The medium-run wealth and health inequality implications of COVID-19.*

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Abstract

We study the joint evolution of the distributions of health and wealth under household level shocks to health and income, and uncertainty about disease outbreaks. We specify a model in which health and wealth are jointly determined, under idiosyncratic income and health risk that is related to disease outbreak risk. We calibrate the model to a number of properties of the pre-COVID-19 UK health and income distributions, including the social mobility matrix and differences in mean health and in health and labour income risk by professional class. We use the model to study the likely medium-run wealth and health inequality implications of the COVID-19 pandemic in the UK, and find that the majority of future time paths imply significant increases in both wealth and health inequality.

Keywords: health, wealth, inequality, incomplete markets
JEL Classification: I14, I12, E21

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1 Introduction

Pandemics create health and economic crises that impact households heterogeneously, increasing risk and inequality in both income and health. The inequality implications of COVID-19 have been examined in several studies (e.g. Stantcheva (2021) for a review, and Marmot *et al.* (2020) focusing on health inequality).[1] Existing analysis has examined the effects on health and income inequality during the pandemic, noting that such changes can have long-lasting implications[2]. However, given that health and wealth are jointly determined and persist, reflecting current as well as past decisions and shocks, an understanding of the scale of the inequality implications of a pandemic requires a quantitative analysis of the medium-run dynamics of health and wealth inequality that are induced by the pandemic.[3] In this paper, we model and compute the dynamic evolution of the joint distribution of health and wealth across households following the COVID-19 pandemic shock, under recurrent disease outbreak risk.

Health and wealth inequality are determined jointly. Given the strong link between health outcomes and income/wealth (e.g. Marmot (2004), Semyonov *et al.* (2013) and Payne (2017)), quantifying the health inequality implications of the pandemic in the medium run requires a model where health depends on wealth, which encapsulates past income shocks. At the same time, health is in effect a utility-bearing asset whose choice in response to shocks and to changes in risk is made simultaneously with wealth. Hence, quantifying the wealth inequality implications of a pandemic in the medium run requires a model where households choose the portfolio of health and wealth. This is particularly relevant in a post-pandemic environment following large shocks to health and income and changes in health and income risk, and thus potentially requiring significant adjustments in the portfolio of health and wealth.

The disease outbreaks during the pandemic waves are a major aggregate-level shock that increases idiosyncratic health risk and, by hampering economic activity directly or via measures to contain the spread of the disease, alter possibilities for earnings, consumption and savings asymmetrically across the population. However, the probability of significant disease outbreaks remains high for a potentially long time period after the main pandemic waves. Following the main waves, recurrent outbreaks may occur due to re-introduction of the virus, new variants, waning immunity, human behaviour (e.g. vaccine refusal), or population turnover leading to reductions in population-level immunity (e.g. Anderson and May (1991) and for COVID-19 e.g. BMJ (2021), Nature (2021) and Kissler *et al.* (2020)). This epidemiological risk is consistent with empirical evidence from the UK and the US for the 1918-19 pandemic, and from England/Wales for the 1890-91 pandemic, revealing several large outbreaks after the main pandemic waves in all cases. To illustrate the empirical pattern we plot in Figure 1 mortality rates averaged across eight major cities in the UK using data we collected from municipal public health administrative records, the Medical Officer for Health reports (see Angelopoulos *et al.* (2021a) for more details on the data and analysis of post-pandemic mortality risk). We analyse the mortality rate data in Section 2 statistically and confirm that there was a higher probability of a large

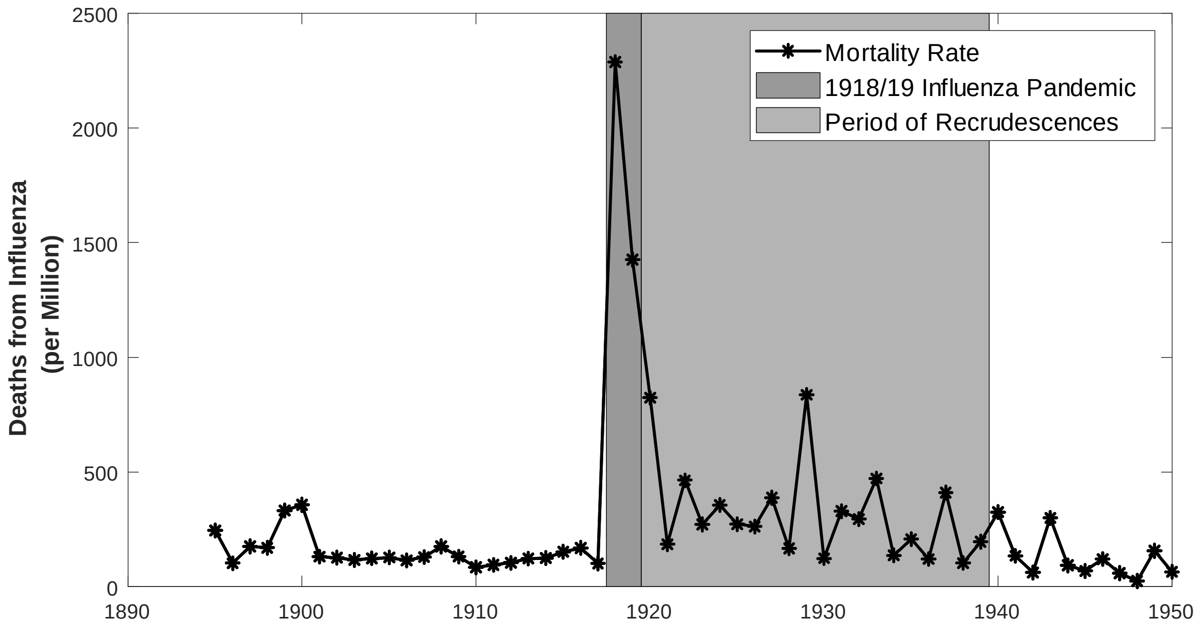
[1] An empirical analysis of the inequality effects of pandemics is in Furceri *et al.* (2020).

[2] See e.g. Blundell *et al.* 2020 and Jorda *et al.* (2020) for economic effects, and Banks *et al.* (2020) and Dennis *et al.* 2020 for health effects.

[3] The extensive review of Stantcheva (2021) identifies only an earlier version of this paper, Angelopoulos *et al.* (2021a), as a study of the wealth inequality implications of COVID-19 for the near future.

outbreak during the two decades that followed the pandemic compared with the period before the pandemic and two decades after the pandemic.

Figure 1: Annual Mortality from Influenza in the UK (1895 - 1950)



Note: Cities include Birmingham, Glasgow, Liverpool, Manchester & Sheffield.
Source: Data obtained from the Medical Officer fo Health reports (see Section 5 for details).[4]

Therefore, analysing post-pandemic dynamics of health and wealth inequality must account for disease outbreak risk even *after* the main pandemic waves. Angelopoulos *et al.* (2021a) use mortality risk estimates from the different geographical regions after the main waves of the 1918-19 and 1890-91 pandemic to inform a model of mortality dynamics after the main pandemic waves in a procedure allowing for model uncertainty. The model predictions imply that the risk of disease outbreaks exceeding 500 deaths per million remains between 25% and 30% with 80% probability for a decade after the main pandemic waves. Large outbreaks can also impact economic activity. Therefore, the post-pandemic medium-run entails possible aggregate-level health and economic shocks that can impact inequality in addition to the initial shock, and that increase risk which affects decision making via precautionary incentives. The general implication of these considerations is that pandemic-induced health and wealth inequality dynamics are stochastic.

Our main object of the quantitative analysis is a stochastic process of a measure, namely of the cross-sectional distribution that emerges from household-level stochastic processes under idiosyncratic and aggregate risk, initiated from the pandemic shock. In particular, we examine the stochastic dynamic evolution of the joint distirbution of the endogenous state variables health and wealth across households after 2020, under economy-wide uncertainty regarding disease outbreaks and the process for economic recovery following the pandemic induced recession, and idiosyncratic, household-level income and health risk. This gives rise to a distribution of possible joint cross-sectional distributions for every year after 2020, depending on realisations of the epidemiological and economic recovery stochastic processes, which we use to make probabilistic statements regarding the endogenous cross-sectional distributional outomes, i.e. wealth and health inequality.

To obtain the stochastic process of health and wealth inequality, we develop a model where both health and wealth are endogenous state variables, and are affected by a combination of random shocks, at the household and the economy level, to health and to labour income, and by purposeful choices at the level of the household, which are made in response to health and income shocks and risk, and to the current level of income and health, and thus the history of health and income shocks received. Households belong to different socioeconomic groups, defined by professions, and the stochastic transitions between groups are determined by a transition matrix that we calibrate to the data. Households receive further labour income as well as health shocks, which are socioeconomic group-dependent, reflecting a social gradient in health.

The portfolio of assets that the households have access to implies that consumption smoothing does not necessarilly imply reduction in both health and wealth, and precaution does not imply building buffer stocks of both health and wealth. Indeed, househods in the model have incentives for consumption smoothing and for a precautionary response to (health and/or earnings) risk. However, as we show, household behaviour also incorporates incentives to treat health and wealth as substitutes in smoothing consumption and in responding to risk. Therefore, allowing for both assets to adjust in response to exogenous changes that impact income and wealth via health is important to uncover the response of wealth net of health.

In this environment, pandemic-induced changes can have significant effects on the cross-sectional distributions of health and wealth, and for their relationship. These are driven by the varation in the options for stock depleting or building, in response to shocks and risk, that is offered by the portfolio of assets, their dependence on initial health and wealth, and because the effects of pandemic changes need not be symmetric across households. Analysis of the model further demonstrates that in an environment with a significant share of borrowing constrained households, the effects of increases in risk on wealth inequality are amplified, and on health inequality likely dampended. On the contrary, the impact effect of the pandemic shock on wealth inequality is mediated, and on health inequality exacerbated. To evaluate the net impact of the different theroretical channels on inequality, a quantitative analysis is required.

We focus on the UK for the quantitative analysis. The UK is characterised by severe health inequalities and a strong link between health and socioeconomic groups and income (see, e.g. Marmot *et al.* (2020)). This is reflected in national-level survey data from the Understanding Society and the Wealth and Asset Survey that we analyse, and which show that households in higher professional groups have higher mean income, wealth and self-reported health, and face lower health risk, measured by the probability of suffering from an acute illness. The data also reveal that there is more variation in terms of both wealth and self-reported health within socioeconomic groups with lower mean income, suggesting that when analysing health inequality, differences between socioeconomic groups is only part of the story, especially when the interest lies in understanding outcomes for the lower income groups. Moreover, the probability of becoming non-employed is higher for households that have suffered from an acute illness, supporting a feedback loop in the relationship between health and income inequality.

We calibrate the model to a number of properties of the pre-COVID UK health and income distributional characteristics, including differences in mean health and in health and labour income risk by socioeconomic group, and the social mobility matrix. To evaluate the model, we examine its fit with respect to the differences between socioeconomic groups in terms of within group inequality in income, wealth and health, which have not been calibration targets. We find that household behaviour, and the mechanisms and channels in the model structure, generate the stylised empirical properties of health and wealth referring to within group inequality. The model, therefore, captures several important elements of the joint distribution of health and wealth prior to the COVID-19 pandemic. We then examine the stochastic dynamic following the COVID-19 shock.

We find substantial and persistent increases in both wealth/income and health inequalities following the COVID-19 pandemic. In particular we find that Gini coefficients increase and between group means diverge, and especially that those who suffer the most are the routine occupations socioeconomic group.

2 Health risk and inequality

We examine economy-wide and idiosyncratic health risk empirically, focusing, in the latter case, on the link between household-level health and economic outcomes. First, we examine disease outbreak uncertainty and present evidence from historical medical records establishing that influenza pandemics have been followed by periods of increased likelihood of outbreaks in deaths from influenza. Second, we examine household-level health risk in conjunction with income, and summarise empirical properties linking the distribution of health with that of income, and the latter with that of wealth.

