt} \text{ for } t \geq T, \tag{13}$$

where S_{jt}, I_{jt} and R_{jt} denote the aggregate level of susceptibles, infected and recovered people. This formulation is consistent with a run up in government debt during the epidemic. Equation (13) implies that the level of government debt remains stable after period T. Equations (11), (12), and (13) satisfy the no-Ponzi scheme condition

$$\lim_{t \to \infty} \frac{b_{gt+1}}{(1 + r^*)^t} = 0.$$

Ricardian equivalence holds for high-income households who can borrow and lend at the same rate as the government. So, the precise path of Γ_{ht} does not affect consumption of high-income households.

4.6 Equilibrium conditions

In equilibrium, households maximize their utility, firms maximize profits, and the government budget constraint holds. The markets for good one and two clear,

$$Y_{1t} = (S_{ht} c^s_{h1t} + I_{ht} c^i_{h1t} + R_{ht} c^r_{h1t}) + (S_{lt} c^s_{l1t} + I_{lt} c^i_{l1t} + R_{lt} c^r_{l1t}),$$

$$\begin{aligned} & b^*_{ht+1} + (S_{lt} c^s_{l2t} + I_{lt} c^i_{l2t} + R_{lt} c^r_{l2t}) + \left(S_{ht} c^s_{h2t} + I_{ht} c^i_{h2t} + R_{ht} c^r_{h2t} \right) \\ = \quad & Y_{2t} + (1 + r^*) \, b^*_{ht}. \end{aligned}$$

The labor market for high- and low-income people clear:

$$N_{lt} = S_{lt} n^s_{lt} + I_{lt} n^i_{lt} + R_{lt} n^r_{lt},$$

$$N_{ht} = S_{ht}n_{ht}^s + I_{ht}n_{ht}^i + R_{ht}n_{ht}^r.$$

The fraction of people in household type j who are susceptible, infected and recovered is the same as the corresponding fractions in the population:

$$s_{jt} = S_{jt},\ i_{jt} = I_{jt},\ \text{and}\ r_{jt} = R_{jt}.$$

Aggregate consumption (C_t) and hours worked (N_t) are given by

$$\begin{aligned} C_t &= P_{1t}\left[\left(S_{ht}c_{h1t}^s + I_{ht}c_{h1t}^i + R_{ht}c_{h1t}^r\right) + \left(S_{lt}c_{l1t}^s + I_{lt}c_{l1t}^i + R_{lt}c_{l1t}^r\right)\right] \\ &\quad \left[\left(S_{ht}c_{h2t}^s + I_{ht}c_{h2t}^i + R_{ht}c_{h2t}^r\right) + \left(S_{lt}c_{l2t}^s + I_{lt}c_{l2t}^i + R_{lt}c_{l2t}^r\right)\right], \end{aligned}$$

$$N_t = \left(S_{lt}n_{lt}^s + I_{lt}n_{lt}^i + R_{lt}n_{lt}^r\right) + \left(S_{ht}n_{ht}^s + I_{ht}n_{ht}^i + R_{ht}n_{ht}^r\right).$$

5 Quantitative analysis

In this section, we describe the model calibration and discuss the model's quantitative properties. We then discuss how containment policies and fiscal transfers impacted inequality in life and death.

5.1 Model Calibration

We set the weekly discount factor, β, to $0.98^{1/52}$. We choose θ so that weekly per-capita hours worked are equal to 28, the average hours worked in the U.S. according to the Bureau of Labor Statistics 2018 time-use survey. The subsistence level, $\bar{c}$, is chosen so that the share of high-skill workers in the total wage bill is 38 percent. We set $\eta = 1/2$, which implies that the share of good one in total consumption expenditures is roughly 50 percent (see Table 3 in Burstein, Eichenbaum and Rebelo (2005)).[4] The constant in the utility function, m, is chosen so that the weighted average value of a statistical life is 3.5 million.[5] This value is in the range discussed by Kniesner and Viscusi (2019).

