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Pandemic-Induced Wealth and Health Inequality and Risk Exposure

Abstract

The main waves of a pandemic and subsequent disease outbreaks in the following years influence the evolution of the distributions of health and wealth, leading to differences in the ability to mitigate future income shocks. We study consumption smoothing and precautionary behaviour associated with the main pandemic waves and recurrent outbreak risk in a model in which health and wealth are jointly determined under income and health risk that are related to disease outbreak risk. We calibrate the model to the UK and find that the impact shock of COVID-19 and recurrent outbreak risk amplify existing inequalities in wealth and health, implying persistent increases in wealth inequality that are characterised by increases in wealth for households in higher income groups and/or with higher initial wealth, and decreases for those in lower income groups and/or with lower wealth. These changes lead to inequality in exposure to post-pandemic income risk and, in particular, an increase in the vulnerability of those already with very little wealth prior to the pandemic. We assess public insurance policy to mitigate income losses for those with low wealth and find that, by disincentivising wealth accumulation and incentivising investment in health for those with low wealth and health, it reduces health inequality and, in the short run, the probability of low consumption, but increases wealth inequality and, in the medium run, the probability of low consumption.

JEL-Codes: E210, D310, I140, D150, E620.

Keywords: pandemics, outbreak risk, wealth inequality, health inequality, risk exposure.

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1 Introduction

Pandemics create health and economic crises that affect households in an unequal manner. The differential effects of the first waves of COVID-19 on income and health across the population have been examined in several studies (see, e.g. Stantcheva (2021) for a review of income inequality implications, and Marmot *et al.* (2020) focusing on health inequality). However, given the persistence of wealth and health, which reflect current as well as past outcomes, pandemic-induced increases in wealth and health inequality and their implications, can be long lasting. The inequality implications can be further amplified by potential recurrent outbreaks that follow the main pandemic waves (e.g. Kissler *et al.* (2020), Giannitsarou *et al.* (2021), Phillips (2021) and Torjesen (2021), for analysis of this potential following the main waves of COVID-19, and Schroeder *et al.* (2021) for evidence from previous pandemics). 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 (1992)).

To understand how pandemic-induced changes in wealth affect household wellbeing, it is essential to account for three key factors: the worsening of health inequality accompanying increases in wealth inequality; the increase in vulnerability to future shocks implied by reductions in existing levels of household wealth; and pre-existing inequalities. Regarding the first, the strong link between health outcomes and income/wealth (see, e.g. Marmot (2004), Semyonov *et al.* (2013) and Marmot *et al.* (2020)) implies that changes in wealth, and its variation across households, matter for household wellbeing via both health and consumption outcomes. The health inequality implications of wealth inequality can be more severe when they follow a pandemic twith substantial direct negative health effects because a deterioration in health driven by changes in wealth applies to an already worsened state of health. Regarding increased vulnerability, persistent increases in wealth inequality imply increased risk exposure for households whose wealth is reduced because the means to self-insure against future income shocks are also reduced. Regarding effects of pre-existing inequalities, the magnitude and severity of reductions in wealth, consumption and health depend critically on the pre-pandemic household conditions to which the reductions apply.

We study changes in wealth and health driven by the main pandemic waves and subsequent outbreaks, across households and over the decades that follow the pandemic. We emphasise the dependency of these changes on different household-level pre-pandemic conditions, and the differential vulnerability to income risk and health risk that they imply. Post-pandemic changes in health and wealth reflect the effect of exogenous shocks and household choices in response to them and to changes in risk associated with the pandemic and recurrent outbreaks. Hence, to understand household behaviour, we firstly examine household incentives for consumption smoothing in response to pandemic shocks, and for precautionary behaviour in response to changes in risk. We then compute the dynamic evolution of the joint distribution of health and wealth following the COVID-19 shock, which incorporates household responses across the distribution, in a calibration that accounts for pre-existing inequalities in the UK and the effect of both the first waves of COVID-19 and recurrent outbreak risk.

The model and computational analysis build on research that models household heterogeneity under imperfectly insured idiosyncratic shocks.[1] In our model, households derive utility from both consumption and health and choose the levels of two state variables, health and wealth, in response to household-specific shocks to income and health that they experience, and the risk of future shocks.[2] Households use their income for consumption, savings that increase future wealth, and expenditure that improves future health. Choices depend on the levels of current income, wealth and health, which reflect the history of health and income shocks received, and on probabilistic assessments of future outcomes. Households belong to different socioeconomic groups, defined by professions, and transitions between groups are stochastic. Household-specific income and health shocks depend on the socioeconomic group, reflecting a social gradient in health, and are conditional on the aggregate state, particularly on disease outbreaks. Aggregate level uncertainty is modelled as a stochastic epidemiological process of disease outbreaks and is informed by estimates of recurrent outbreaks from previous pandemics. Disease outbreaks increase health risk, influence income and limit consumption asymmetrically across the population.

In addition to permitting a positive relationship between shocks to income, socioeconomic group and health, the model links health and wealth via household choices. Higher resources allow increased savings to augment future wealth and expenditure to improve health. Because income shocks are imperfectly insured, households who have had higher income (as a result of a series of good income shocks) also tend to have higher wealth and health, leading to positive cross-sectional relationships between income, health and wealth. These relationships are consistent with existing research (Marmot (2004), Marmot *et al.* (2020)), and are reflected in national-level survey data for the UK from the UK Household Longitudinal Study, Understanding Society (ISER (2020))), and the Wealth and Asset Survey (ONS (2018)) that we analyse in Section 2.