2.1 Post-pandemic outbreaks

Epidemiological analysis suggests that initial viral outbreaks may be followed by subsequent outbreaks (see e.g. Anderson and May (1991), Oxford *et al.* (2013)). This remains a contemporary concern (e.g. BMJ (2021), Nature (2021) and Kissler *et al.* (2020) in the context of COVID-19).[5]

To investigate disease outbreaks in the begining of the 20th century in the UK, we use information included in public health records that were kept at the municipal level since Victorian times, the "Medical Officer for Health" (MOH) reports.[6] We use data for eight major cities to obtain the mortality rates from influenza between 1895 and 1950 that we plot in Figure 1.[7] Inspection of this figure suggests several spikes in the average mortality rate post-1920, across these five cities. The outbreaks in 1922, 1929, 1933 and 1937 are particularly pronounced, especially in comparison to the mortality rates pre-1918. To confirm increased outbreak risk post- versus pre-1918, we estimate a two-state Markov

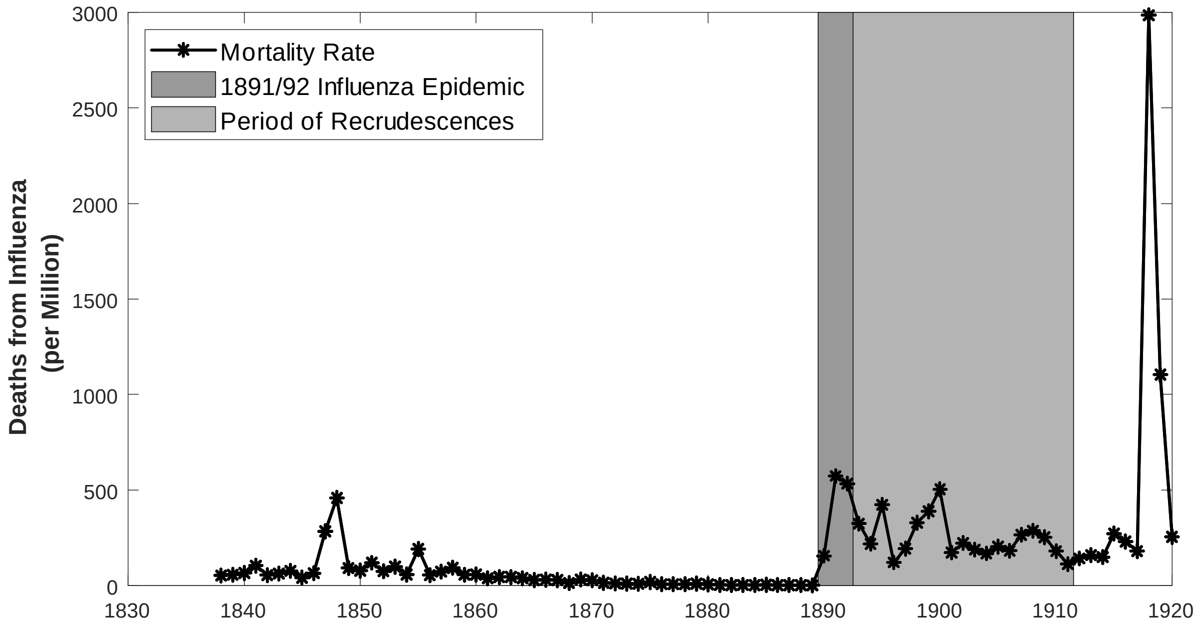
[5] With respect to COVID-19, in particular, the tendency of SARS-CoV-2 to form variants has been noted (e.g. Kemp *et al.* (2021), Plante *et al.* (2021)). For a discussion of the implications see Lauring & Hodcroft (2021) and news articles by Gray (2021) and Fisher *et al.* (2021), containing further references.

[6] The "Medical Officer for Health" reports were annual administrative documents covering a range of public health-related issues at the municipal level. The first reports begin in the mid-19th century, and coverage extends to most municipalities in the UK until the early 1970s. Many of the reports have been digitized and can be viewed on the Wellcome Trust Collection website. For more details, see: https://wellcomelibrary.org/moh/about-the-reports/about-the-medical-officer-of-health-reports/

[7] Note that the mortality rates are very similar with those reported for England and Wales in Langford (2002), for the period 1895-1920, where the two datasets overlap (see Figure 2 below).

switching model using mortality rates between 1895 and 1950 and reject the null of a common distirbution of mortality charactersing the whole period (see Appendix A for more details). In particular, the distribution for the period immediately after 1918 has a higher mean and variance, implying increased probability of high mortality rates.

Figure 2: Annual Mortality from Influenza in England and Wales (1838 - 1920)



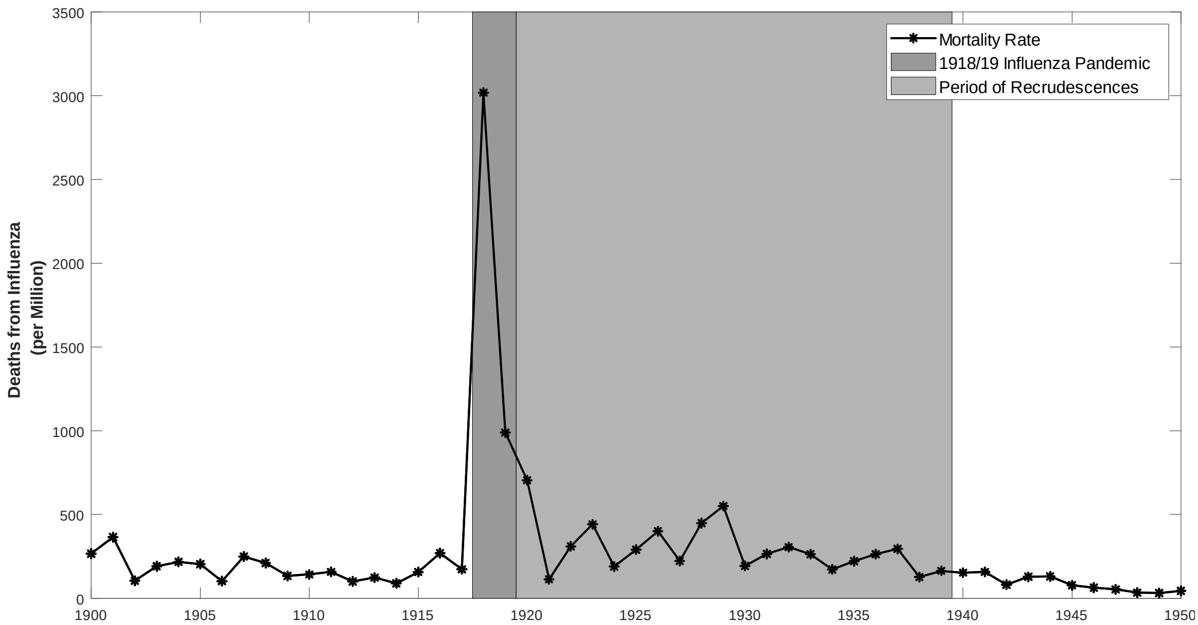
Note: Death rates for 1911 - 1920 refer to females only.
Source: Data taken from Langford ((2002), Table 5, p.13).

Using data on influenza mortality for England and Wales, reported in Langford (2002), we find a similar pattern of post-pandemic increased frequency of disease outbreaks following the 1889-90 pandemic. This pandemic began in the last months of 1889 and claimed over 1 million lives worldwide, making it one of the largest global pandemics of the time (see Charles Rivers Editors (2020); see also Beveridge (1991) for an overview of historical influenza outbreaks).[8] We plot the data in Figure 2 below, noting the spikes in mortality rates post-1890.[9] The pattern of higher post-pandemic disease outbreak frequency is not confined to the UK. Using data on vital statistics published by the Center for Disease Control (see Linder and Grove (1943) and Grove and Hetzel (1968)), we construct a further time series of mortality from influenza for the USA between 1900 and 1950. The data is plotted below in Figure 3. Again, one can see a number of secondary spikes in mortality in the two decades after the 1918/19 outbreak. Estimating the Markov chain regime switching model for the data series for England and Wales and the US in Figures 2 and 3 also confirms that the decades immediately after 1890 and 1918, respectively, are characterised by higher mortality risk than the decades just before the pandemics.

[8] Vijgen *et al.* (2005) suggest that the cause of the pandemic was a human coronvirus.

[9] See the correspondence of the British Medical Journal, from the 22nd of January 1898 (p. 249) for a contemporary discussion of the outbreak as recrudescence of the 1890-91 pandemic.

Figure 3: Annual Mortality from Influenza in the US (1900 - 1950)



Source: Data constructed from CDC records (see Linder & Grove (1943) and Grove & Hetzel (1968)).

2.2 Health, Wealth and Income in the UK pre-COVID-19

We examine selected aggregate level empirical properties of inequality in wealth and health, using data from Understanding Society (UnSoc) for the UK and the Wealth and Asset Survey (WAS) for Great Britain.[10] Understanding Society is a large longitudinal survey covering a wide range of social and economic factors, including information about respondent's health, which are observed annually since 2009-2010. The Wealth and Assets Survey is a bi-annual survey of household wealth and a range of household socioeconomic characteristics, with the first wave in 2006-2008. Understanding Society does not include measures of wealth, whereas WAS does not include measures of health. However, both include information on the socioeconomic classification of the employment of respondents, thus allowing us to examine health and wealth inequality by socioeconomic groups defined by this classification. For both datasets, we define as household members the head of a household, aged between 25 and 60, and their spouse or partner (if applicable). Details on the data, sample selection and the construction of variables are in Appendix A.

The UnSoc data includes a measure of self-assessed health, SF-12 Physical Component Summary (PCS), which is observed repeatedly for each individual. The SF-12 PCS measure is commonly used in public health research to compare different groups of individuals (see e.g Dundas *et al.* (2017)). We standardise this measure to take values in the interval $[0.1, 1]$ and calculate the average across household members as a proxy for household-level health.

[10] We aim to present results for the UK, where possible and complement these with results for Great Britain from WAS. The results in this Section from UnSoc for the UK are very similar if we use the sample for Great Britain instead (see Appendix A).

In Table 1, we show the mean value of this measure of health for different socioeconomic groups. In particular, we follow the 8-class National Statistics Socioeconomic Classification (NS-SEC) (for details, see Rose *et al.* (2005)) of professional classes and allocate each household to the highest socioeconomic group of any member. We group the 8 NS-SEC classes plus all those classed as economically inactive and unemployed into four groups that have clearer differences, and make the results here comparable to the discretisation we employ in the model analysis below. We term these four groups as Professional, Intermediate, Routine, and Non-employed (which includes the inactive and unemployed households; for details, see Appendix A) and calculate the mean household income per group. Household income is the post-policy labour income from the head and spouse (see also Appendix A for details). As can be seen in Table 1 (columns 2 and 3), households in socioeconomic groups with higher mean income also have a higher level of health on average.

Table 1: Income, health and health risk by socioeconomic group

	[1]	[2]	[3]	[4]
Socioeconomic Group	Relative Income	Health	Gini Health	Severe Health cond.
Professionals	1.51	0.72	0.05	1.9
Intermediate	1.07	0.71	0.07	2.0
Routine	0.75	0.68	0.08	2.3
Non-employed	0.50	0.57	0.18	6.4
All	1	0.68	0.09	2.7

Note that income is household-level labour income, after taxes and including transfers
Source: Pooled Sample UnSoc Waves 1-9, see Appendix A for details

The results in columns 2 and 3 in Table 1 are indicative of between-group health inequality, consistent with the link between the social gradient and health inequality that has been analysed in the literature (see, e.g. Marmot (2015, 2020) and Payne (2017)).[11] We complement these results with an examination of how within-group variation in health and health risk related to the social or income gradient. In column 4, we show the Gini measures of health inequality within each of the socioeconomic groups. As can be seen, groups with lower mean income also have higher health inequality between households that belong to these groups, in the sense that good health is concentrated more among fewer households within the group. We also calculate the proportion of households that have a member who has suffered a severe health shock as a measure of health risk.[12] Again, groups with lower mean income are also more likely to experience a severe health shock.

Therefore, socioeconomic group, income, health risk, and the level and variation of health are related, implying health inequality. Socioeconomic groups with higher mean income also have a higher level of health on average, are less likely to experience a severe health shock, and also experience more uniform allocation of health within their socioeconomic group. To further quantify health inequality we calculate the Erreygers index that

[11]The link betwen health and income in Table 1 for the UK using Understanding Society data is also broadly consistent with patterns in the US from the PSID data, see e.g. Cole et al. (2019).

[12]We look at the effects of severe health events, and in particular heart disease, heart failure, emphysema, chronic bronchitis, stroke, heart attacks and cancer. See Appendix A for details.

measure the concentration of health with regards to a household's position in the income distribution (Erreygers (2009); see also Appendix A for more detail). In the pooled UnSoc sample, this index takes a value of 0.079 indicating a positive relationship between income and health.

We also examine the relationship between socioeconomic group transitions and health. To do so, we construct a socioeconomic mobility matrix, that shows the proportion of households who move between the four groups we work with from one year to the next for two groups of households, those for whom one member has received a severe health shock, and those without experiencing health shocks. The two social mobility matrices are shown in Table 2.

Table 2: Socioeconomic Mobility

Transitions of healthy households				
$t \setminus t+1$	Professional	Intermediate	Routine	Non-employed
Professional	**0.903**	0.083	0.008	0.006
Intermediate	0.034	**0.923**	0.029	0.014
Routine	0.009	0.0992	**0.858**	0.041
Non-employed	0.006	0.069	0.103	**0.822**

Transitions of households post severe illness				
$t \setminus t+1$	Professional	Intermediate	Routine	Non-employed
Professional	**0.903**	0.082	0.009	0.007
Intermediate	0.028	**0.915**	0.032	0.024
Routine	0.003	0.080	**0.856**	0.062
Non-employed	0.002	0.018	0.038	**0.942**

Notes: Wave to wave transitions

Source: UnSoc Waves 1-9, see Appendix A for details

The results in Table 2 first show that mobility is low, both before and after a severe health shock. They also show that the most important household labour income risk, namely a move to the non-employment group implying zero earnings from the highest potential earner in the household, increases with a significant worsening in health. In particular, the probability of moving to the non-employment group increases for all groups when one of their members has suffered a severe illness. Hence, health risk also has labour income risk implications. Finally, the matrices in Table 2 show that the increase in labour income risk depends on current conditions, particularly on the current socioeconomic group. The reason is that a household faces an increased conditional probability of moving to the non-employment group if it currently belongs to a socioeconomic group with a lower mean labour income.

Wealth inequality in WAS has been analysed in e.g. Angelopoulos *et al.* (2019, 2020). Here, we summarise the main properties for samples (i.e. groups of households) that are selected from WAS to match as closely as possible the selection criteria and groups used for the results from the UnSoc data. Table 3 summarises between and within-group wealth inequality for the same socioeconomic groups as in Tables 1 and 2. As can be seen, there is significant between-group wealth inequality, and within-group wealth inequality is higher for socioeconomic groups with lower mean income.