We set the share of high-income workers in the labor force to 18 percent. This value is obtained by combining data from the Bureau of Labor Statistics on the distribution of employment across sectors and the share of high-skill workers in each of these sectors reported

[4]This is a conservative estimate of the importance of non-tradable goods because it abstracts from distribution costs associated with tradable goods.

[5]The underlying value of life implied by our calibration for low and high-income individuals is 2 and 10 million dollars, respectively.

by Jaimovich et al. (2020). These authors define high-skill workers in a given industry as workers whose wage exceeds the average wage of college graduates in that industry.

We choose bond holdings in the initial steady state so that average household net worth is equal to \$68,000, the estimate produced by the U.S. Census for 2010. Since low-income families have zero bond holdings and high-income households represent 18 percent of the population, bond holdings for high-income households are \$68,000/0.18 = \$380,000. The productivity parameter A is set so that per capita income is \$58,000 in the pre-epidemic steady state.

Consistent with the evidence in Drefahl et al. (2020), we assume that the mortality rate is roughly 40 percent higher for low-income people than for high income people.[6] This evidence is based on Swedish data. We presume that the difference in mortality rates for low- and high-income people are larger in the U.S. because of the high incidence of comorbidity amongst poor people and the absence of a universal health-care system. So, our calibration provides a conservative estimate of the role of pre-existing inequality in Covid-mortality rates.

We set the parameters that control recovery and death for high-income people to satisfy three conditions. First, the case fatality rate, $\pi_{hd}/(\pi_{hd}+\pi_{hr})$, is 0.357 percent. Second, the average time to recovery or death for both groups ($1/(\pi_{hd}+\pi_{hr})$ and $1/(\pi_{ld}+\pi_{lr})$, respectively) is 14 days. Third, π_{ld} is 40 percent higher than π_{hd}. We obtain the following parameter values: $\pi_{ld}=0.0025$, $\pi_{hd}=0.0018$, $\pi_{lr}=0.4975$ and $\pi_{hr}=0.4982$.

We set the initial seed of infection in January 2020 (ε) to 0.001. To fit the data on spending and employment, we choose π_1, π_2, π_{l3}, π_{h3}, and π_4 so that the model satisfies three conditions. First, in the beginning of the epidemic, 1/12 of the infections occur through consumption, 5/12 through work, and 6/12 from non-economic interactions. Second, the parameters are consistent with the "Merkel scenario," which means that eventually 60 percent of the population is infected in the absence of containment or actions by households to reduce the chances of getting infected. Third, the differential behavior of spending and hours worked for high- and low-income people in the competitive equilibrium is broadly consistent with the evidence in Chetty et al. (2020). This requirement implies that: (i) infections

[6] We obtain this estimate by averaging the case fatality rates for men and women reported in Table 3 of Drefahl et al. (2020). In the last tercile of the income distribution the average mortality rate across men and women is (0.76+0.26)/2 = 0.51. The analogue number for the second to last tercile is (0.51-0.01)/2 = 0.25. The average of the bottom 82 percent is given by ((0.33-0.18)$\times$ 0+0.33$\times$ 0.51+0.33$\times$ 0.25)/(1-0.18) = 0.38.

through work are about 20 times more likely for low-income people than for high-income people, and (ii) consumption of good one is 5 percent more contagious than consumption of good two. The resulting parameters of the transmission function are: π_1 =7.4040×10^{-9}, π_2 =1.1457×10^{-7}, $\pi_{h3} = 8.3779\times10^{-4}$, $\pi_{l3} = 5.2498\times10^{-4}$ and $\pi_4 = 0.3743$.

Recall that the term $1-\epsilon_t^\tau$ captures the effect on infection rates of private sector reorganization, and changes in people's behavior such as mask uses. We choose the time path for ϵ_t^τ so that the model can capture the fact that spending recovered in the 3rd quarter without a corresponding surge in the number of Covid deaths. As a result, we assume that $1-\epsilon_t^\tau$ falls gradually until it declines by 70 percent between the middle and the end of April.