Despite the positive cross-sectional relationship between health and wealth, theoretical analysis reveals that at the household level these act as substitutes in household responses to the effects of the pandemic. In particular, household behaviour incorporates incentives to treat them as substitutes in smoothing consumption following negative income shocks and in responding to changes in income risk, provided that the utility function does not imply strong preferences to substitute health for consumption. On the one hand, because allocating resources to future wealth or health reduces available resources for consumption via the budget constraint, a larger allocation to wealth (health) creates incentives for a smaller allocation to health (wealth). On the other hand, substitutability in consumption and health in the utility function generates incentives for complementarity in the response of health and wealth. As long as substitutability between consumption and health is sufficiently bounded, a bigger response in wealth (health) is met by a smaller response in health (wealth), and even allows as a possibility that health (wealth) changes in the opposite direction. These incentives are embedded in household responses to negative income shocks and heightened risk implied by the pandemic, and have opposite effects: following an unexpected income drop consumption smoothing requires that at least one

[1] Studies in this literature extend original contributions of Bewley (1986), Imrohoroglu (1989), Huggett (1993), and Aiyagari (1994) (see DeNardi (2015) and Krueger *et al.* (2016) for reviews).

[2] Research using models with imperfectly insured idiosyncratic shocks (without, or, conditional on, aggregate shocks) and more than one state variables typically focuses on different financial assets, or human capital in addition to physical assets (see Krebs (2003), Toda (2014) and Kaplan *et al.* (2018)). Here, we model health jointly with wealth as endogenous state variables.

of wealth and health (but not necessarily both) must fall; while precautionary motives require building buffer stocks of at least one of health and wealth (but not necessarily both). The substitutability between health and wealth in response to the pandemic, combined with the conflicting effects of consumption smoothing and precaution, imply that the effects of the pandemic on the joint evolution of health and wealth inequality depend on a quantitative evaluation of underlying trade-offs, which further depends on initial conditions associated with the pre-pandemic distribution.

Our quantitative analysis focuses on the UK. Analysis of data from the UK Household Longitudinal Study and the Wealth and Asset Survey shows that households in socioeconomic groups with higher mean income also have higher wealth and self-reported health. They also face lower health risk, as measured by the probability of experiencing a severe health event that substantially deteriorates their health. The data also reveal more variation in terms of both wealth and self-reported health within socioeconomic groups with lower mean income, suggesting that differences within socioeconomic groups are particularly important when the interest lies in understanding effects on lower-income households. We calibrate the model to match several key properties of the pre-COVID-19 UK health and income distributional characteristics, including differences in mean health, health and labour income risk by socioeconomic group, and mobility between socioeconomic groups. 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 were not included as calibration targets. We find that household behaviour and the mechanisms and channels in the model structure generate the stylised empirical properties of within-group health and wealth inequality.

We then examine the stochastic dynamics following the shock in 2020, which we calibrate using information on drops in post-policy income obtained from the HM Treasury distributional model, increase in health risk (e.g. excess mortality and reductions in treatment for other ailments; Marmot *et al.* (2020), Roser *et al.* (2020) and Gardner and Fraser (2021)), and a consumption limit, motivated by economic restrictions, to match the observed change in consumption/savings for the top quintile (Davenport *et al.* (2020), Hacioglu-Hoke *et al.* (2021), Tenreyro (2021)). The aggregate-level risk of disease outbreaks is captured by uncertainty about the length of the main pandemic waves and by a $\sim$25% probability per year of a recurrent outbreak for a decade after the main waves, based on estimates in Schroeder *et al.* (2021)[3], with outbreaks having half the effects of the main waves on income, health and limits on consumption.

The model environment implies a distribution of possible joint cross-sectional distributions for each year after 2020, depending on realisations of the stochastic epidemiological process, which we use to make probabilistic statements regarding the endogenous cross-sectional distributional outcomes, i.e. wealth and health inequality, with reference to initial conditions and pre-existing inequality. Examining outcomes for households at the left tails of these distributions reveals the scale of wealth reduction for the wealth-poor and allows us to quantify the extent and implications of the increase in risk exposure for these households that result from the pandemic.

Our first main result from the computational solution for the UK is that the pandemic amplifies pre-existing inequalities in wealth and health. In particular, we find persistent

[3]Schroeder *et al.* (2021) use mortality risk estimates from different geographical regions after the main waves of the 1918-19 and 1890-91 pandemics to inform a model of mortality dynamics post-2020 in a procedure allowing for model uncertainty.

increases in wealth inequality, which are characterised by: increases in the levels of wealth and health for households in the higher labour income groups or with higher initial wealth (e.g. a 10% increase for households at the 90% percentile of the pre-COVID-19 wealth distribution); and decreases for those in the lower labour income groups or with lower initial wealth (e.g. a 10% (12%) decrease for households at the 25th (10th) percentile of the pre-COVID-19 wealth distribution). In addition to the reduction in the level of wealth at the left tail of the distribution, there is also an increase in the thickness of the tail, resulting from an increase in the proportion of households that are in debt and with very low wealth. Model simulations suggest that the increase in inequality persists for more than a decade. Comparisons with a scenario in which there are no further disease outbreaks after the main pandemic waves suggest that the risk of recurrent outbreaks implies inequality effects that are more adverse and last longer.

These results are driven by the combined effects on household choices of: first, consumption smoothing and limits on consumption associated with the initial effect of the pandemic in the first year; and second, precautionary incentives induced by outbreak risk. Regarding the initial effect of the first year, the shock associated with the initial waves of the pandemic includes income drops and limits on consumption. The drops in income imply consumption smoothing incentives, which tend to reduce at least one of wealth and health, while the limit on consumption tends to increase at least one of the assets. Our quantitative analysis shows that consumption smoothing incentives dominate for households with low initial wealth and in low-income socioeconomic groups and drive an overall reduction in wealth. On the other hand, for high-income groups and high-wealth households, the effects from the limit on consumption are stronger than the consumption smoothing incentive, thus explaining overall increases in wealth associated with the upper tail of the wealth distribution. Regarding recurrent outbreak uncertainty, following the regressive drop in wealth after the initial pandemic impact, precautionary incentives in response to outbreak risk amplify further wealth inequality and increase its persistence over time. The increase in wealth inequality happens because households that increased their wealth during the main waves have increased resources to create and maintain additional buffers relative to households that depleted their wealth to compensate for income drops.