Table 3: Wealth inequality

Socioeconomic Group	relative mean	gini	% indebtness
Professionals	1.91	0.60	7%
Intermediate	1.08	0.66	14%
Routine	0.37	0.80	31%
Non-employed	0.23	1.01	48%
All	1.00	0.71	19%

Note: Wave to wave transitions. Gini can take values above one because we allow for negative values of net worth. Qi, i=1,2,...,5 denote the quintiles of the wealth distribution of each socioeconomic group.
Source: WAS Waves 1-5 and own calculations.

3 A model with health and wealth heterogeneity

We consider an economy composed of a continuum of infinitely lived household dynasties distributed on the interval $I = [0, 1]$ with measure 1. Households derive utility from consumption and health, and they can use their income to consume, invest in a single riskless asset, and improve their health in an environment where both income and health are subject to exogenous shocks. In particular, households may randomly suffer a significant illness and receive further shocks that determine their labour income. The distributions of these shocks depend on aggregate conditions meaning that they are allowed to differ between normal periods and periods during and after an epidemic crisis. Time is discrete and denoted by $t = 0, 1, 2, ...,$ which refer to annual steps. We model quantities at the household level, assuming perfect sharing in consumption, health and asset ownership between members.

Over time, household dynasties differ in the number and duration of significant illnesses they have suffered, and in the spells with higher and lower labour income. We restrict our attention to severe illnesses, which represent significant health deterioration, and we define them as health shocks from which a household member does not fully recover. Therefore, they may include death of a member, which is especially important in capturing effects during periods of epidemic crisis. Although the household member does not fully recover from a severe illness, the household may recover, stochastically, by replacing the ill member with a new healthy member (e.g. an offspring). Therefore, severe illness shocks are persistent at the level of the household-dynasty, but not permanent. This specification is reflected in the modelling of the relevant stochastic processes and their calibration to both pre- and post-COVID-19 data, which we discuss in the next section.

3.1 Household level choices and constraints

Each household[13] wishes to maximise their expected lifetime utility:

$$E_0 \sum_{t=0}^{\infty} \beta^t u(c_t, h_{t+1}), \tag{1}$$

[13]To simplify notation, to suppress the indexation of household level variables by the household identifier $i \in I$ and present the problem of a "typical" household without the i superscripts.

where $\beta \in (0,1)$ is a parameter capturing discounting of future periods, c_t is consumption, and h_t is the level of health of the household, defined as the average level of health across members. The level of health is a state variable, whose law of motion will be specified below, following the convention that h_t denotes the state at the beginning of the period, and thus h_{t+1} incorporates the changes in the level of health during period t. Consumption is non-negative, i.e. $c_t \geq 0$, and health, h_t, takes values in a closed and bounded set, reflecting the finiteness of the human body, i.e. $h_t \in H = [h^{\min}, h^{\max}]$, where $h^{\min} \geq 0$. The utility function $u : \mathbb{R}_{\geq 0} \times H \rightarrow \mathbb{R}$ is bounded, twice continuously differentiable, strictly increasing and strictly concave.[14]

The household receives income from existing asset holdings a_t, determined by an interest rate $r(z_t)$, where z_t is a stochastic process capturing the aggregate state of the economy. It also receives labour income, $w(n_t, l_t, z_t)$, which is determined by idiosyncratic, household-specific, random factors, n_t and l_t, as well as the aggregate state, z_t. The idiosyncratic factors determine the highest profession of the household (n_t) and capture remaining idiosyncratic variation in productivity between households (l_t), for example, determined by the profession of additional members, how well the members' skills are valued in their jobs, how supportive or productive their work environment is, and personal circumstances that may affect productivity. The stochastic processes determining these household-specific shocks depend on the aggregate economic state z_t, as well as on idiosyncratic, household-specific health shock, s_t, which also depend on the aggregate state z_t.

The household uses its income in period t for consumption, buying assets a_{t+1} that will generate income in the next period, and expenditure to improve health, $x_t \in \mathbb{R}_{\geq 0}$. The budget constraint is given by:

$$c_t + a_{t+1} + x_t = (1 + r(z_t))a_t + w(n_t, l_t, z_t), \tag{2}$$

where $a_t \in A = [a^{\min}, +\infty)$, and $a^{\min} \leq 0$ defines a borrowing limit. The random variables are given by $r(z_t) : Z \rightarrow \left(-1, \frac{1-\beta}{\beta}\right)$, $w(n_t, l_t, z_t) : N \times L \times Z \rightarrow \mathbb{R}_{\geq 0}$, where the state spaces defining the domains will be defined in the next sub-section and the ranges are chosen so that the economic problem is well defined (see e.g. Aiyagari (1994), Acikgoz (2018) and Zhu (2018)).

Health evolves according to:

$$h_{t+1} = \delta(s_t, z_t)h_t + m\left(x_t\right). \tag{3}$$

The random variable $\delta(s_t, z_t) : S \times Z \rightarrow D \in (0,1)$, where D is a compact set, denotes stochastic health persistence and captures the effects of adverse health shocks that work to increase the rate at which health deteriorates. The function $m\left(x_t\right) : X \in \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$, capturing improvements in health via own activity (x_t), is twice continuously differentiable, increasing and concave, and satisfies $\lim_{x_t \rightarrow 0} m_{x_t} = +\infty$.

3.2 Exogenous processes

The aggregate state z_t is determined by a stochastic process that follows a Markov chain with the $(\widetilde{z} \times \widetilde{z})$ transition matrix Q_Z and state space $Z = [\overline{z}_1, \overline{z}_2, ..., \overline{z}_{\widetilde{z}}]$. We normalise $\overline{z}_1$

[14] For a more general introduction to health in economic models, see Grossman (2017).

to denote a pandemic period, $\overline{z}_2, ..., \overline{z}_{\widetilde{z}-1}$ to capture periods that follow a pandemic. Thus that may incorporate epidemiological and potential economic effects of the pandemic, and $\overline{z}_{\widetilde{z}}$ as periods that are sufficiently distanced from a pandemic that any pandemic effects at the aggregate level exogenous variables are negligible.

There are three exogenous stochastic processes, (n_t), (l_t) and (s_t), which generate the household-specific shocks. The respective state spaces are given by $N = [\overline{n}_1, \overline{n}_2, ..., \overline{n}_{\widetilde{n}}]$, $L = [\bar{l}_1, \bar{l}_2, ..., \bar{l}_{\widetilde{v}}]$, and $S = [\overline{s}_1, \overline{s}_2, ..., \overline{s}_{\widetilde{s}}]$. Conditional on $(z_t)_{t=0}^{\infty} \in Z$, the stochastic process for the joint distribution $(e_t)_{t=0}^{\infty} = (n_t, l_t, s_t)_{t=0}^{\infty}$ is assumed to follow a Markov chain with a $\left(\left(\widetilde{n} \times \widetilde{l} \times \widetilde{s}\right) \times \left(\widetilde{n} \times \widetilde{l} \times \widetilde{s}\right)\right)$ transition matrix that depends on next period's aggregate state z', denoted by $Q^{z'}$, and state space $E = N \times L \times S = [\overline{e}_1, \overline{e}_2, ..., \overline{e}_{\widetilde{e}}]$, with $\widetilde{e} = \widetilde{n} \times \widetilde{l} \times \widetilde{s}$. The elements of the transition matrix $Q^{z'}$ are denoted $\pi^{z'}(e_{t+1}|e_t)$, and give the probability that in period $t+1$, when the aggregate state in $t+1$ is given by $z_{t=1} = z'$, the household will be in idiosyncratic state e_{t+1}, conditional on being in state e_t in period t. Therefore, the realisation of the aggregate state in period $t+1$ matters for the conditional probability of idiosyncratic shocks. In particular, the probability of household level economic and health shocks period $t+1$ differs depending on whether $t+1$ is a period of pandemic or not, for the same household-level state in period t. The transition matrices for all $z' \in Z$ satisfy that $\sum\limits_{e_{t+1} \in E} \pi^{z'}(e_{t+1}|e_t) = 1$ for all $e_t \in E$, where the superscripts denote the dependence of conditional probabilities on the aggregate state in period $t+1$. Conditional on the aggregate state, households draw idiosyncratic shocks from $(Q^{z'}, E)$ independently from each other, but, for a given household, the draws from the underlying (n_t), (v_t) and (s_t) need not be independent.

At the level of household, uncertainty is summarised by the stochastic process $(y_t)_{t=0}^{\infty} = (e_t, z_t)_{t=0}^{\infty}$, which follows a Markov chain with a $((\widetilde{e} \times \widetilde{z}) \times (\widetilde{e} \times \widetilde{z}))$ transition matrix Q and state space $Y = E \times Z = [\overline{y}_1, \overline{y}_2, ..., \overline{y}_{\widetilde{y}}]$, with $\widetilde{y} = \widetilde{e} \times \widetilde{z}$.[15] The elements of the transition matrix Q are denoted $\pi(y_{t+1}|y_t) \equiv \pi(e_{t+1}, z_{t+1}|e_t, z_t)$, and $\sum\limits_{z_{t+1} \in Z} \sum\limits_{e_{t+1} \in E} \pi(e_{t+1}, z_{t+1}|e_t, z_t) = 1$ for all $e_t \in E$ and $z_t \in Z$. We assume that the Markov chain (Q, Y) has a unique invariant distribution, with probability measure ξ.

3.3 Effects of pandemic-induced changes on health and wealth

A change in the aggregate-level process (z_t) in period t requires adjustments in health and wealth on the part of the household, which impact health and wealth inequality if the change affects households asymmetrically and/or if the response depends on initial conditions. We first examine household incentives to adjust health and wealth that the optimal response incorporates, and then discuss factors that contribute to changes in health and wealth inequality.

3.3.1 Household choices of health and wealth

We examine the first-order necessary conditions for optimality that link two consecutive periods. Assuming interior solutions for health, optimality requires that the two Euler

[15] See also Imrohoroglu (1989) for a similar representation of household level uncertainty, in an environment with aggregate as well as idiosyncratic uncertainty.

conditions are satisfied[16]:

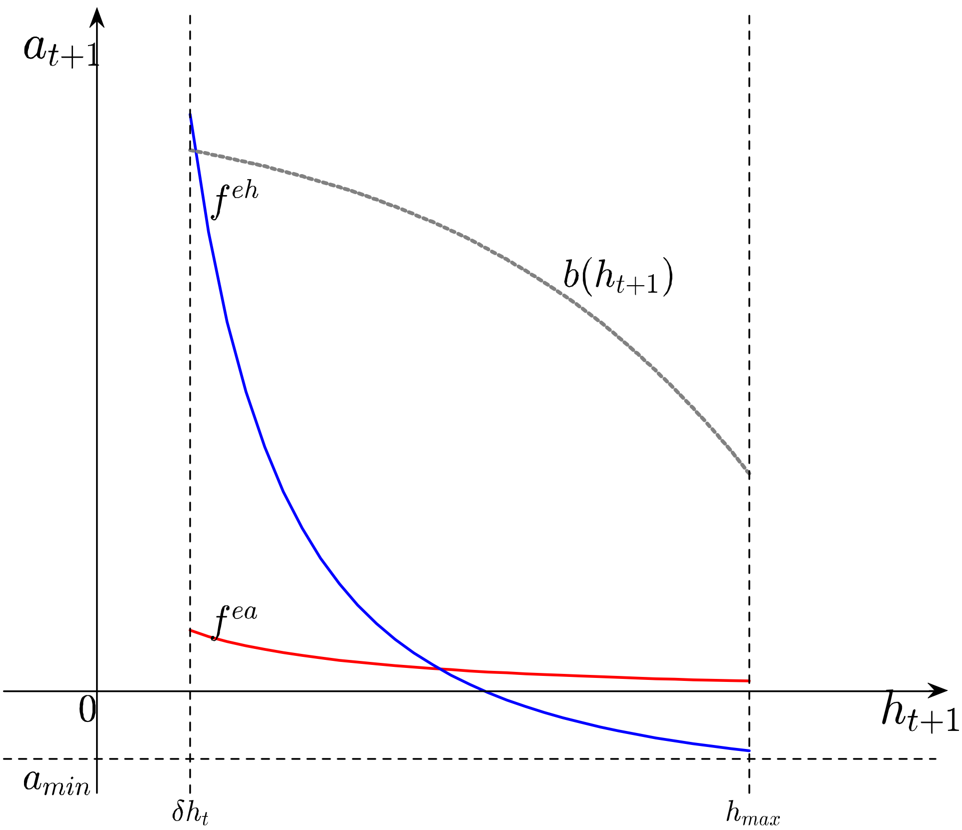
$$u_{c_t} \geq \beta E\left[u_{c_{t+1}}(1+r(z_{t+1}))\right], \text{ and} \tag{4}$$

$$u_{c_t} x_{h_{t+1}}(h_t,h_{t+1}) - u_{h_{t+1}} = \beta E\left[u_{c_{t+1}}\left(-x_{h_{t+1}}(h_{t+1},h_{t+2})\right)\right], \tag{5}$$

where $x(h_t,h_{t+1}) = m^{-1}(h_{t+1} - \delta(s_t,z_t)h_t)$ is obtained using (3).

Assume that $-u_{c_t c_t} x_{h_{t+1}}(h_t,h_{t+1}) + u_{c_t h_{t+1}} > 0$.[17] Then, Lemma 1 in Appendix B shows that for a given stochastic process (z_t), for any $(a_t, a_{t+2}) \in A$, $(h_t, h_{t+2}) \in (h^{\min}, h^{\max})$, and $e_t \in E$, if a_{t+1} and h_{t+1} that satisfy (4) in period t exist, the locus of their combinations is a downward slopping function. Similarly, the locus of combinations of a_{t+1} and h_{t+1} that satisfy (5) in period t is a downward slopping function. Moreover, when $h_{t+1} \to \delta(s_t,z_t)h_t$, higher values for a_{t+1} are required to satisfy (5), compared with (4). Denote the locus of a_{t+1} and h_{t+1} that satisfy (4) and (5) by the functions f^{ea}, $a_{t+1} = f^{ea}(h_{t+1})$ and f^{eh}, $a_{t+1} = f^{eh}(h_{t+1})$, respectively. An example of these functions is plotted in Figure 4.