The term ϵ_t^c captures government-imposed containment measures. We choose the level and time path for ϵ_t^c with two objectives in mind. First, we want the model to be consistent with the mid-March upsurge of workplace closings in the U.S. reported by Oxford University's Coronavirus government response tracker. Second, we want the model to be consistent with troughs for consumption and employment of different groups while not overshooting the expansion that occurred in the 3rd quarter. These considerations led us to chose a value of ϵ_t^c equal to 30 percent from mid-March on.

Congress passed the Coronavirus Aid, Relief, and Economic Security (CARES) Act on March 27, 2020. Under this law, the U.S. government distributed 267 billion dollars stimulus payments to lower income households (Garner, Safir and Schild (2020)). This value implies a transfer per low-income household of $267,000/(260\times0.82)$, where 260 is the number of people 16 and older in the U.S., measured in millions, and 0.82 is the share of low-income workers in the population. Low-income workers received payments from the CARES act in a lump sum manner and chose to smooth out the use of those funds over the time. This assumption is consistent with findings in Cox et al. (2020) who argue that transfers associated with stimulus programs can explain the disproportionate increase in liquid balances for low-income people. These balances were spendt over time in a way that smoothed consumption. To mimic the resulting consumption pattern in our model, we assume that per capita government transfers to low income people were \$50 a week for half a year, starting in mid April. So, in the model the government effectively smooths consumption of low income households over time.

Finally, we model people's expectations as follows. The epidemic starts in the first week of January but people don't take it into account in their choices of consumption and labor until mid-March. So, all economic variables remain at their steady-state values until mid

March. But people's health status is evolving according to equations (3), (4), (5), (6), (7), and (8). In mid-March, people become aware of the epidemic as well as the path for government transfers to low-income workers, taxes on high-income workers, containment measures, and changes in transmission probabilities associated with business reorganization and seasonality.

5.2 Quantitative properties of the model

Recall that, for tractability, our model has only two types of people. To map the data into this framework, we convert Chetty et al. (2020)'s three income categories into two categories: high income (the top quartile) and low income (the weighted average of the three bottom quartiles). Figure 4 displays income and spending for these two groups as well as total Covid deaths. The red and blue solid (dotted) lines correspond to the high- and low-income group in the data (model), respectively.

This figure shows that our model captures the key qualitative features of the data that we emphasized in the introduction. First, economic activity troughs in the spring of 2020 and then partially recovers in the summer. Second, the spending by high-income people falls by in percentage terms *more* than that of low-income people. Third, employment of high-income people falls in percentage terms by *less* than that of low-income people. Fourth, consumption of high-income people falls by more than employment, so that their income is smoother than their consumption.

From a quantitative point of view the model does reasonably well, particularly at matching the spending of low-income people and, to a lesser extent, their employment. However, the model understates the mid-summer recovery of spending by high-income people as well as the fall in their employment. Finally, the model does a reasonable, albeit imperfect, job of accounting for total Covid deaths up to mid summer.

In our model, the initial sharp decline in economic activity is fuelled by people's realization in March that there is an ongoing epidemic. The behavior of high-income people is governed by two key considerations. First, they are much less prone to becoming infected at work than low-income people. Second, they have a higher value of life than low-income people which makes them more sensitive to the dangers of becoming infected through market activity. Taken together, these considerations imply that employment falls by *less* for high-income people than for low-income people. High-income people cut their consumption by *more* than low-income people. This result partially reflects the fact that high-income

Figure 4: Spending, Employment and Deaths

people have access to financial markets, which they use to increase their savings.[7]

The behavior of low-income people is governed by the following key considerations. Wages in the nontradable good sector are sticky, so employment is demand determined. Both high- and low-income people cut back on all forms of consumption. Recall that nontradable goods are more infectious than tradable goods, So, high-income people cut back on their consumption of nontradable goods relative to tradable goods by a large amount. Low-income people are closer to the subsistence level, $\bar{c}$, so they reduce their consumption of nontradable goods by less than tradable goods. Since high-income people represent the bulk of spending in both categories, their behavior dominates and there is a disproportionate decline in the demand for nontradable goods. The result is a disproportionately large decline in the employment of low-income people.