Our second main result from the computational solution for the UK is that households with initially lower resources to mitigate income shocks are more vulnerable to income shocks following the pandemic. The post-pandemic increased variation in wealth accumulation between households in high- and low-income groups and with high and low initial wealth implies differential exposure of these households to exogenous reductions in income. Households with low wealth or in low-income socioeconomic groups prior to the pandemic are particularly vulnerable to post-pandemic income drops because reductions in wealth during the main waves have hampered their ability for self-insurance. For example, the elasticity of the reduction of consumption to a surprise one-off reduction in income that happens three years after the main pandemic waves is around 40% for households at the lower wealth deciles (10th to 25th percentiles) prior to COVID-19; this elasticity is around only 10% for households at the 90th percentile.

The post-pandemic increases in vulnerability to income risk reflect the inability of low wealth households to implement their optimal self-insurance plans because of the reduction of their wealth during the main pandemic waves. Indeed, further counterfactual analysis shows that the low wealth and highly risk-exposed households would have increased their wealth in response to the increase in income risk in the absence of the effects of the first waves. The increased vulnerability, especially because it reflects limited potential for self-insurance, can motivate policy to mitigate income losses for those with low wealth. We assess such policies and find that they reduce health inequality and vulnerability in the short run by reducing the share of households with very low consumption. However, they also imply a trade-off between health and wealth inequality and an intertemporal trade-off regarding safeguarding consumption from income risk. In particular, given the substitutability in health and wealth in responding to income drops and changes in risk, public insurance of income risk crowds in investment in health and crowds out self-insurance via wealth accumulation for households with low wealth.

Our analysis focuses on pandemic effects for wealth and health inequality and the increase in vulnerability to income risk that they imply in the decades that follow a pandemic. Our results contribute to research on the inequality implications of pandemics, which has: (i) either focused on the short-run, in the case of COVID-19[4], or on an examination of common patterns in terms of longer-run implications[5], whereas we use the short-run effects to inform the medium-run dynamics; and (ii) focused on pandemic effects on different measures of income or health (see e.g. the studies in (i)), whereas we emphasise the co-determination of health and wealth, and its implications for increased risk exposure.[6] To analyse the joint evolution of the cross-sectional distributions of health and wealth induced by changes brought about by the pandemic requires information on the pre-pandemic distributions of health and wealth and the effects of the pandemic. The experience of COVID-19 has highlighted the importance of understanding the implications of pandemic-induced inequality and also generated the information needed to permit a counterfactual model analysis to isolate pandemic effects from confounding factors.[7]

The paper is organised as follows. In Section 2, we use survey data to summarize relevant properties of the distributions of health, income and wealth in the UK before COVID-19. In Section 3 we present the model and stochastic processes and analyse theoretically incentives incorporated in household choices in response to changes in the aggregate-level process capturing effects of the pandemic. In Section 4 we explain the calibration of the model and of the effects of the pandemic on the exogenous stochastic processes. Results from the computational solution and policy assessment are analysed in Section 5, before summarising concluding remarks in the Section 6.

[4]See e.g. Adams-Prassl *et al.* (2020), Blundell *et al.* (2020), Bourquin *et al.* (2020), Davenport *et al.* (2020), Glover *et al.* (2020), Jorda *et al.* (2020), Cribb *et al.* (2021), Crossley *et al.* (2021), Hacıoğlu-Hoke *et al.* (2021), Miescu and Rossi (2021), and Stancheva (2021), for economic effects, and Banks *et al.* (2020), Dennis *et al.* (2020), Gardner and Fraser (2021) and Marmot *et al.* (2020) for health.

[5]See e.g. Furceri *et al.* (2020) for an empirical analysis and Scheidel (2018) for historical analysis.

[6]Reseach focusing on the economic implications of COVID-19 often incorporates health shocks in economic models (e.g. Eichenbaum *et al.* (2021), Farboodi *et al.* (2021), Glover *et al.* (2021), Kaplan *et al.* (2020), whereas we distinguish health shocks from an endogenous health state variable.

[7]Here, we focus on the legacy of changes in income, consumption and health during the main pandemic waves and subsequent outbreaks, in the form of their implications for wealth and health inequality, and risk exposure. We note that post-pandemic inequality may change for additional reasons, such as changes in the labour market, or in institutions and policies, or additional aggregate-level shocks. Some of these changes might arise as longer-run, structural implications of the pandemic.

2 Health, wealth and income pre-COVID-19

To summarise key characteristics of pre-existing health and wealth inequality, we examine selected aggregate level empirical properties of inequality in health and wealth, using data from the UK Household Longitudinal Study, Understanding Society, for the UK and the Wealth and Asset Survey for Great Britain. Understanding Society (UnSoc) is a large longitudinal survey covering a wide range of social and economic factors, including information about respondents' health, which has been recorded annually since 2009-2010. The Wealth and Assets Survey (WAS) is a biannual survey of household wealth and a range of household socioeconomic characteristics, with the first wave in 2006-2008.[8] Although UnSoc does not include measures of wealth and WAS does not include measures of health, both include information on the socioeconomic classification of the respondents' employment, 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 of the data, sample selection and the construction of variables are shown in Appendix A.

In this paper, we use a measure of the overall level of health and a measure of a severe health event. For the first, we use information on self-assessed health status, and for the second, information on severe health events. The UnSoc data includes a measure of self-assessed health, the 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. We also utilize information on the following (severe) health events: heart disease, heart failure, emphysema, chronic bronchitis, stroke, heart attacks and cancer.

In Table 1, we show the mean value of self-assessed 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-ranked profession of the head or the spouse. We group the 8 NS-SEC classes plus all those classed as economically inactive and unemployed into four groups with clear differences, and which makes the group classification here comparable to the discretisation we employ in the model analysis below. We term these four groups *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 here is the post-policy labour income from the head and spouse (see also Appendix A for details).

Columns [1] and [2] in Table 1 reveal that households in socioeconomic groups with higher mean income also have higher health on average and are thus indicative of a social gradient in health, in the form of between-group health inequality, which has been analysed in the literature (see, e.g. Marmot (2015, 2020) and Payne (2017)).[9] We complement these

[8] 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).