Figure 4: Choice of a_{t+1} and h_{t+1}.



Note:

The combination of a_{t+1} and h_{t+1} that solves both (4) and (5) for given $(a_t, h_t, e_t, a_{t+2}, h_{t+2})$ is an intersection point of f^{ea} and f^{eh} that is within the feasibility constraints. These

[16] In our calibration, the bounds for health do not bind, whereas the lowed bound for wealth does.

[17] For example, this assumption is satisfied if we assume that preferences are additively separable, or supermodular, in health and consumption. If $u_{c_t h_{t+1}} < 0$, a sufficient condition for the results below is that $u_{c_t c_t} < u_{c_t h_{t+1}}$, for every c, h, if $x_{h_{t+1}}(h_t,h_{t+1}) > 1$. Our calibration satisfies this suffcient condition.

determine an area defined by the vertical lines at $\delta(s_t, z_t)h_t$ and $h^{\max}$ for $h_{t+1}^{\min}$ and $h_{t+1}^{\max}$, respectively, the horizontal line at $a^{\min}$ for $a_{t+1}^{\min}$, and the function $a_{t+1}^{\max} = b(h_{t+1}) = (1 + r(z_t))a_t + w(y_t) - x(h_{t,} h_{t+1})$ (see Lemma 1 in Appendix B).[18] The situation depicted in Figure 4 is an example, because, for different $(a_t, h_t, e_t, a_{t+2}, h_{t+2})$ there may be more than one intersections within the permissible region, or none. However, the optimal choice of a_{t+1} and h_{t+1}, for any given (a_t, h_t, e_t), which is made jointly with $(a_{t+j}, h_{t+j})_{j=2}^{\infty}$, must be an intersection point of downward slopping f^{ea} and f^{eh} functions.[19] Therefore, the properties that apply to the intersection point of f^{ea} and f^{eh} will also appy to the optimal choice of a_{t+1} and h_{t+1} for the problem in sub-section 2.1.

3.3.2 Pandemic-induced changes and household incentives

The insight that the optimal choice of a_{t+1} and h_{t+1} under a specific stochastic process (z_t) is the intersection of downward slopping f^{ea} and f^{eh} functions has useful implications regarding the analysis of pandemic effects on household choices via changes in the aggregate-level process (z_t). We study incentives incorporated in the optimal choice of health and wealth for the household problem in sub-section 2.1 following a surprise change in (z_t), by examining the choice of a_{t+1} and h_{t+1} for given $(a_t, a_{t+2}) \in A$, $(h_t, h_{t+2}) \in \left(h^{\min}, h^{\max}\right)$ (see Lemma 2 in Appendix B) that is, in effect, in a two-period version of the household's problem. Given that they are conditional on $a_{t+2} \in A$, and $h_{t+2} \in \left(h^{\min}, h^{\max}\right)$, the results below do not necessarily characterise optimal choices of (a_{t+1}, h_{t+1}) of the problem in sub-section 2.1. This is because $(a_{t+j}, h_{t+j})_{j=2}^{\infty}$ are also chosen optimally following the change in (z_t), and (a_{t+2}, h_{t+2}) matter for the choice of (a_{t+1}, h_{t+1}) (see Lemma 3 in Appendix B). However, because the results apply for any $a_{t+2} \in A$, and $h_{t+2} \in \left(h^{\min}, h^{\max}\right)$, the incentives incorporated in the choice of (a_{t+1}, h_{t+1}) are also included in the optimal choice of (a_{t+1}, h_{t+1}) of the fully dynamic problem in sub-section 2.1.

We make use of Lemma 2 in Appendix B, which shows that if a household in period t under process (z_t^s) chooses $(a_{t+1}^s, h_{t+1}^s) \in \left(\left(a^{\min}, +\infty\right), \left(h^{\min}, h^{\max}\right)\right)$ that satisfy (4) and (5), then under a different aggregate-level stochastic process (z_t^p) that implies higher *rhs* relative to the *lhs* for (4) and (5) conditional on $(a_t, a_{t+2}) \in A$, and $(h_t, h_{t+2}) \in \left(h^{\min}, h^{\max}\right)$, at least one of a_{t+1} and h_{t+1} increase (decrease) relative to (a_{t+1}^s, h_{t+1}^s). In terms of Figure 4, an increase (decrease) in the *rhs* of (4) and (5) relative to the *lhs* shifts the f^{ea} and f^{eh} functions outwards (inwards).[20]

Consider changes in the process (z_t^s) at period t that are associated with effects of a pandemic, in period t, and/or as a result of increased post-pandemic epidemiological uncertainty. In particular, assume that the household chose a_t^s and h_t^s in period $t-1$ under the process (z_t^s) and then, at the beginning of period t (z_t^s) changes to (z_t^p), also implying changes in idiosyncratic processes to (e_t^p). The household draws the period t idiosyncratic shock from (e_t^p), and makes choices given (a_t^s, h_t^s, e_t^p) and assuming future shocks will be determined by (z_t^s, e_t^s). Proposition 1 in Appendix B summarises the effects of some of these changes, conditinal on $a_{t+2} \in A$, and $h_{t+2} \in \left(h^{\min}, h^{\max}\right)$. In particular:

[18] Note that, given a_t and h_t, $a_{t+1}^{\max}$ is a negative and concave function of h_{t+1}, as a result of the assumptions imposed on the $m(x_t)$ function.

[19] This is because the optimal choice of a_{t+1} and h_{t+1} must be the choice of a_{t+1} and h_{t+1} for some $(a_t, h_t, e_t, a_{t+2}, h_{t+2})$ and Lemma 1 implies that the choice of a_{t+1} and h_{t+1} is an intersection point of downward slopping f^{ea} and f^{eh} functions for any $(a_t, h_t, e_t, a_{t+2}, h_{t+2})$.

[20] An example is depicted in Figure B1 in Appendix B.

i) A surprise drop in earnings or asset income in period t leads to a fall in at least one of a_{t+1} and h_{t+1} (i.e. $a^p_{t+1} \leq a^s_{t+1}$ and/or $h^p_{t+1} \leq h^s_{t+1}$).

ii) A surprise upper limit on consumption c^l in period t leads to an increase in at least one of a_{t+1} and h_{t+1} (i.e. $a^p_{t+1} \geq a^s_{t+1}$ and/or $h^p_{t+1} \geq h^s_{t+1}$) for the subset of households for which (a^p_{t+1}, h^p_{t+1}) implies $c^p_t > c^l$.

iii) An increase in the probability of future drops in earnings or asset income leads to an increase in at least one of a_{t+1} and h_{t+1} (i.e. $a^p_{t+1} \geq a^s_{t+1}$ and/or $h^p_{t+1} \geq h^s_{t+1}$).

iv) A positive probability for a future upper limit on consumption leads to a fall in at least one of a_{t+1} and h_{t+1}(i.e. $a^p_{t+1} \leq a^s_{t+1}$ and/or $h^p_{t+1} \leq h^s_{t+1}$).

The changes in (z_t) capture effects of the pandemic on household income during the initial outbreak year (i), or restrictions on consumption during the outbreak year (ii), and effects of post-pandemic epidemiological risk on household income (iii) and on restrictions on consumption (iv). Another important effect of a pandemic is the increase in health risk, working via the random variable $\delta(s_t, z_t)$ to affect periods from t onwards. However, the effects of such a change on (4) and (5) cannot be singed for all possible parameter values and state variables.

The model incorporates incentives for consumption smoothing and for precaution, using either asset. In particular, the results in regarding the earnings drop as a result of the pandemic shock in (i) reflect consumption smoothing incentives, while the results regarding earnings risk in (iii) a form of precautionary behaviour.[21] However, it is useful to note that the options offered to the households by having a portfolio of two assets, health and wealth, imply that consumption smoothing in this context does not necessarilly imply reduction in both health and wealth, and precaution does not imply building buffer stocks of both health and wealth. In fact, a bigger change in one asset requires a smaller change in the same direction of the other asset (see part b) of Lemma 2 in Appendix B). In this sense, the households view the two assets as substitutes in smoothing consumption and in responding to risk. More generally, the results in Lemma 2 and Proposition 1 in Appendix B leave open the possibility of increases in one asset, as a result of income losses, and of decreases in one asset as a result of income risk.

3.3.3 Implications for inequality

Health and wealth choices differ across households that differ in their initial combination of (a_t, h_t) (see Lemma 3, Appendix B). Therefore, household health and wealth accumulation following pandemic-induced changes depends on initial health and wealth. The different possibilities offered by the portfolio of assets for responses to shocks and risk is important in this dimension. In particular, it implies more variation in the range of possible responses, because household responses to a pandemic-induced change refer to whether both assets change in the same direction, which asset changes more, and which asset increases/decreases, if assets change in different directions. In addition, it implies a dependence of the response on the initial levels of health and wealth as well as on the combination of (a_t, h_t). As a result, pandemic-induced changes can have significant effects on the cross-sectional distributions of health and wealth, and for their relationship, even when the pandemic implies only change in (4) and (5), and when this change is the same across all households. In reality, the health and wealth inequality implications of a pandemic are further complicated by the fact that the pandemic changes considered in the

[21] The results in (ii) and (iv) are natural implications of exogenous restrictions.

previous sub-section occur simultaneously (e.g. there may be a drop in current income and an increase in income risk), and by the fact that each one need not be symmetric across households (e.g. income losses or increase in health risk may be asymmetric).

Moreover, the inequality implications of a pandemic can be significantly dampened or amplified by the choices of households that are borrowing constrained. For a household that is borrowing constrained under the (z_t^s) process, the Euler equations are:

$$u_{c_t} > \beta E\left[u_{c_{t+1}}(1 + r(z_{t+1}^s)\right], \text{ and} \tag{6}$$

$$u_{c_t} x_{h_{t+1}}(h_{t,}^s h_{t+1}^s) - u_{h_{t+1}} = \beta E\left[u_{c_{t+1}}\left(-x_{h_{t+1}}(h_{t+1,}^s h_{t+2})\right)\right]. \tag{7}$$

In this case, a change in period t to (z_t^p) that increases the *lhs* in (6) and (7) relative to the *rhs* (for example, due to earnings drops in period t) does not change savings behaviour: the household remains borrowing constrained. This household must instead reduce next period health to satisfy (7). A change that increases the *rhs* relative to the *lhs* (for example, increased probability of future income drops due to new outbreaks) is likely to lead to an increase in next period assets for some households, but not for others, depending on the size of the increase of the *rhs* and on households' (a_t^s, h_t^s, e_t^p). For households that do not increase their assets, health must increase to satisfy (7).

These considerations imply that for pandemic-induced changes that increase the *lhs* relative to the *rhs* (earnings drops in t), while households with assets above the borrowing limit decrease their assets and/or health, households on the borrowing limit will only decrease health. This will tend to decrease the wealth inequality impact of the pandemic, and increase the health inequality impact. On the other hand, for changes that increase the *rhs* relative to the *lhs* (probability of future income drops associated with new outbreaks), while households with assets above the borrowing limit increase their assets and/or health, a fraction of households on the borrowing limit will not increase wealth, but will increase health. This will tend to increase wealth inequality. Together, these points imply that in an environment with a significant share of borrowing constrained households, the effects of epidemiological risk on wealth inequality are amplified, and on health inequality likely dampended; while the surprise effects of the pandemic on wealth inequality are mediated, and on health inequality exacerbated. Given that in the data for the UK about 19% of households are borrowing constrained, these effecs can be substantial.

To evaluate the effects of a pandemic on health an wealth inequality, a quantitative evaluation that will take into consideration all the relevant channels for an empirically relevant initial (i.e. pre-pandemic) distribution is required. This requires that we solve for the stochastic processes for household-level health and wealth and construct the relevant cross-sectional distributions.

3.4 Stochastic processes for health and wealth

The stochastic processes for the household level endogenous variables $(a_{t+1})_{t=0}^{\infty}$, $(h_{t+1})_{t=0}^{\infty}$, $(c_t)_{t=0}^{\infty}$ and $(x_t)_{t=0}^{\infty}$ encapsulate the effect of the exogenous (household and aggregate level) stochastic processes and of household decision making in the stochastic environment. These stochastic processes across households give rise to the relevant cross-sectional distributions of endogenous outcomes for each time period.

Each household determines the stochastic processes for the household level economic and health variables, as the plans $(a_{t+1})_{t=1}^{\infty}$, $(h_{t+1})_{t=1}^{\infty}$, $(c_t)_{t=1}^{\infty}$ and $(x_t)_{t=1}^{\infty}$ that maximise

(1) subject to (2) and (3), for given initial values $(a_1, h_1, y_1) \in A \times H \times Y$. We solve this problem by computing the policy functions $a_{t+1} = g^a(a_t, h_t, y_t)$, $h_{t+1} = g^h(a_t, h_t, y_t)$, $c_t = g^c(a_t, h_t, y_t)$ and $x_t = g^x(a_t, h_t, y_t)$, that solve the recursive problem:

$$V(a_t, h_t, y_t) = \max_{c_t, a_{t+1}, x_t, h_{t+1}} \{u(c_t, h_{t+1}) + \beta E[V(a_{t+1}, h_{t+1}, y_{t+1})|y_t]\}, \tag{8}$$

$$\begin{aligned} &\text{subject to} \\ c_t + a_{t+1} + x_t &= (1 + r(z_t))a_t + w(n_t, l_t, z_t), \\ h_{t+1} &= \delta(s_t, z_t)h_t + m(x_t), \ \delta(s_t, z_t)h_t \leq h_{t+1} \leq h^{\max}, \\ c_t, x_t &\geq 0, \ a_{t+1} \geq a^{\min}, \text{ and } h^{\min} \leq h_t \leq h^{\max}, \end{aligned}$$

where $V(a_t, h_t, y_t)$ denotes the optimal value of the objective function starting from state (a_t, h_t, y_t), and $y_t \equiv (n_t, l_t, s_t, z_t)$.[22] We obtain them using computational methods described in Appendix B.