The model is consistent with the partial recovery in economic activity during the summer. This recovery is fueled by the assumed drop in infection rates during this period, the phasing out of containment, and the implementation of government transfers.

[7] In the data, savings also increased for low-income people. This increase primarily reflected the pattern of government transfers and consumption smoothing behavior, see Cox et al. (2020).

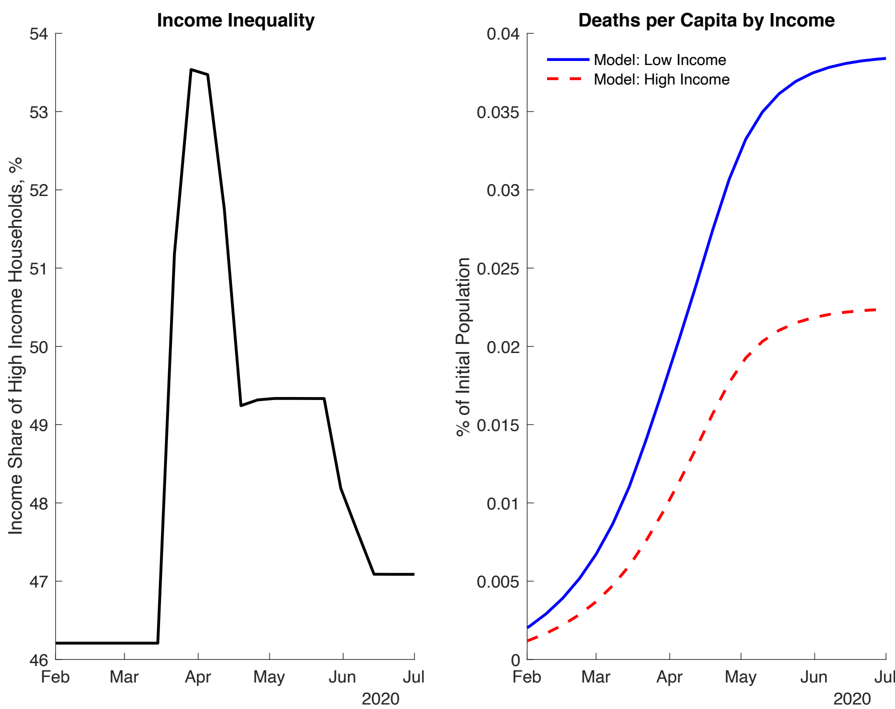
Figure 5 summarizes the model's implications for inequality in life and death. At the beginning of the epidemic, high-income people account for 18 percent of the population and 46 percent of total income. Their share of income is substantially higher at the peak of the epidemic in April. This result reflects the sharp relative decline in employment of low-income people and the presence of sticky wages. Consistent with this intuition, much of the inequality wanes as the economy partially recovers in the summer. In this precise sense, the model captures the rise in inequality induced by the epidemic.

The second panel of Figure 5 displays Covid mortality rates for high- and low-income people. The model is consistent with the unequal health impact of the epidemic. This inequality reflects two forces. The first force is pre-existing inequality in comorbidity rates and access to quality health care. This inequality would have led to a higher death toll among low-income people, regardless of the economic impact of Covid. The second force is the unequal impact of the Covid recession on different types of people. Low-income people are more likely to become infected at work. In addition, they spend a higher fraction of their income on goods whose consumption is associated with higher infection rates. Taken together, these considerations imply that their health is disproportionately impacted by the epidemic.

To isolate the effect of pre-existing inequality in comorbidity rates and access to quality health care, we solve the model assuming that the case fatality rate is the same for high- and low-income people ($\pi_{ld} = \pi_{hd}$). Figure 6 displays the cumulative mortality rates in this version of the model as well as in the benchmark model. Two key results emerge. First, the death rate among low-income people would have been 30 percent lower if they had the same case-fatality rate as high-income people. So, the model implies that pre-existing inequality is a powerful force generating inequality in death. Broadly speaking, this finding is consistent with our empirical findings summarized in Section 2 about the link between pre-existing inequality and higher mortality rates across countries and U.S. states.