[9] The link between health and income in Table 1 for the UK using UnSoc data is also broadly consistent with patterns in the US from the PSID data; see, e.g. Cole *et al.* (2019).

results by examining how within-group variation in health and health risk are related to income, another aspect of the social gradient in health. In column [3], we show the Gini measures of concentration of good health within each of the socioeconomic groups, which reveal that groups with lower mean income also have higher within-group health inequality. We also show in column [4] the proportion of households with a member (i.e. head or spouse) who has experienced a severe health event as a measure of health risk. Again, groups with lower mean income are also more likely to have experienced a severe health event. Therefore, socioeconomic group, income, health risk, and the level and variation of health are related, implying that health inequality has multiple dimensions.

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

	[1]	[2]	[3]	[4]
Socioeconomic Group	Mean income	Mean health	Gini health	Severe health event
	(relative to All)	(relative to All)		(% of households)
Professionals	1.57	1.06	0.05	1.9
Intermediate	1.08	1.03	0.07	1.9
Routine	0.75	1.00	0.08	2.3
Non-employed	0.46	0.84	0.17	6.1
All	1	1	0.09	2.7

Income is household-level labour income, after taxes and including transfers.
Health is the SF-12 Physical Component Summary standardised in $[0.1, 1]$ and averaged across head and spouse. Source: Pooled Sample UnSoc Waves 1-9.

Table 2: Socioeconomic mobility

Transitions of households that have not experienced a severe health event

$t \setminus t+1$	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 that have experienced a severe health event

$t \setminus t+1$	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**

Note: Transitions are between UnSoc waves (wave to wave).
Source: UnSoc Waves 1-9.

We also examine the relationship between health and socioeconomic mobility. To do so, we construct a socioeconomic mobility matrix that shows the proportion of households that move between the four groups from one year to the next, distinguishing between two groups of households, those for whom one member has experienced a severe health event, and those that have not experienced a severe health event. The two social mobility matrices are shown in Table 2.

The results in Table 2 first show that mobility is low, both before and after a severe health event. 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 following a severe health event. In particular, the probability of moving to the non-employment group is higher for all groups when a household member has experienced a severe health event. Hence, health risk also has labour income risk implications. Furthermore, the matrices in Table 2 show that the increase in labour income risk depends on current conditions, particularly on the current socioeconomic group. Specifically, 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 summarize the main properties for groups of households constructed from WAS to match as closely as possible the selection criteria and groups used for the results from the UnSoc data. Table 3 summarizes 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	Mean wealth	Gini wealth	% in debt
Professionals	1.91	0.60	7%
Intermediate	1.08	0.66	14%
Routine	0.37	0.80	31%
Non-employed	0.23	1.00	48%
All	1	0.71	19%

Note: Wealth is household-level net worth (see Appendix A). Gini can take values above one because net worth takes negative values. Source: WAS Waves 1-5.

The evidence presented in this section suggests that health, wealth, income and socioeconomic group are interrelated. In the next section, we present an economic model that can account for these relationships, modelling households whose wellbeing is derived from both consumption and good health, and whose choices can affect both quantities in an uncertain environment.

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 $I = [0, 1]$. Households derive utility from consumption and health, and they can use their income to consume, invest in a single financial asset, and improve their health in an environment where both income and health are subject to exogenous shocks. In particular, households may randomly experience a severe health event and receive 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 a pandemic crisis. Time is discrete and denoted by

$t = 0, 1, 2, ...$, which refer to annual steps. We model quantities at the household level.

Although household dynasties are infinitely lived, household members, and thus households, are stochastically replaced over time following a process that captures severe health events. We restrict our attention to severe health events that represent a significant health deterioration, and we define them as health shocks from which a household member does not fully recover. Therefore, they may include the death of a member. Although the household member does not fully recover from a severe illness implied by the health events we model, the household may recover, stochastically, by replacing the ill member with a new healthy member (e.g. an offspring). This implies that severe health events are persistent at the level of the household-dynasty, but not permanent.[10] It also implies that, over time, household dynasties differ in the number and duration of severe health events their members have experienced, which is in addition (and related) to the spells with higher and lower labour income.

3.1 Household level choices and constraints

Each household[11] wishes to maximise their expected lifetime utility:

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

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.[12] 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 $u : \mathbb{R}_{\geq 0} \times H \to \mathbb{R}$ is bounded, twice continuously differentiable, strictly increasing and strictly concave.[13]

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, $w(n_t, l_t, s_t, z_t)$, which is determined by idiosyncratic, household-specific, random factors, n_t, l_t, and s_t, as well as the aggregate state, z_t. The idiosyncratic factor n_t determines the highest profession of the household, while l_t captures remaining idiosyncratic variation in productivity between households, 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 (n_t, l_t) depend on the aggregate economic state z_t, as well as on the idiosyncratic, household-specific health shock, s_t, which also depends on the aggregate state z_t. We define the joint stochastic process of n_t, l_t and s_t as $e_t = (n_t, l_t, s_t)$.

[10] These considerations inform the calibration of the health process, which is analysed in Section 4.

[11] To simplify notation, we 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.

[12] We assume perfect sharing of consumption and asset ownership across household members.

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

The household uses its income in period t for consumption, purchase of 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:

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

where $a_t \in A = [a^{\min}, +\infty)$, and $a^{\min} \leq 0$ defines a borrowing limit. The random variables are given by $r(z_t) : Z \rightarrow \left(-1, \frac{1-\beta}{\beta}\right)$, $w(e_t, z_t) : E \times Z \rightarrow \mathbb{R}_{\geq 0}$, 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 (2020)).

Health evolves according to:

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

The random variable $\delta(e_t, z_t) : E \times Z \rightarrow D \in (0, 1)$, 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 $m(x_t) : X \in \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$, 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 $\overline{z}_1$ to denote a pandemic period, $\overline{z}_2, ..., \overline{z}_{\widetilde{z}-1}$ to capture periods that follow a pandemic and in which recurrent disease outbreaks are possible, and $\overline{z}_{\widetilde{z}}$ as periods that are sufficiently distanced from a pandemic that any new disease outbreak is a new pandemic.