The cross sectional distribution of households over the joint state space of household-level state variables, $A \times H \times E$, which is denoted by $\lambda_t(a_t, h_t, e_t; z_t)$ changes over time as a result of time variation in the aggregate state z_t. We compute the time series of λ_t using numerical methods we discuss in Appendix B. In our analysis post-COVID-19, we focus on the specific time series of λ_t obtained by selecting the initial state variables to be determined in a pre-COVID-19 stationary equilibrium letting the first periods reflect the COVID-19 shock. We discuss the pre-COVID-19 economy in Section 4 and the scenarios we simulate following COVID-19 in Section 5.

4 Heath and wealth inequality pre-COVID-19

The economy pre-COVID-19 is characterised by the long term absence of pandemic outbreaks and decision making that does not account for the possibility for future pandemic outbreaks. We model this as the stationary equilibrium of a version of the model economy described in Section 3 where crises do not happen, and exogenous aggregate state remains fixed over time at the level $\overline{z}_{\tilde{z}} \equiv z^*$. If crises had happened in the past, their effect on the cross-sectional distributions has dissipated. In this special case where the aggregate state is equal to z^* in each period *ex ante* (i.e. with certainty), we assume that the Markov chain (Q^*, E) for the joint distribution (e_t) has a unique invariant distribution, with a probability measure that we denote by ξ^*.[23] Households make decisions believing that crises will not happen in the future, so that the stochastic processes for $(a_{t+1})_{t=0}^{\infty}$, $(h_{t+1})_{t=0}^{\infty}$, $(c_t)_{t=0}^{\infty}$ and $(x_t)_{t=0}^{\infty}$, when the initial period $t = 0$ is in the stationary regime, are generated by setting $z_t = z^* \; \forall t$. In such a stationary environment, the cross sectional distribution of wealth also does not change over time. In particular, this environment gives rise to a stationary equilibrium that is characterised by the cross-sectional distribution

[22] As a function of the household-level state variables, the policy functions are time varying, depending on the aggregate state in z_t: $a_{t+1} = g^a(a_t, h_t, e_t; z_t)$, $h_{t+1} = g^h(a_t, h_t, e_t; z_t)$, $c_t = g^c(a_t, h_t, e_t; z_t)$, and $x_t = g^x(a_t, h_t, e_t; z_t)$.

[23] Note that the state space for idiosyncratic shocks E is the same in the stationary environment analysed here and in that under aggregate uncertainty. However, idiosyncratic risk can differ between the two via differences in the probabilities in the transition matrix and in the random variables that map the state space to labour income and health.

over households $\lambda^*(a_t, h_t, e_t)$.[24] Household-level quantities, on the other hand, are characterised by sequences of economic and health variables that vary over time as a result of the exogenous household-specific processes and household decision making, which are in turn conditional on the aggregate level quantities. In particular, household decisions depend on the history of the shocks that have been experienced and on uncertainty about future household-level outcomes, which is captured by the joint process $e_t = (n_t, l_t, s_t)$ associated with transition matrix $Q^* = \pi^*(e_{t+1}|e_t)$.

We calibrate the model to annual frequency data so that the stationary equilibrium matches particular properties of the data when the Markov chain (Q^*, E) reflects the stochastic environment in the UK before the COVID-19 pandemic. We first explain how we calibrate parameters in (Q^*, E) using information on the relevant stochastic environment directly. We then describe how we calibrate the remaining parameters of the model, some by using information directly from the data or existing empirical analysis, and others via a simulated minimum distance procedure that minimises the distance between model predictions and relevant data targets. Finally, we show that the stationary equilibrium predicted by the model fits the empirical properties of the wealth and health distributions that we have not targeted. Further details on the data and methods used to calibrate the model are in Appendix C.

4.1 Stochastic processes

We use household level information from Understanding Society to construct model relevant variables of health and labour income. In particular, to measure health outcomes we use the SF-12 Physical Component Summary (PCS) score, and to measure health risk we use information on severe health events, as in Section 2. We use the NS-SEC classification to allocate households in each period into socioeconomic groups, and, to obtain a measure of labour income relevant for the decision making that we model, we construct total household post-policy labour income.[25] For all these quantities, the definitions of the household, household members and household level quantities are the same as in Section 2 and are discussed in more detail in Appendices A and C.

4.1.1 Health process

We assume that S includes three possible outcomes, a state $\overline{s}_1$ where no household member has had a severe illness[26], a state $\overline{s}_2$ where a household member is experiencing a severe illness during the current period, and a state $\overline{s}_3$ where the household has a member who has suffered from such an illness in previous years. This state space is motivated by empirical observation, as described in Appendix C.1. In particular, in the data, a severe illness is associated with a sharp drop in health before returning to a recovery, post-illness state, with lower health than the pre-illness state. Indeed, we find that, on average, across the households, h_t drops by almost 10% from $\overline{s}_1$ to $\overline{s}_2$, whereas $\overline{s}_3$ is about 5% lower than $\overline{s}_1$.[27]

[24] The mathematical representation of this environment is in Appendix B.

[25] We use post-policy labour income (i.e. after taxes and including benefits) because this is the quantity that the households have available to allocate to consumption, savings, and expenditure to promote health.

[26] See Section 2 and Appendix A for the definition of a severe illness (health shock).

[27] See also Figure C.1 in Appendix C. As shown in Appendix C.1, these results are robust to removing several observable components from the measure of health, as well as medical conditions other than the

These observations on the evolution of health after severe illness shocks, in conjunction with data availability and the model structure, lead us to assume the following structure for the transition probabilities of the illness state. A household in the state $\overline{s}_1$ faces a positive probability of moving to state $\overline{s}_2$, and a zero probability of moving to state $\overline{s}_3$. We allow the transition probability from $\overline{s}_1$ to $\overline{s}_2$ to depend on the states in N, to capture the social gradient in health (see, e.g. Marmot (2003, 2004), Wilkinson and Pickett (2008, 2014)), which is summarised in Tables 1 and 2 as the difference in health risk between socioeconomic groups. We calculate these probabilities using UnSoc data. Once in $\overline{s}_2$, we assume that households transition in the next period to state $\overline{s}_3$ with probability one. In other words, we use state $\overline{s}_2$ to capture the impact effect of the severe health shock, while $\overline{s}_3$ captures long term effects.

We next consider transitions from $\overline{s}_3$. In the data, we do not observe individuals who fully recover from a severe illness, resulting from the nature of the health shocks that we model. However, our infinitely lived household dynasties model structure assumes that after some years, household members are replaced by a new healthy member (e.g. their offspring), i.e. a new member in state $\overline{s}_1$. Hence, when a household member suffers a severe illness, the household will at some point recover. Our sample and variable definitions in Section 2 focus on household members' health and income under the age of 60, implying a general replacement age of 60. The average age of first experiencing a severe illness is 48.8, which then implies an average of 11.2 years spent in state $\overline{s}_3$.[28,29] Nevertheless, some households spend more (less) time in this state because they moved to $\overline{s}_2$ before or after the average age for the severe illnesses. Therefore, in terms of the process (s_t), we assume that once a household reaches $\overline{s}_3$, it can move back to state $\overline{s}_1$ with some probability that reflects the randomness in the time spent in $\overline{s}_3$. In particular, we assume that when a household moves to $\overline{s}_3$, it faces an expected duration of remaining in this state of 11.2 years, implying an exit probability from $\overline{s}_3$ and back to $\overline{s}_1$ of 8.95%. We set this exit probability to be the same for all states in N.

Overall, our modelling and calibration imply that household dynasties differ in the number and duration of spells of illnesses that they have faced over time. Some households have long runs of $\overline{s}_1$, while some experience severe illness for one of their members, which costs them one year in $\overline{s}_2$ and another couple of years in $\overline{s}_3$. Some of these latter households face short spells in $\overline{s}_3$ and some longer spells. Because we do not observe deaths from severe illnesses in the sample (see Appendix A), calculating the transition probability from $\overline{s}_1$ to $\overline{s}_2$ as we describe here underestimates the true extent of health risk faced by a household.[30] As the discussion in Appendix A shows, this bias should not be very strong, because the proportion of such deaths is small in the pre-COVID-19 period. We capture the increase in health risk during pandemics via the increased probability of death for working age households (due to the pandemic). To inform our calibration of the transition probability from $\overline{s}_1$ to $\overline{s}_2$, we use excess mortality data. In this sense, the transition probability from $\overline{s}_1$ to $\overline{s}_2$ in the pre-COVID-19 economy can be viewed as including the normalisation of

severe illnesses.

[28] Generally, households who have experienced a health shock are liable to receiving further shocks. We focus on the first shock and subsume subsequent health episodes into the after illness state.

[29] In our sample, we do observe very few households with more than one member experiencing a severe illness. For simplicity, we treat these households the same as those households where only one member has received a severe health shock.

[30] As noted, regural deaths above the age of 60 are not part of the model structure and thus are not part of the health risk we study.

health risk with respect to death from severe illness..

4.1.2 Income process

We define N by four states representing the socioeconomic groups in Section 2. Note that these have been defined to include a group for households with inactive and/or unemployed members (called non-employed), because of the importance of this state for health outcomes apparent in Section 2, but also because this situation implies the worst labour income state, and is thus important in terms of measuring variation in labour income.[31] In particular, a movement from any other state in N to the non-employed state represents the most important labour income change for a household, and thus these relevant transition probabilities capture a significant part of income risk.

The process (l_t) accounts for labour income variation within groups, reflecting income risk conditional on the socioeconomic group and illness status. To obtain an empirical measure for this type of labour income shocks, we use post-policy labour income, $\underline{w}_{i,t}$, for household i in period (wave) t, by removing the effects of household characteristics which are known, as opposed to stochastic factors, as well as socioeconomic group membership that we want to condition on.[32] In particular, we run a regression of the natural logarithm of $\underline{w}_{i,t}$ on a number of household characteristics for which we have information from UnSoc:

$$\ln(\underline{w}_{i,t}) = \beta_0 + \beta_1 D_{i,t} + \epsilon_t. \tag{9}$$

In this specification, $D_{i,t}$ contains a third order polynomial of age and dummy variables capturing the region of residence, sex of the head of the household, year in which the interview took place, the natural logarithm of household size, and a dummy for the household's socioeconomic group.[33] We use the residuals from (9) to construct the process of labour income for each group.

We obtain L by assuming in each case that for each $\overline{n}$, $L_{\overline{n}}$ has three states: i) lower than the 30th percentile of the distribution of the residuals from (9) for the specific $\overline{n}$; ii) between the 30th and 70th percentile and iii) above the 70th percentile. The discretisation of the distribution of within-group residual post-policy labour incomes is motivated by Groes *et al.* (2015), who show that this discretisation captures essential properties of the earnings implications of worker mobility between occupations. Our approximation allows for 12 states in $N \times L$ to capture differences in mean post-policy labour income between socioeconomic groups and the variation in residual post-policy labour income within each group, thus capturing variations in post-policy labour income risk by class.

Using UnSoc data, we have information about whether a household is in any of the twelve states in $N \times L$ in different years, separately for the state $\overline{s}_1$ and the states $\overline{s}_2$ and $\overline{s}_3$. Since the household is in $\overline{s}_2$ only for one period, we assume that the transition probabilities between the $N \times L$ states are the same for illness states $\overline{s}_2$ and $\overline{s}_3$. Therefore, we calculate

[31] In particular, we want to allow our model to capture the situation of individuals who leave the labour force for health-related reasons. As these individuals are unlikely to be actively looking for employment, we would miss these households if we only considered the unemployed.

[32] See, e.g. Kambourov and Manovskii (2009) for a similar approach to obtain a proxy for earnings risk within professional groups, albeit in a setting that does not model the state of health.

[33] Note that some of the variables in $D_{i,t}$ are time-invariant, whereas others are common across households. To simplify the presentation, we include all these observable characteristics that we need to partial out in $D_{i,t}$.

the transition probabilities between the $N \times L$ states by the respective proportions of households who move between the $N \times L$ states separately for $s_t = \bar{s}_1$ and $s_t = \bar{s}_2, \bar{s}_3$.

We show in Appendix C.3 the constituent parts and the construction of the 36×36 transition matrix Q^* for the joint distribution (n_t, l_t, s_t) implied by the above calibration strategy. This transition matrix captures the dependence of health risk on socioeconomic conditions and the dependence of income risk on health status observed in the data (see Table 1 in Section 2). The transition probabilities from $\bar{s}_1$ to $\bar{s}_2$ in Q^* are calculated as the share of households in each group that have experienced a health shock in a given period, conditional on not having had a health shock in the past. Moreover, the transition probabilities $\Pr(n_{t+1} \mid n_t, s_t = \bar{s}_1)$ and $\Pr(n_{t+1} \mid n_t, s_t = \bar{s}_2, \bar{s}_3)$ implied by Q^* in Appendix C are those in Table 2 in Section 2.