Second, even when $\pi_{ld} = \pi_{hd}$, the Covid mortality rate would have been 23 percent higher for low-income people versus high-income people (0.0027 versus 0.0022 percent). The reason is that low-income people work in jobs that expose them to a higher probability of infection. The latter result is consistent with the health literature cited above as well as the economic literature (e.g. Kaplan, Moll and Violante (2020)).

Figure 5: Inequality in Life and Death

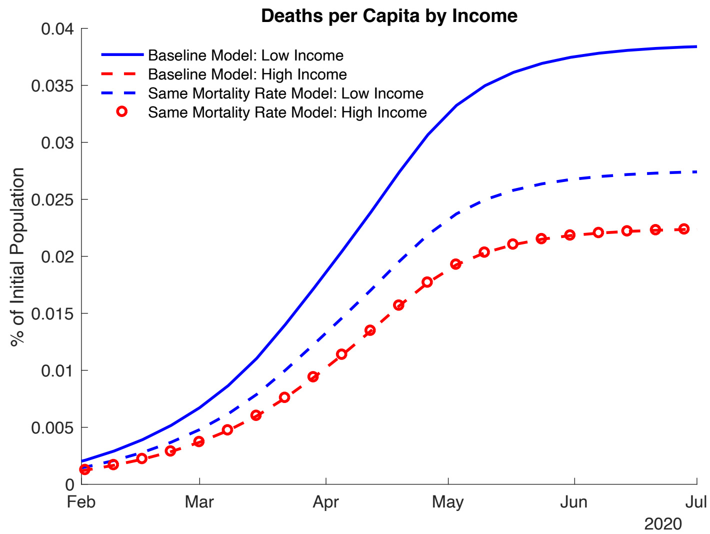


5.3 Policy interventions

Our model embodies two important policies implemented during the epidemic: containment and fiscal transfers to low-income people. We use the model to assess how these policies impacted inequality in life and death.

The pink lines in column one and two of Figure 7 shows how income inequality and deaths per capita would have evolved in the absence of transfers to low-income people. Two key results emerge. First, the rise in income inequality generated by the epidemic would have been much more persistent absent fiscal transfers. The reason is that transfers increase the demand for nontradable goods and employment of low-income people. Second, the mortality rates would have been slightly lower for both income groups had there been no transfers. Absent transfers economic activity would have been lower, resulting in lower infection rates. Overall, transfers reduced income inequality and stimulated economic activity without having a large impact on the death toll of the epidemic. So, according to our model there is not much of a trade off between using transfers to reduce Covid-related income inequality and the adverse health outcomes of higher economic activity.

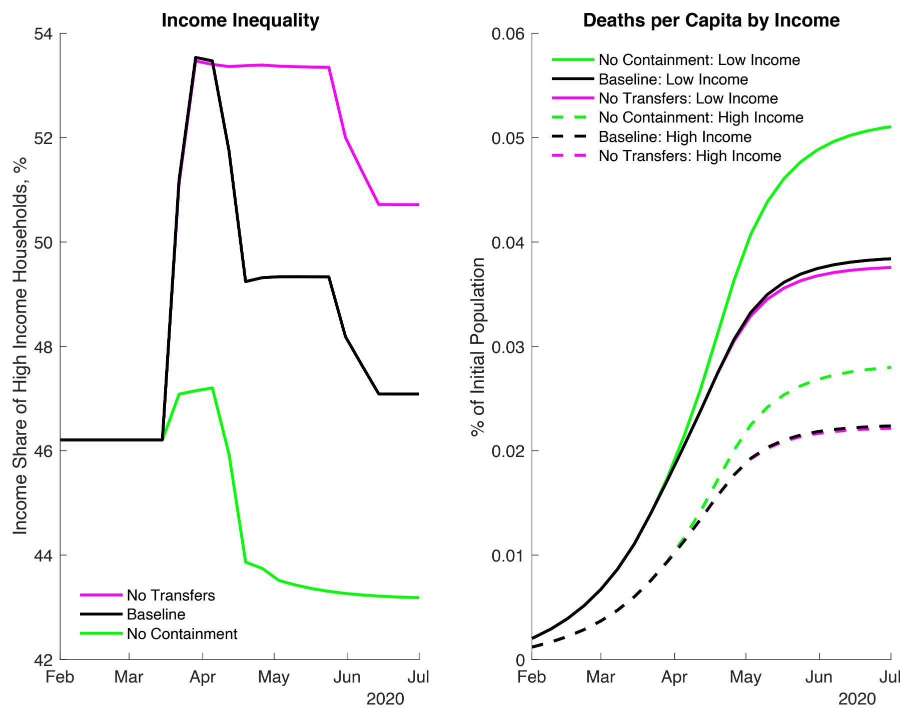
Figure 6: Effects of Mortality Rate on Deaths