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, $Q^{z'}$,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', 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 $\sum_{e_{t+1} \in E} \pi^{z'}(e_{t+1}|e_t) = 1$ 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), (l_t) and (s_t) need not be independent.

At the level of household, uncertainty is summarized 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 $\widetilde{y} = \widetilde{e} \times \widetilde{z}$.[14] 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 $\sum_{z_{t+1} \in Z} \sum_{e_{t+1} \in E} \pi(e_{t+1}, z_{t+1}|e_t, z_t) = 1$ 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 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. 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 $(a_1, h_1, y_1) \in A \times H \times Y$. These stochastic processes across households give rise to the relevant cross-sectional distributions of endogenous outcomes for each time period. 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.

3.4 Effects of pandemic-induced changes on choices

A change in the aggregate-level process (z_t) in period t requires adjustments in health and wealth on the part of the household. Insights on how pandemic-induced affect household choices of wealth accumulation and improvement of the level of health can be obtained by theoretical analysis of the model. 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.

3.4.1 Household choices of health and wealth

We examine the first-order necessary conditions for optimality that link two consecutive periods. Assuming interior solutions, optimality requires that the two Euler conditions are satisfied[15]:

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

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

where $x(h_{t,} h_{t+1}) = m^{-1} (h_{t+1} - \delta(e_t, z_t) h_t)$ is obtained using (3) and expresses the cost required to achieve a level of health given the current level of health and shocks to health. Assume that:

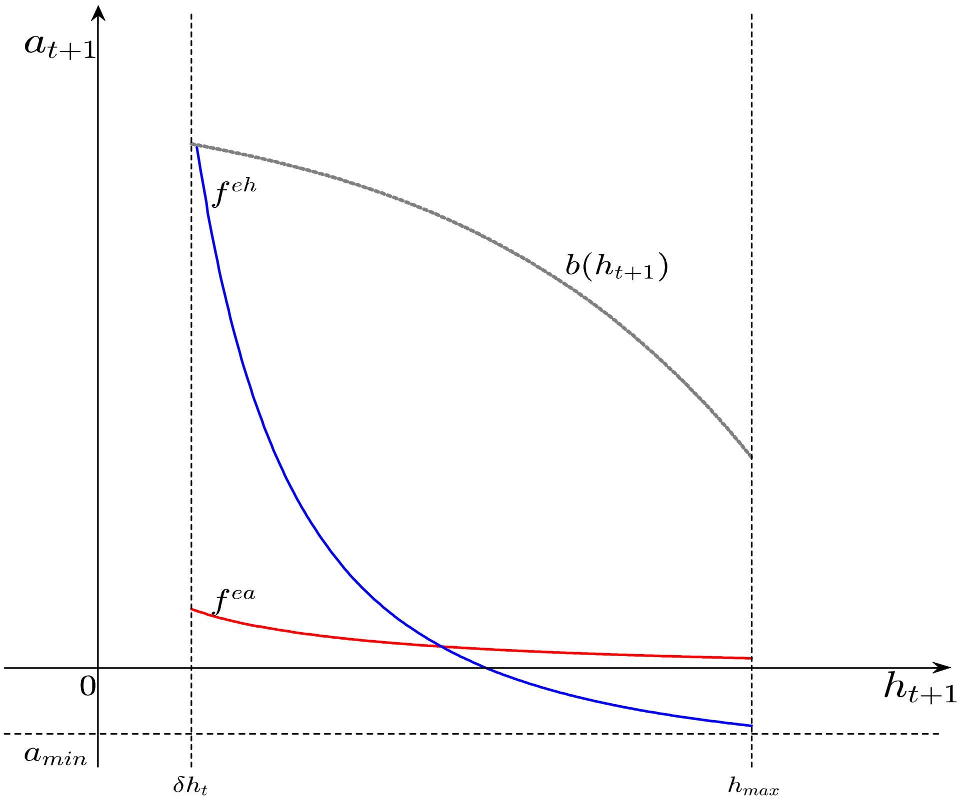
$$-u_{c_t c_t} + \frac{u_{c_t h_{t+1}}}{x_{h_{t+1}}(h_{t,} h_{t+1})} > 0. \tag{6}$$

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

[15] We examine later implications of a binding borrowing limit, which does arise in the calibrated solution. On the other hand, the bounds for health are not binding in the calibration.

The assumption in (6) requires that if health decreases the marginal utility of consumption, $u_{c_t h_{t+1}} < 0$, then this effect, standardised by the marginal cost of health in consumption units, $x_{h_{t+1}}(h_t, h_{t+1})$, needs to be bounded in absolute value by the effect of consumption on the marginal utility of consumption, $u_{c_t c_t}$. Assumption (6) 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, derived from (6), 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 sufficient condition.

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



Note:

Lemma 1 in Appendix B shows that for a given stochastic process (z_t), for any $(a_t, a_{t+2}) \in A$, $(h_t, h_{t+2}) \in \left(h^{\min}, h^{\max}\right)$, 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 $h_{t+1} \to \delta(e_t, z_t)h_t$, 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 1.

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 determine an area defined by the vertical lines at $\delta(s_t, z_t)h_t$ and $h^{\max}$ for $h^{\min}_{t+1}$ and $h^{\max}_{t+1}$, respectively, the horizontal line at $a^{\min}$ for $a^{\min}_{t+1}$, and the function $a^{\max}_{t+1} = b(h_{t+1}) =$

$(1+r(z_t))a_t + w(y_t) - x(h_t, h_{t+1})$ (see Lemma 1 in Appendix B).[16] The situation depicted in Figure 1 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.[17] Therefore, the properties that apply to the intersection point of f^{ea} and f^{eh} will also apply to the optimal choice of a_{t+1} and h_{t+1} for the problem in sub-section 3.1.

3.4.2 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 3.1 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. Note that in the fully dynamic problem $(a_{t+j}, h_{t+j})_{j=2}^{\infty}$ 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 below 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 3.1.