4.2 Model parameters

To calibrate the possible outcomes of the random variable $w(n_t, l_t, s_t)$, we use ϵ_t from (9), re-centred around the conditional mean of post-policy labour income, relevant for each group, so that we approximate cross-household variation in post-policy labour income net of variation in the factors we control for in (9).[34] In our data, post-policy labour income does not differ significantly between the three states of shocks to health.[35] Therefore, we calculate the average value of re-centered residual post-policy labour income as $w(n_t, l_t, s_t)$ for each subset of households in $N \times L$, and independently of $s_t = \bar{s}_1, \bar{s}_2, \bar{s}_3$. We finally re-scale $w(n_t, l_t, s_t)$ so that its expected value across the population in the invariant distribution ξ^* is normalised to 1. These outcomes for $w(n_t, l_t, s_t)$, which are shown in Appendix C.3 are implied by our calibration for the stochastic process (n_t, l_t, s_t).

The Markovian process for labour income $w(n_t, l_t, s_t)$ captures between-group labour income inequality and transitions between these groups by construction. As shown in Table 4, our modelling and calibration also capture differences between socioeconomic groups in terms of within-group variation in residual post-policy labour income, as measured by the Gini index or the variance of logarithms. The between-group differences in residual post-policy labour income variation reflect differences in higher moments of the income distribution, and they also reflect between-group differences in income risk, conditional on the socioeconomic group.

[34] Partialing out variation due to non-stochastic factors that are not included in the model is typical in the literature, see, e.g. Meghir and Pistaferri (2011).

[35] In the relevant literature though (see, e.g. Lenhart (2019) and Jones and Zantomio (2020)), the evidence is rather mixed.

Table 4: Comparison of Data and Model Labour Income

	Relative Mean		Gini		Var Log	
Groups	UnSoc	Model	UnSoc	Model	UnSoc	Model
Professionals	1.53	1.49	0.22	0.19	0.18	0.13
Intermediate	1.07	1.03	0.24	0.21	0.23	0.16
Routine	0.74	0.71	0.21	0.18	0.17	0.12
Non-employed	0.49	0.48	0.25	0.21	0.28	0.18
All	1	1	0.29	0.27	0.34	0.26

Note: Labour Income in UnSoc refers to recentred residuals of post-policy labour income, for details see Appendix A and C
Source: Pooled Sample UnSoc Waves 1-9 and model calculations

As can be seen in Table 4, in the data as well as in the invariant distribution implied by the Markov chain, moving across groups from the group of professional occupations to the group of non-employed, within-group unexplained post-policy labour income inequality rises, falls and rises again, with the non-employed group having the highest inequality. Overall, the Markov chain approximation captures well the qualitative properties we see in the data.

We set the discount factor $\beta = 0.96$, which is commonly used with annual frequency data for the UK (see, e.g. Faccini *et al.* (2011), Harrison and Oomen (2010) and Angelopoulos *et al.* (2020)). We set the value of $r\,(z_t = z^*)$ to 0.56% to match the average real long-term bond yield in the UK between 2009-2018. The health depreciation rate in the absence of severe illness, $\delta(s_t = \overline{s}_1)$, is set to be 0.9624, which implies a household can spend a maximum of 60 years without investing in their health before reaching the lower bound on health. We normalise the lower and upper bounds for health, $h^{\min}$ and $h^{\max}$ respectively, to $[0.1, 1]$ (see Appendix A for details).

We chose the remaining parameters to minimise the distance between model predicted quantities from their empirical counterparts, and we summarise them in Table 5. We first specify the utility and health improvement functions, $u\,(c_t, h_{t+1})$ and $m\,(x_t)$, respectively. The utility function takes a standard constant relative risk aversion form[36]:

$$u\,(c_t, h_{t+1}) = \frac{(c_t^{\phi} h_{t+1}^{1-\phi})^{1-\sigma}}{1-\sigma}, \tag{10}$$

where $\phi \in (0, 1)$ is a parameter determining the relative weights of consumption and health in the utility function, and σ is a coefficient that determines risk aversion. The coefficient of a relative risk aversion for consumption is estimated to be about 1.5 for the UK (Faccini *et al.* (2011)), which pins down σ as $1 + (0.5/\phi)$. The functional form for the effective production of new health, $m\,(x_t)$, takes the form of a production function and is given by:

$$m\,(x_t) = q x_t^{\gamma}, \tag{11}$$

[36]This utility function satisfies the conditions $\lim\limits_{c\to 0} u_c(\cdot) = +\infty$, $\lim\limits_{c\to\infty} u_c(\cdot) = 0$, $\lim\limits_{h\to 0} u_h(\cdot) = +\infty$, $\lim\limits_{h\to\infty} u_h(\cdot) = 0$, and $\lim\limits_{c\to\infty} \inf -\frac{u_{cc}(\cdot)}{u_c(\cdot)} = 0$. These assumptions imply that the household should choose a positive level of consumption and health, and also incorporate incentives for a finite maximum desired level of consumption and health. On assumptions regarding the utility function when modeling economic choices under idiosyncratic risk, see, for example, Aiyagari (1994), Acikgoz (2018) and Zhu (2018).

where $\gamma \in (0, 1)$ measures the marginal productivity of investment in health, and $q \geq 0$ is a linear productivity parameter.

The two further possible outcomes of the random variable $\delta(s_t = \bar{s}_2)$ and $\delta(s_t = \bar{s}_3)$, the parameters γ, q, ϕ and the borrowing limit $a^{\min}$ are chosen to mininimise the distance between model predicted quantities from their empirical counterparts, using model simulations. We describe this procedure in detail in Appendix C.5. We target the conditional means of health for the three states in S, the variance of health across the population (which is 0.014 using UnSoc data), the share of households with non-positive wealth (which is 19%, using data from WAS), and the share of private health expenditure in consumption, which is 8.9%.[37] Table 5 summarises the calibrated parameters.

Table 5: Calibrated Parameters

β	σ	$a^{\min}$	r	γ
0.96	1.6504	-0.0059	0.0056	0.5190
$\delta(s_t = \bar{s}_1)$	$\delta(s_t = \bar{s}_2)$	$\delta(s_t = \bar{s}_3)$	ϕ	q
0.9624	0.8128	0.9606	0.7687	0.1018

Note: For details on the calibration procedure, see Appendix C.

4.3 Health and wealth inequality

We solve the calibrated model to obtain the stationary equilibrium and confirm that it matches the key stylised facts regarding wealth and health inequality in Section 2. In Table 6, we present relevant model predictions for household health and wealth.

Table 6: Model Predictions of endogenous variables

	Health		Wealth		
Soc. Groups	Mean	Gini	Relative Mean	Gini	Indebted
Professional	0.75	0.08	1.88	0.45	8%
Intermediate	0.69	0.09	1.01	0.54	14%
Routine	0.63	0.10	0.47	0.65	33%
Non-employed	0.59	0.11	0.31	0.74	40%
All households	0.68	0.10	1	0.59	19%

Note: Indebted refers to the share of households with zero or less than zero assets.
Source: Model Calculations

The first two columns show the models predictions for health. Comparing the socioeconomic group-specific means and Gini coefficients with those obtained from the data (presented in table 1), it can be seen that the model matches the data well, despite the calibration not explicitly targeting any group-specific means or measures of variation of health within groups. In terms of means, there is a clear social gradient in health that matches the patterns we observed in the data. Quantitatively, the professional occupations group is healthier in relative terms, but the ranking is correct, and relative differences between the three remaining groups are also quantitatively similar. In terms of within-group variation in health, the model predictions also follow the pattern outlined in Table

[37] This is calculated using data from the Stoye (2017) and is discussed further in Appendix C.5.

1 - within-group health variation increases as mean health decreases.

We then examine the model predictions regarding wealth inequality, captured by the variation in wealth between and within socioeconomic groups (see also Angelopoulos *et al.* (2019) for wealth inequality analysis under socioeconomic groups). In the remaining columns of Table 6, we present the relevant model predictions. The model captures the empirical variation in wealth inequality between socioeconomic groups we presented in Table 3. In particular, between-group wealth inequality in the model tracks the data very well, and the model also captures the qualitative features of within-group inequality between groups.

The model generally underpredicts the extent of wealth inequality, which is consistent with existing research in this class of models (see, e.g. Krueger *et al.* (2016) for a review) and for the UK in particular (e.g. Angelopoulos *et al.* (2019, 2020)). The main reason is difficulty with matching the long right tail in the wealth distribution. However, factors the may explain wealth at the top 1% of the distribution are not central to the dynamics of health inequality post-crisis and the role of the social gradient in health, so to simplify the model, we focus on the wealth distribution among the 99% of the wealth distribution. Indeed for the left tail of the wealth distribution, represented here by the share of indebted households by groups, the model predictions match the data well.

Importantly, the model captures the extent of health inequality we observe in the UnSoc data, defined as the co-determination of health with income. The Erreyges and Wagstaff indices for health with respect to earnings are 0.105 and 0.115 respectively, which are slightly above the values in the data, but nontheless suggest that the model generates a significant correlation between labour income and health. In addition to health inequality defined in terms of income, our model also allows us to measure health inequality in terms of co-determination of health with wealth. In this case, the Erreyges and Wagstaff indices are about twice as large, 0.215 and 0.234, respectively, suggesting that health has a much stronger correlation with wealth than income. Many studies find links between wealth and health (for example, Seymonov *et al.* (2013), Caesarini *et al.* (2016) and Schwandt (2018)), and, conceptually, this relationship is indeed at the heart of the social gradient explanations of health inequality (see, e.g. Marmot (2003, 2004), Wilkinson and Pickett (2008, 2014)). However, quantifying it relative to the health-income inequality at the national level is empirically challenging, given data availability. Given the ability of our model to predict the remaining distributions and relationships well, we can have some confidence in using its prediction to infer the extent of health inequality in terms of wealth.

5 Post-pandemic distributional dynamics

To study post-pandemic inequality dynamics, we need to compute key statistics that summarise the distributions of health and wealth over time and under epidemiological uncertainty. In particular, we need to calculate the probability distribution of these statistics (of the health and wealth distributions, e.g. of the Gini index) over possible paths of the aggregate state, at any point in time. To this end, we first calibrate the post-pandemic exogenous stochastic processes combining information from the COVID-19 shock, to measure the impact of the pandemic on the economy, and the experience of previous pandemics to approximate recurrent outbreak risk.

5.1 Exogenous processes post pandemic

The period after the surprise impact of the pandemic, in particular, COVID-19 in 2020, is characterised by epidemiological uncertainty. There is uncertainty about how long COVID-19 will last, and about whether there will be recurrent outbreaks. This is reflected in the transition matrix for z_t. In turn, an outbreak affects the idiosyncratic shock processes.

5.1.1 Aggregate (disease outbreak) uncertainty

Drawing on current research and historical evidence presented in section 2, we specify the state space Z of the aggregate level stochastic process (z_t) as $Z = \{C, R, N, O\}$. If $z_t = C$, there is a large scale epidemic (a pandemic), which affects the stochastic processes defining idiosyncratic health and income uncertainty. If $z_t = R$, there is a recurrent disease outbreak, which also affects economic and health outcomes, although not as severely as during the pandemic state C. These states correspond to periods of outbreaks that may follow the pandemic. Periods where $z_t = R$ refer to years of low disease incidence, without health or economic impacts, although there remains the probability of a disease outbreak in the near future (i.e. an R in the near future is possible). Together, R and N characterize the medium run environment after an outbreak, when the main source of the outbreak has been brought under control, but there is still a risk of recurrent outbreaks. In contrast, the last state $z_t = O$ indicates a period where there is no outbreak and it is sufficiently distanced from the pandemic so that future outbreaks are less likely. Hence, the O state represents a situation where the disease has been completely brought under control through vaccinations or other methods.

The above modelling also informs the calibration of the transition matrix of the aggregate state Q_Z. We set the expected duration of the pandemic period C to two years, which is in line with the main waves of the 1890-91, 1918-19 and COVID-19 pandemics. The Markov switching model using the data from the historical pandemics estimates the probability of exiting the post-pandemic period of recurrent outbreak risk to be 0.079, implying an expected duration of 12.66 years. We set therefore the probability of exiting the states R or N to move to O accordingly. Once in O, there is a possibility of further pandemics.[38] We also set this to the probability of the pandemic state occuring as estimated from the Markov switching model, 0.027, implying a pandemic outbreak roughly every 35 years. Finally, we set the probability of a recurrent outbreak, conditional on being in the post-pandemic period to 28.6%, using estimates from the post-COVID-19 model predictions for outbreaks exceeding 500 deaths in Angelopoulos *et al.* (2021a). The aggregate state transition matrix is given by:

$$Q_Z: \quad \begin{array}{ccccc} z_t \backslash z_{t+1} & C & R & N & O \\ C & 0.5 & 0.143 & 0.357 & 0 \\ R & 0 & 0.263 & 0.263 & 0.079 \\ N & 0 & 0.263 & 0.263 & 0.079 \\ O & 0.027 & 0 & 0 & 0.973 \end{array}$$

[38] Medical researchers and public health experts have warned of the rising possibility of global epidemics brought about by intensifying animal agriculture, increasing urbanisation and global connectivity and antibiotic resistance (Zappa *et al.* (2009), Alirol *et al.* (2011), MacIntyre and Bui (2017)).

5.1.2 Pandemic effects on exogenous processes

This subsection describes the characteristics of the idiosyncratic processes in each of the four aggregate states for z_t. Further details are in Appendix D. The state O has been defined as a state where the effects of the pandemic and its subsequent turbulent period on idiosyncratic health and income risk have faded. Therefore, we assume that in terms of idiosyncratic processes O is identical to the situation before COVID-19 (see Section 4).