The green lines in column one and two of Figure 7 shows how income inequality and deaths per capita would have evolved in the absence of containment. Both groups consume more in this scenario. Since wages are sticky in the nontradable good sector and the demand for nontradable goods is higher, there is more employment for low-income workers. The spending effects are particularly strong in the mid summer since low-income workers continue to receive fiscal transfers and there is no containment. As a result, income inequality temporarily dips below its pre-epidemic level.

In sum, containment disproportionately reduced the employment and income of low-income workers, magnifying income inequality. At the same time, containment dramatically reduced mortality rates for all people. This reduction was roughly 31 percent for low-income workers and 27 percent for high-income workers. So containment per se greatly increases income inequality but saved many lives of both high- and low-income people.

Figure 7: Sensitivity of Inequality in Life and Death



6 Conclusion

In this paper, we develop a model that allows us to analyze why poor people suffered disproportionately from the Covid epidemic. While simple, our model accounts for key aspects of the Covid recession in the U.S.. First, economic activity steeply declined at the onset of the epidemic and then partially recovered in the summer. Second, employment fell disproportionately more and consumer spending disproportionately less for low-income people, relative to high-income people. Finally, consumer spending by high-income people fell, in percentage terms, by substantially more than their employment.

For the U.S., our model suggests that pre-existing inequality in health conditions was a key driver of the disproportionately high toll suffered by poor people. But inequality in the nature of occupations contributed a great deal as well. Neither of these forces could have been effectively countered once the epidemic began. As a result, the poor paid a terrible price.

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7 Appendix

Table 4: *World panel, robustness over different controls*

	(1) Baseline	(2) Spec 1	(3) Spec 2	(4) Spec 3
Gini Index	3.51**	3.00**	4.07**	3.63**
	(1.40)	(1.40)	(1.81)	(1.43)
GDP per capita	0.54	-1.01	0.59	0.37
	(0.43)	(0.90)	(0.49)	(0.46)
65 or older, share of pop	0.98	0.18	1.22	0.91
	(1.09)	(1.12)	(1.35)	(1.09)
Urban share	2.33*	1.30	2.38	1.91
	(1.37)	(1.55)	(1.89)	(1.50)
Physicians per 1000	-0.24	-0.04	-0.29	-0.10
	(0.73)	(0.69)	(0.91)	(0.71)
Tot. Health Expenditure		1.51**		
		(0.69)		
Average Jan-March Temp			0.03	
			(0.19)	
Comorbidity				-0.73
				(0.81)
Constant	-25.77**	-13.34	-29.11**	-20.65*
	(9.98)	(12.75)	(12.96)	(11.47)
Observations	69	69	52	69
R-squared	0.21	0.26	0.25	0.22

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: All variables included in the regression are in logs. Sources are outlined in the main text. Robust Standard Errors are reported in parenthesis.