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 1, an increase (decrease) in the *rhs* of (4) and (5) relative to the *lhs* shifts the f^{ea} and f^{eh} functions outwards (inwards).[18]

Moreover, as shown in Lemma 2, the change in a_{t+1} relative to a_{t+1}^s is a negative function of the change h_{t+1} relative to h_{t+1}^s, and vice versa. The result in Lemma 2 implies substitutability in using the two assets to respond to the change in the exogenous process. This result reflects preferences and constraints over health and consumption. To achieve the adjustment in the marginal utility of consumption needed following a change in the exogenous process so that the household responds optimally (i.e. so that the Euler conditions in (4) and (5) are satisfied), health and wealth need to change. On the one hand, the budget constraint implies that a bigger response in wealth (health) allows for a smaller response in health (wealth) to respond to the change in the exogenous process. This is because the budget constraint implies that allocating resources to savings (future wealth) and to health reduces consumption. At the same time, the changes in wealth or health are evaluated in terms of utility. Suppose preferences imply substitutability

[16] 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.

[17] 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 $(a_t, h_t, e_t, a_{t+2}, h_{t+2})$.

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

between health and consumption. In that case, when consumption drops because of an increase in savings to respond to exogenous changes, the marginal utility of health is increased, which tends to increase health as a response, to maintain optimality. Hence, on the other hand, substitutability in consumption and health in the utility function tends to increase both wealth and health as a response to exogenous changes, thus to create a complementarity in the response of health and wealth. Strong substitutability between health and consumption (in particular, one that violates (6)), leaves open the possibility of a response where changes in wealth are a positive function of changes in health. The condition in (6) requires that the effect of a change in consumption on the marginal utility of health, expressed in the marginal utility of consumption via the standardisation by the marginal cost of health in terms of consumption, is less important than its direct effect on the marginal utility of consumption. As long as substitutability between consumption and health is sufficiently bounded, a bigger response in wealth (health) is met by a smaller response in health (wealth), and even allows as a possibility that health (wealth) changes in the opposite direction.

The incentives embedded in the response to changes in the exogenous process also characterise responses to pandemic-induced changes. 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 recurrent outbreak risk. 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 summarizes the effects of some of these changes, conditional on $a_{t+2} \in A$, and $h_{t+2} \in \left(h^{\min}, h^{\max}\right)$. In particular:

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

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. $a_{t+1}^p \geq a_{t+1}^s$ and/or $h_{t+1}^p \geq h_{t+1}^s$) for the subset of households for which (a_{t+1}^p, h_{t+1}^p) implies $c_t^p > c^l$.

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

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. $a_{t+1}^p \leq a_{t+1}^s$ and/or $h_{t+1}^p \leq h_{t+1}^s$).

The changes in (z_t) capture effects of the pandemic on household income during the initial outbreak year (in (i)), or restrictions on consumption during the outbreak year (in (ii)), and effects of post-pandemic outbreak risk on household income (in (iii)) and on restrictions on consumption (in (iv)). Another effect of a pandemic is the increase in health risk, working via the random variable $\delta(e_t, z_t)$ 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 analysis shows that the model incorporates incentives for consumption smoothing and for precaution, using either asset. In particular, the results regarding the income drop as a result of the pandemic shock in (i) reflect consumption smoothing incentives, while the results regarding income risk in (iii) a form of precautionary behaviour.[19] However, it is useful to note that the options offered to the households by having a portfolio of two

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

assets, health and wealth, imply that consumption smoothing in this context does not necessarily imply reduction in both health and wealth, and precaution does not necessarily 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 changes in 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 changes in income risk.

3.4.3 Implications for inequality

The adjustments in health and wealth on the part of the household following a change in the aggregate-level process (z_t) in period t impact health and wealth inequality if the change affects households asymmetrically and/or if the response depends on initial conditions. Indeed, Lemma 3 in Appendix B confirms that health and wealth choices differ across households that differ in their initial combination of (a_t, h_t). The different possibilities offered by the portfolio of assets for responses to shocks and risk (compared with a single-asset economy) 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 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:

$$u_{c_t} > \beta E\left[u_{c_{t+1}}(1 + r(z_{t+1}^s)\right], \text{ and} \tag{7}$$

$$u_{c_t} x_{h_{t+1}}(h_t, h_{t+1}^s) - u_{h_{t+1}} = \beta E\left[u_{c_{t+1}}\left(-x_{h_{t+1}}(h_{t+1}^s, h_{t+2})\right)\right]. \tag{8}$$

In this case, a change in period t to (z_t^p) that increases the *lhs* in (7) and (8) relative to the *rhs* (for example, due to income drops in period t) does not change savings behaviour: the household remains borrowing constrained. This household must instead reduce next period health to satisfy (8). A change that increases the *rhs* relative to the *lhs* (for example, increased probability of future income drops due to new outbreaks, or a consumption limit in t) 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 (8).

These considerations imply that for pandemic-induced changes that increase the *lhs* relative to the *rhs* (e.g. income 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* (e.g. probability of future income drops associated with new outbreaks, a consumption limit in t), 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. Given that in the data for the UK about 19% of households are borrowing constrained, these effects can be substantial.

4 Calibration and exogenous processes

We calibrate the model to pre-COVID-19 health and income data, and confirm that its predictions are consistent with pre-COVID-19 health and wealth inequality. We then use information on the effects of COVID-19 to calibrate the shock to households' health risk and income in 2020, and estimates of the probability of recurrent outbreaks based on data from previous pandemics and analysis for COVID-19 in Schroeder *et al.* (2021).

4.1 Calibration to pre-COVID-19 distributions

The economy pre-COVID-19 is characterised by the long term absence of pandemics and decision making that does not account for the possibility of future pandemics. We model this as the stationary equilibrium of a version of the model economy described in Section 3 where pandemics do not happen, and the exogenous aggregate state remains fixed over time at the level $\overline{z}_{\tilde{z}} \equiv z^*$. 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^*. Households make decisions believing that pandemics 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 and health also does not change over time. In particular, this environment gives rise to a stationary equilibrium that is characterised by the cross-sectional distribution over households $\lambda^*(a_t, h_t, e_t)$.[20] 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. 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 data so that the stationary equilibrium matches 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 about the relevant stochastic environment directly. We then

[20]The mathematical representation of this environment is in Appendix C.