The changes in the idiosyncratic processes in the case of a major disease outbreak ($z_t = C$) are calibrated based on evidence on the effects of COVID-19. There is an increase in health risk, as captured by an increase in the probability of severe illness relative to the base calibration in Section 4. We assume an increase in health risk by 50% on average. Some of this higher risk is due to excess mortality. The excess mortality rate among 15 to 64 year olds during the first year of the COVID-19 epidemic, in particular from the last week of March 2020 to the last week of March 2021, was 20.17% (using data in Roser *et al.* (2020)). However, excess mortality is a lower bound on the increase in health risk. For example, compared with 2019, in 2020 there was a reduction of completed treatment pathways by 28% and in hospital referrals by 20% (Gardner and Fraser (2021)) and a reduction in emergency admissions by 20% (NHS England data on Adjusted Monthly A&E Attendance and Emergency Admissions data). This evidence suggests an increase in health risk between 20% and about 100%. Moreover, the increase in health risk differs by socioeconomic group, and following e.g. Marmot *et al.* (2020), it is lower for professionals and higher for routine. In particular, we assume an increase in health risk by 14%, 43%, 100% and 50% for professionals, intermediate, routine, and non-employed, respectively.

There are also losses in net labour income during C. HM Treasury (2021) have calculated the COVID-19 induced drops in household income (post policy), over and above earnings increases and drops up to 10% of earnings (which could be associated with a non-epidemic period).[39] We use the HM Treasury (2021) results to calibrate the implied income drops that correspond to the pre-COVID-19 income levels in the model. These are in addition to the usual income gains/losses via the idiosyncratic income process.

The HM Treasury (2021) estimates imply a progressivity in income drops, i.e. income drops were bigger for higher deciles. This is consistent with existing evidence suggests that despite the potential of COVID-19 effects to increase earnings inequality, post-policy income inequality did not increase during 2020 (see e.g. Stantcheva (2021)). To calculate the HM Treasury (2021) estimates of income loss in terms of socioeconomic groups, we translate the per income decile drops to the groups we model using the pre-COVID-19 income distribution (see Figure 5). Note that these are progressive in terms of net labour income with respect to income and socioecoomic groups. However, when we express them in terms of total resources, the drop is regressive.

Figure 5 here

We also assume that economic activity restrictions imply restrictions on consumption. In the UK (Tenreyro (2021) (and in the EU (Dossche and Zlatanos (2020))), restrictions in consumption are linked to increased savings, with the effect being higher for

[39] HM Treasury (2021) used Understanding Society data to estimate, for different earnings levels, the probability of job losses, earnings drops more than 10%, and furlough, and calculated income changes using the HM Treasury distributional analysis model.

higher income groups (Hacioglu-Hoke *et al.* (2021), Bank of England (2020), Tenreyro (2021)). Evidence in Davenport *et al.* (2021) suggests that amongst the two highest income quintiles, consumption dropped approximately 25% in the first months of the crisis, with smaller increases for lower income groups and negative changes for the lower income groups (consistent with patterns in Bank of England (2020), Tenreyro (2021) for later in the year). For the top quintile, this drop in consumption is bigger than what the income drop on its own predicts. Therefore, to align the model with the data, we impose an upper limit on consumption, calibrated so that the average consumption level of the top quintile fell by 25% compared to their pre-COVID mean consumption level. The model predictions for the change in savings/consumption by quintile in 2020 are then following the patterns in the data.

We assume that during recurrent outbreak periods, R, the increase in health risk is half of its increase in C and that net labour income income losses are half of those in C. Moreover, the upper limit on consumption of the top income quintile is set to imply half of the drop in consumption for the top quintile, compared with C. During periods N, all idiosyncratic health and income processes are assumed to the same with those pre-pandemic, or else with those in state O.

Consistent with the experience during COVID-19, we assume that the interest rate is zero during C periods. The interest rate in the remaining aggregate states is calibrated as follows: i) the expected long-run interest rate is equal to the interest rate prevailing in the stationary world: $E(r) = r(z^*)$; ii) the interest rates are raised cautiously post pandemics so that $r(R) = r(N) = \frac{r(O)}{2}$. The risk premium for borrowing is assumed to remain at 1% throughout.

5.2 Health and wealth inequality post pandemic

To calculate the required probability distributions of health and wealth following the pandemic, we work as follows. We solve the typical household's problem in Section 3 under the stochastic environment described in the previous sub-section, for the household-level parameters described in Section 4. We simulate a panel of 5000 sequences of the evolution of the aggregate state, initialising each sequence from the invariant distribution λ^*, associated with Q^*, i.e. without pandemic risk (see Section 4). Then, we simulate the evolution of the distribution of all exogenous and endogenous variables, beginning from the distribution λ^*, for every path of aggregate state variables. For details of this Monte-Carlo procedure, see Appendix C. The result of this procedure is a panel of joint distributions of health and wealth, relating the exogenous and endogenous variables of the model to possible paths for the aggregate state. In particular, we have a distribution of 5000 descriptive statistics of the joint distribution of health and wealth at every point in time. Each cross-sectional distribution has been obtained under a random realisation of the path of the aggregate state. This procedure allows us to analyse possible outcomes of the joint distribution of health and wealth in terms of the probability that they will arise.

Our baseline results are obtained using the aggregate transition matrix in (**??**).We show results from this analysis for economy-wide statistics, and also by socioeconomic group. We plot the median statistic in each time period, and the interquartile range (the 50% interval around the median) and the 90% interval around the median.

To contextualise the importance of post-pandemic epidemiological uncertainty for health and wealth inequality, we also repeat the above analysis for two different counterfactual experiments: when the pandemic is an one-off event and will never return, but the households actually make choices under uncertainty; and when the pandemic is an one-off event and will never return, and the households know it.[40] By comparing these two scenarios to the baseline results, we see the effects of post-pandemic epidemiological uncertainty, i.e. of recurrent outbreak risk and shocks. By comparing these two scenarios directly, we can see how much post-pandemic recurrent outbreak risk affects behaviour via precautionary incentives.

6 Post-pandemic distributional dynamics

To study post-pandemic inequality dynamics, we need to compute key statistics that summarise the distributions of health and wealth over time and under epidemiological and economic recovery uncertainty. In particular, we need to calculate the probability distribution of these statistics (of the health and wealth distributions, e.g. of the Gini index) over possible paths of the aggregate state, at any point in time.

To calculate the required probability distributions, we work as follows. We solve the typical household's problem in Section 3 under the stochastic environment described in Section 5 for the remaining household-level parameters described in Section 4. We simulate a panel of 5000 sequences of the evolution of the aggregate state, initialising each sequence from the invariant distribution λ^*, associated with Q^*, i.e. without pandemic risk (see Section 4). Then, we simulate the evolution of the distribution of all exogenous and endogenous variables, beginning from the distribution λ^*, for every path of aggregate state variables. For details of this Monte-Carlo procedure, see Appendix B. The result of this procedure is a panel of joint distributions of health and wealth, relating the exogenous and endogenous variables of the model to possible paths for the aggregate state. In particular, we have a distribution of 5000 descriptive statistics of the joint distribution of health and wealth at every point in time. Each cross-sectional distribution has been obtained under a random realisation of the path of the aggregate state. This procedure allows us to analyse possible outcomes of the joint distribution of health and wealth in terms of the probability that they will arise. Our analysis below focuses on the 10th, 25th, 50th, 75th and 90th percentile of the probability distributions of health and wealth inequality statistics.

Our baseline results are obtained using the aggregate transition matrix in (**??**). To contextualise the importance of post-pandemic epidemiological uncertainty for health and wealth inequality, we also repeat the above analysis for two different versions of (**??**). First, we consider the effects of a smaller probability of disease recrudescence, implying that, in expectation, there is one mild disease outbreak per decade in the medium run after the major pandemic event (recall that in the base calibration, there are three such outbreaks per decade in expectation). Second, we consider the case where the aggregate transition matrix zeroes out epidemiological risk after the pandemic. In this case, the only

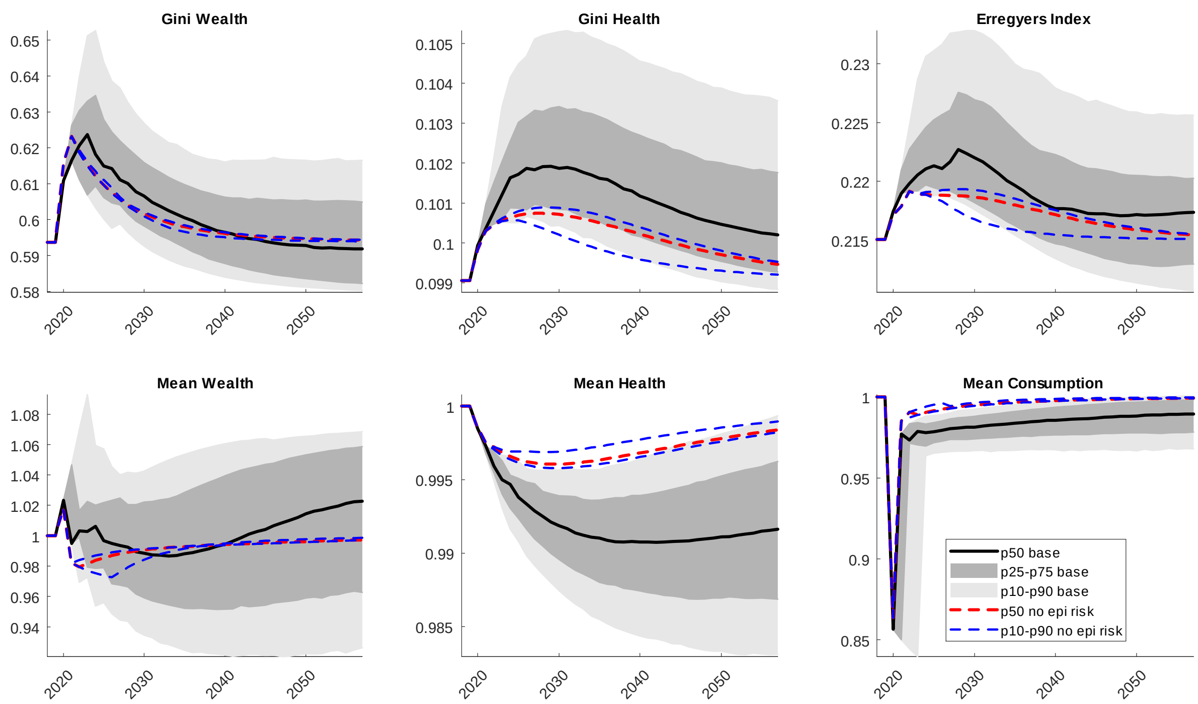
[40] The one-off pandemic is defined as the pandemic effects in 2020, half of these in 2021, and then back to pre-COVID-19 effects for the exogenous processes.

uncertainty that households face is the duration of an economic boom recovering from the COVID-19 pandemic. Both alternative transition matrices are shown in Appendix D.5.

6.1 Economy-wide effects

We first examine post-pandemic inequality dynamics by studying economy-level quantities. In Figures 5 and 6, we plot the time evolution of the 10th, 25th, 50th, 75th and 90th percentile of the distribution of: the Gini indices describing the concentration of wealth and health across the whole economy; the Erregyers index of the relationship between concentration in health and wealth; and, the average values, across households, of assets, health, and consumption. In Figure 5, results are shown for the baseline aggregate transition matrix in (**??**), relative to a scenario with only economic recovery risk (i.e. without possible disease outbreaks post 2021). In Figure 6, epidemiological uncertainty is determined by the aggregate transition matrix that implies a low probability of recrudescence (see Appendix D).

Figure 5: Simulated transitions to long run stochastic steady state under epidemiological risk



Note: Model simulation based on a sample of 5000 sample economies.
Circles denote location of median outcome 50 years after the initial shock.

We start with Figure 4 and first examine inequality. Regarding wealth inequality, we observe significant increases after the pandemic. Under epidemiological risk, the Gini index increases and then starts to decline, with a maximum median increase of about three points. Therefore, in half of possible the paths after the pandemic, wealth inequality increases by more than three Gini points at the peak. In fact, increases in the Gini index of more than five points have a high probability of 25%, and even increases in inequality of more than six points have a 10% probability. To contextualise the scale of such increases, we note that using WAS data, we calculate that the Gini increased by 4.5 points following the 2008 recession, between 2007 and 2013. Moreover, in the majority of post-pandemic paths, wealth inequality increases further after the initial shock and its immediate inequality implications.

There are also persistent increases in health inequality. In particular, both the Gini index of the distribution of health and the Erregyers index of health inequality show significant increases following the pandemic. The changes in these statistics appear relatively small in magnitude. However, to contextualise these magnitudes, we should note that they are orders of magnitude bigger than changes we observe in Understanding Society in the ten-year period since 2009, i.e. after its first wave. In particular, the Gini index oscillates between 0.088 and 0.092, where the Erregyers index between 0.071 and 0.084 there.

We then contrast these results with the counterfactual experiment, also shown in Figure 6, where epidemiological risk is shut down. On the one hand, examining the dynamic evolution of the median outcome of the joint wealth and health distribution statistics, we do not see fundamental differences. The changes relative to the pre-pandemic health-wealth distribution are generally more adverse and last longer when we also allow for epidemiological risk, but the magnitudes are broadly similar. On the other hand, the differences between the two scenarios become substantial when we examine worse paths of aggregate state. While epidemiological risk implies that big increases in inequality are possible, the differences from the median when we only allow for economic recovery risk are negligible. In other words, while the 50th percentile of, e.g. the wealth Gini, is similar with and without epidemiological risk, the 25th percentile differs by two Gini points, and the 10% by four Gini points.