Table 5: *OECD panel, robustness over different controls*

	(1) Baseline	(2) Spec 1	(3) Spec 2	(4) Spec 3
Gini Index	3.74**	3.37*	2.36	3.73**
	(1.62)	(1.68)	(2.84)	(1.65)
GDP per capita	1.26***	-0.60	0.80	1.29*
	(0.46)	(0.78)	(0.51)	(0.64)
65 or older, share of pop	0.07	-0.72	-0.46	0.07
	(1.44)	(1.51)	(1.80)	(1.45)
Urban share	0.70	-0.02	-0.71	0.77
	(1.51)	(1.52)	(2.42)	(1.62)
Physicians per 1000	0.38	-0.02	-0.08	-0.14
	(1.10)	(1.04)	(1.57)	(1.11)
Tot. Health Expenditure		1.59**		
		(0.59)		
Average Jan-March Temp			-0.04	
			(0.20)	
Comorbidity				0.09
				(1.23)
Constant	-24.67**	-11.35	-7.08	-25.50*
	(10.48)	(12.45)	(12.17)	(14.45)
Observations	37	37	24	37
R-squared	0.20	0.26	0.11	0.21

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All variables included in the regression are in logs. Sources are outlined in the main text. Robust Standard Errors are reported in parenthesis.

Table 6: *World panel, robustness over different Gini Inequality Measures*

	(1) Baseline	(2) Spec 1	(3) Spec 2	(4) Spec 3	(5) Spec 4
UN Income Gini Index	3.51**				
	(1.40)				
GDP per capita	0.54	0.49	0.72	0.07	0.47
	(0.43)	(0.42)	(0.47)	(0.56)	(0.55)
65 or older, share of pop	0.98	0.69	0.41	0.05	0.55
	(1.09)	(0.95)	(0.90)	(1.19)	(1.40)
Urban share	2.33*	2.18	2.98**	2.89	3.08*
	(1.37)	(1.37)	(1.48)	(1.76)	(1.64)
Physicians per 1000	-0.24	-0.30	-0.70	-0.23	-0.79
	(0.73)	(0.69)	(0.55)	(0.84)	(0.71)
Solt Income Gini measure 2014		3.23**			
		(1.33)			
Solt Income Gini 2017			3.23**		
			(1.44)		
World Econ Forum Income Gini Index				1.42	
				(1.33)	
World Econ Forum Wealth Gini Index					2.00
					(1.64)
Constant	-25.77**	-7.77	-12.33*	-14.47**	-21.20**
	(9.98)	(5.98)	(6.88)	(5.88)	(10.25)
Observations	69	68	58	59	62
R-squared	0.21	0.18	0.26	0.17	0.18

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All variables included in the regression are in logs. Sources are outlined in the main text. Robust Standard Errors are reported in parenthesis.

Table 7: *OECD panel, robustness over different Gini Inequality Measures*

	(1) Baseline	(2) Spec 1	(3) Spec 2	(4) Spec 3	(5) Spec 4
UN Income Gini Index	3.74**				
	(1.62)				
GDP per capita	1.26***	1.21**	0.75	-0.01	1.37**
	(0.46)	(0.50)	(0.55)	(0.46)	(0.56)
65 or older, share of pop	0.07	-0.18	0.75	-0.45	0.10
	(1.44)	(1.31)	(1.21)	(0.90)	(1.31)
Urban share	0.70	1.07	2.11	0.77	1.40
	(1.51)	(1.53)	(1.56)	(1.53)	(1.68)
Physicians per 1000	-0.14	-0.10	-0.86	0.29	-0.21
	(1.10)	(1.04)	(0.96)	(0.95)	(1.07)
Solt Income Gini measure 2014		3.50**			
		(1.70)			
Solt Income Gini 2017			2.98*		
			(1.60)		
World Econ Forum Income Gini Index				3.73***	
				(1.13)	
World Econ Forum Wealth Gini Index					4.08**
					(1.64)
Constant	-24.67**	-8.06	-9.89	-13.29*	-29.98***
	(10.48)	(6.93)	(6.71)	(6.82)	(10.77)
Observations	37	37	35	36	36
R-squared	0.20	0.17	0.21	0.23	0.20

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All variables included in the regression are in logs. Sources are outlined in the main text. Robust Standard Errors are reported in parenthesis.