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 minimizes 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 D.

4.1.1 Stochastic processes

We use household level information from the UnSoc 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 for 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.[21] 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 D.

Health shocks process We assume that the state space of shocks to health, S, includes three possible outcomes, a state $\overline{s}_1$ where no household member has experienced a severe health event[22], a state $\overline{s}_2$ where a household member is experiencing a severe health event during the current period, and a state $\overline{s}_3$ where the household has a member who has experienced such an event in previous years. This state space is motivated by empirical observation, as described in Appendix D. In particular, in the data, a severe health event is associated with a sharp drop in the level of self-reported health before recovering to a state with lower health than prior to the health event. Indeed, we find that on average across the households, health h_t drops by almost 10% after going from $\overline{s}_1$ to $\overline{s}_2$, whereas $\overline{s}_3$ is about 5% lower than $\overline{s}_1$.[23]

These observations on the evolution of health after severe health events, in conjunction with data availability and the model structure, lead us to assume the following structure for the transition probabilities of the stochastic process capturing shocks to health. 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 socioeconomic group (i.e. on the states in N), to capture the social gradient in health (see, e.g. Marmot (2003, 2004), Wilkinson and Pickett (2008), Pickett and Wilkinson (2015)), which is summarized in Tables 1 and 2 as the difference in health risk between socioeconomic groups.[24] We calculate these probabilities using UnSoc data.

[21] 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.

[22] See Section 2 and Appendix A for the definition of a severe health event.

[23] See also Figure D1 in Appendix D. As shown in Appendix D, these results are robust to removing several observable components from health, as well as medical conditions other than the severe health events.

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

Once in $\overline{s}_2$, we assume that households transition in the next period to $\overline{s}_3$ with probability one. In other words, we use $\overline{s}_2$ 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 health event, resulting from the nature of the health shocks that we study. However, our model, structured around infinitely lived household dynasties, 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 health event, 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 health event is 48.8, which implies an average of 11.2 years spent in state $\overline{s}_3$.[25] Nevertheless, some households spend more (less) time in this state because they moved to $\overline{s}_2$ before (or after) the average age for 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 they have faced over time. Some households have long runs of $\overline{s}_1$, while some experience a severe illness for one of their members, which costs them one year in $\overline{s}_2$ and then another few 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 health events 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 a household faces. 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.[26] However, as explained later, 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 changes in the transition probability from $\overline{s}_1$ to $\overline{s}_2$ during the pandemic, 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 normalization of health risk with respect to death from severe health events.

Income process We have defined 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.[27] In particular, a movement from any other state in

[25] Generally, households that have experienced a severe health event are liable to experience further events. We focus on the first health event and incorporate effects of subsequent health events into the post-event state.

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

[27] 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,

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) captures shocks that generate variation in labour income within groups. 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.[28] 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:

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

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.[29] We use the residuals, $\epsilon_{i,t}$, from (9) to construct the process of labour income for each group.

We obtain the state space for (l_t), L, by assuming in each case that for each socioeconomic group, $\overline{n}$, $L_{\overline{n}}$ 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 $\overline{s}_3$. Therefore, we calculate 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 $s_t = \overline{s}_1$ and $s_t = \overline{s}_2, \overline{s}_3$.[30] 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 $\overline{s}_3$.

We show in Appendix D 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 $\overline{s}_1$ to $\overline{s}_2$ in Q^* are calculated as the share of households in each group that have experienced a severe health event in a given period, conditional on not having experienced a severe health event in the past.

we would miss these households if we only considered the unemployed.

[28] 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.

[29] 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 $D_{i,t}$.

[30] We denote these transition matrices as Q^*_{pre} (for $s_t = \overline{s}_1$) and Q^*_{post} (for $s_t = \overline{s}_2, \overline{s}_3$) in Appendix D.

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 D are those in Table 2 in Section 2.

To calibrate the possible outcomes of the random variable $w(e_t)$ that measures the level of labour income for any state in the Markov process for labour income, we use ϵ_t from (9),[31] 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).[32] We re-scale $w(e_t)$ so that its expected value across the population in the invariant distribution ξ^* is normalized to 1. These outcomes for $w(e_t)$ are shown in Appendix D Table D2.

The Markov process for labour income 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.

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 re-centred residuals of post-policy labour income; for details see Appendices A and D
Data source: Pooled sample UnSoc Waves 1-9.

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

4.1.2 Model parameters

We set the discount factor in the utility function $\beta = 0.96$, 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 allow the return to savings to differ

[31] 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).

[32] In the UnSoc data, post-policy labour income does not differ substantially between the three states of shocks to health, once the socioeconomic group has been accounted for. Therefore, we calculate the average value of re-centred residual post-policy labour income as $w(n_t, l_t)$ for each subset of households in $N \times L$, and independently of $s_t = \bar{s}_1, \bar{s}_2, \bar{s}_3$.

from the borrowing rate. In particular, we set the return to savings $r(z_t = z^*)$ to equal 0.56% to match the average real long-term bond yield in the UK between 2009-2018, and assume that the borrowing rate includes a penalty of 1%, so that $r(z_t = z^*)$ equals 1.56% for households with negative wealth. We normalise the lower and upper bounds for health, $h^{\min}$ and $h^{\max}$ respectively, to $[0.1, 1]$ (see Appendix A for details). The health depreciation rate in the absence of severe health shocks, $\delta(s_t = \overline{s}_1)$, is set to be 0.9624, which implies a household can spend a maximum of 60 years before reaching the lower bound on health unless they make additional investments in health.