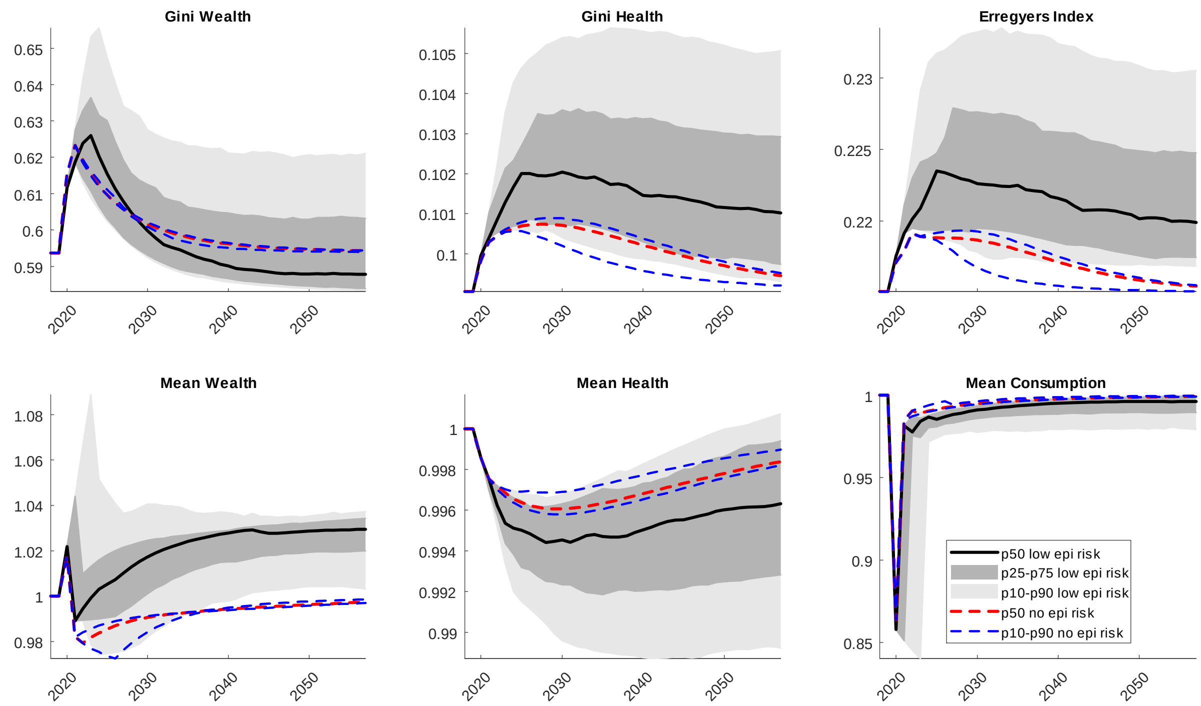
Naturally, given that epidemiological uncertainty entails only downside risk, its effect on the distribution of possible inequality outcomes is negative, i.e. epidemiological risk shifts inequality outcomes towards worst realisations. The results in Figure 5 are important because they show that this impact is large in terms of both magnitude of the change and likelihood. Under epidemiological risk, severe increases in inequality have a high probability, whereas under economic recovery risk only they are low probability events.

We continue with economic and health outcomes on average, across households, under both epidemiological and economic recovery risk. We observe an initial increase in mean household wealth, which is consistent with the increases in savings documented in empirical research for 2020 (e.g. Hacioglu et al. (2020) and ONS (2020)). This increase, driven by the restrictions in consumption during the pandemic (see Section 5 for a discussion), is short-lived and followed by a subsequent reduction before returning to pre-pandemic levels. The initial change in mean consumption mirrors the initial rise in mean wealth. Following the initial drop, mean consumption bounces back quickly to recover from lockdown restrictions, but it increases slowly back to the pre-pandemic values thereafter. Health also drops, and in this case, the effects are more persistent because the world with pandemic risk implies lower health in expectation than the pandemic-free world, which defines the stationary equilibrium that serves as the starting point in Figure 5.

As with inequality, not accounting for post-pandemic epidemiological risk has important implications for the extent of uncertainty regarding future paths of mean outcomes; under economic recovery risk only, the outcomes under the 10th and 90th percentile are much closer to the median. The drop in mean health is naturally bigger under epidemiological risk. On the other hand, mean wealth drops more, after the initial rise, in the absence of epidemiological risk. This bigger drop happens because epidemiological risk creates precautionary incentives, as households have a stronger motivation to create buffer stocks to mitigate economic and health implications of possible future disease outbreaks.

We then move to examine how much the effects of epidemiological risk depend on the calibration of recrudescence risk by plotting, in Figure 6, results under a lower probability of recrudescence. The difference between the results in Figure 5 and Figure 6 can also be viewed as the effect of epidemiological and other policies aimed at preventing or mitigating future outbreaks. The striking result from comparing these two figures is that not much of what was discussed previously has changed, despite reducing the conditional recrudescence probability by two thirds, from 30% to 10%. The nature of the effects of epidemiological risk is that as long as future disease outbreaks remain positive probability events, severe inequality increases remain possible. To count on epidemiological risk reduction in order to protect against such inequality increases, policy and societal preparedness must, in effect, reduce disease outbreaks to extreme events.

Figure 6: Simulated transitions to long run stochastic steady state, low epidemiological risk



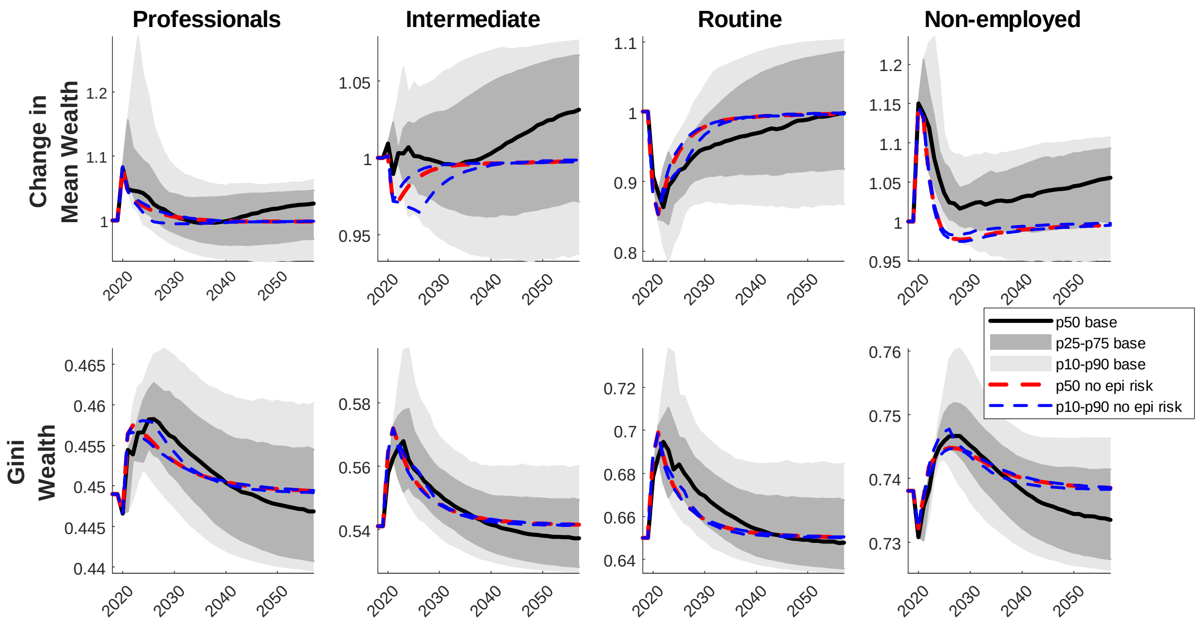
Note: Model simulation based on a sample of 5000 sample economies.

6.2 Between and within group inequality

We next analyse the between and within-group medium run inequality implications of the pandemic and the increase in risk that it implies. We plot in Figure 7 the mean wealth per socioeconomic group relative to the pre-COVID-19 stationary equilibrium for the baseline calibration of recrudescence risk. As with economy-wide results, a lower (but positive) recrudescence risk does not alter the main predictions significantly (see Figure D.11 in Appendix D;).

We note in Figure 7 differences in the changes in mean wealth between the three groups with positive earnings. Professionals increase wealth on average due to the consumption restrictions associated with lockdown measures, which are tighter for higher-income households, and essentially maintain their pre-pandemic level of wealth in the medium-run. Intermediate professions are characterised by smaller increases in wealth on average, whereas the group of households with routine jobs has a big drop in average wealth, which also takes a long time to return to pre-pandemic levels. Regarding the group of non-employed households (inactive plus unemployed), we observe an increase in mean wealth. This increase results from a combination of factors. First, we assumed no reduction in the non-market income for this group (i.e. in benefits policies) during the pandemic. Second, there are positive wealth effects from those who join this group from the remaining groups, as they become unemployed due to the recession.[41] These observations imply that changes for this group in our experiments do not have a useful interpretation, so we do not discuss them further below.

Figure 7: Between and within group wealth inequality



Note: Model simulation based on a sample of 5000 sample economies.

The message from the dynamic paths of group-level average wealth in the medium run after the pandemic is that between-group inequality increases for working households. Under epidemiological risk, this increase can be substantial and persistent, with a relatively high probability. For example, the 25th percentile implies persistent drops of nearly 10% on average for the routine group for more than 20 years following the pandemic and nearly

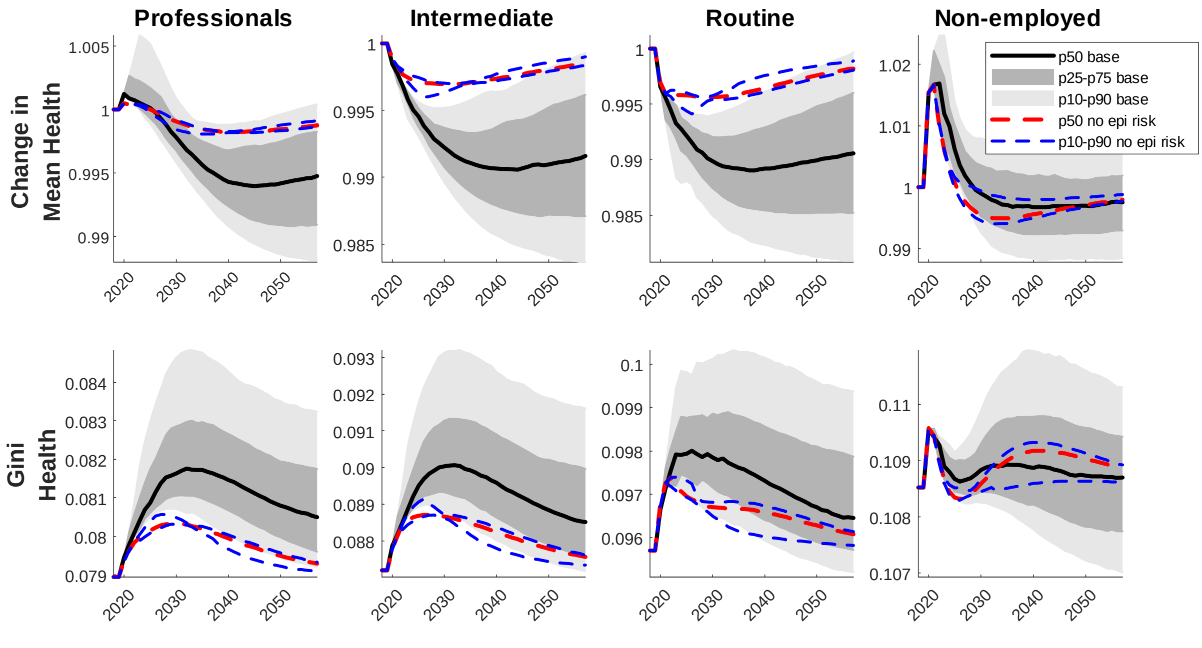
[41]To demonstrate the importance of the latter effect, we show in Appendix **XXX** the effects for this group relative to a counterfactual where the statistics are calculated using the population shares pre-COVID-19. The positive effects are absent, confirming that there is no improvement for the households already in the non-employed group.

5% for the intermediate group, with little change for professionals. Ignoring epidemiological risk implies that such increases in between-group inequality are only relatively short-lived and between-group inequality should decrease rapidly post-recession.

We next examine within-group wealth inequality in Figure 7. The differences in the Gini indices between the two scenarios of aggregate uncertainty are similar to those for the Gini index for the whole economy (see Figure 5). Both show that within-group inequality increases for most of the paths for all socioeconomic groups following a pandemic, but epidemiological risk implies that very big increases are possible.

We finally look at between and within-group health inequality in Figure 8 for the base calibration and summarise two main results.[42] First, there is a deterioration of the health of intermediate and routine groups, on average, relative to the group of professionals. Notice that the increase in health risk due to the pandemic is symmetric in our calibration. Therefore, the disproportionate decline in health for the groups of intermediate and routine jobs reflects the asymmetric economic effect of the recession and is thus indicative of health inequalities related to socioeconomic factors. Second, ignoring epidemiological risk underestimates the increase in health inequality, which, as just noted, takes place via the economic inequality implications of the epidemiological risk. In other words, epidemiological risk sets in motion a chain reaction that ends up increasing health inequality via increases in economic inequality.

Figure 8: Between and within-group health inequality



Note: Model simulation based on a sample of 5000 sample economies.

[42]See Figure D.12 in Appendix D for results with the lower recrudescence risk.

7 Conclusions

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