We choose the remaining parameters to minimise the distance between model predicted quantities and their empirical counterparts, and we summarize 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[33]:

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

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 $m(x_t)$ takes the form of a production function and is given by:

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

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

Table 5: Calibrated parameters

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

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

The two further possible outcomes of the random variable $\delta(s_t = \overline{s}_2)$ and $\delta(s_t = \overline{s}_3)$, capturing depreciation in health for households that have experienced a severe health shock, the parameters γ, q, ϕ and the borrowing limit $a^{\min}$ are chosen to minimise the distance between model predicted quantities and their empirical counterparts, using model simulations. We describe this procedure in detail in Appendix D. We target the conditional mean 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,

[33]This utility function satisfies the conditions $\lim_{c\to 0} u_c(\cdot) = +\infty$, $\lim_{c\to\infty} u_c(\cdot) = 0$, $\lim_{h\to 0} u_h(\cdot) = +\infty$, $\lim_{h\to\infty} u_h(\cdot) = 0$, and $\lim_{c\to\infty} \inf -\frac{u_{cc}(\cdot)}{u_c(\cdot)} = 0$. 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 (2020).

which is 8.9%.[34] Table 5 summarizes the calibrated parameters.

4.1.3 Health and wealth inequality in the stationary distribution

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

Table 6: Model outcomes for health and wealth

Socioeconomic Gr.	[1] Mean health	[2] Gini health	[3] Mean wealth	[4] Gini wealth	[5] % in debt
	(relative to All)		(relative to All)		(% of households)
Professionals	1.10	0.08	1.88	0.45	8%
Intermediate	1.01	0.09	1.01	0.54	14%
Routine	0.93	0.10	0.47	0.65	33%
Non-employed	0.87	0.11	0.31	0.74	40%
All	1	0.10	1	0.59	19%

Note: % in debt refers to the share of households with zero or less than zero assets.

Comparing means and Gini coefficients by socioeconomic group in the first two columns of Table 6 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 in the data, but the model 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 1: within-group health variation increases as mean health decreases.

We also examine the model outcomes 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 outcomes. 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 by group.

The model further allows us to study the relationship between health and wealth going beyond comparison of outcomes between socioeconomic groups. To quantify health inequality across the population in the data, we calculate the Erreygers and Wagstaff indices that measure the concentration of health across the income distribution (Erreygers (2009) and Wagstaff *et al.* (1991); see also Appendix D for more details). In the pooled UnSoc sample, the Erreygers and Wagstaff indices take a value of 0.081 (0.089), indicating a positive relationship between income and health. The Erreygers (Wagstaff) index for health with respect to earnings in the model is 0.105 (0.115). In addition to health in-

[34] This is based on Stoye (2017) and is discussed further in Appendix D.

equality 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 Erreygers (Wagstaff) index is about twice as large, 0.215 (0.234), suggesting that health has a much stronger concentration with respect to wealth than with respect to income. Many studies find links between wealth and health (for example, Seymonov *et al.* (2013), Cesarini *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), Pickett and Wilkinson (2015)). Our results quantify the strength of the wealth-health nexus relative to the income-health nexus using national-level data across households.

4.2 Post-pandemic exogenous processes

After the surprise impact of COVID-19 in 2020, there is uncertainty about disease outbreaks. In particular, there is uncertainty about how long the main waves will last and whether, and for how long, there will be recurrent outbreaks. This is reflected in the transition matrix for z_t, which we discuss first. In turn, an outbreak affects the idiosyncratic shock processes, and we explain how we capture this next.

4.2.1 Disease outbreak uncertainty

Drawing on current research and historical evidence, we specify the state space Z of the aggregate level stochastic process (z_t) as $Z = \{C, R, U, O\}$. If $z_t = C$, there is a pandemic, which affects the stochastic processes defining idiosyncratic health and income uncertainty. If $z_t = R$, there is a 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 $z_t = U$ 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 U characterise the medium-run environment after a pandemic, when there is still 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 very unlikely. 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 and 1918-19 pandemics and expectations about the COVID-19 pandemic. Using data from historical pandemics, we employ a Markov switching model to estimate the probability of exiting the post-pandemic period of recurrent outbreak risk to be 7.9%, implying an expected duration of 12.66 years (see Appendix D for details of the model and estimation results). We set, therefore, the probability of moving from the states R or U to O accordingly. Once in O, there is a possibility of further pandemics.[35] We also set this to the probability of the pandemic state

[35] 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)).

occurring as estimated from the Markov switching model, 2.7%, implying a pandemic roughly every 35 years. Finally, we set the probability of an 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 Schroeder *et al.* (2021). The aggregate state transition matrix is thus given by:

$$Q_Z : \begin{array}{ccccc} z_t \backslash z_{t+1} & C & R & U & O \\ C & 0.5 & 0.143 & 0.357 & 0 \\ R & 0 & 0.263 & 0.658 & 0.079 \\ U & 0 & 0.263 & 0.658 & 0.079 \\ O & 0.027 & 0 & 0 & 0.973 \end{array} .$$

4.2.2 Pandemic effects on exogenous processes

This subsection describes the assumptions made about the characteristics of the idiosyncratic processes in each of the four aggregate states of the process 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 base calibration in Section 4.1).

The first effect of a major disease outbreak ($z_t = C$) is an increase in health risk. This feature is captured in the model by increasing the probability of experiencing a severe health event relative to the base calibration for the pre-COVID-19 period. 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% while for the whole 2020 was 10.43% (using data in Roser *et al.* (2020)). However, excess mortality underestimates the increase in health risk. There are also implications from the so-called "long-COVID" and an increase in health risk from other diseases due to the congestion effects of the pandemic on health care. For example, compared with 2019, in 2020 there was a reduction of 28% in completed treatment pathways, and of 20% in hospital referrals (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). Moreover, the increase in health risk differs by socioeconomic group (e.g. Marmot *et al.* (2020), Windsor-Shellard and Nasir (2021), Bambra and Lynch (2021)), being higher for socioeconomic groups with lower mean income. Therefore, we assume an increase in health risk by 14%, 43%, 100% and 50% for professionals, intermediate, routine, and non-employed, respectively. Note that because of the correlation between transitions in socioeconomic group and level of health (see Section 4.1), the increase in health risk also implies an increase in income risk by increasing the probability of moving to non-employment.

The second effect of $z_t = C$ is a loss in net labour income. 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-pandemic period).[36] 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

[36] 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

are in addition to the usual income gains/losses via the idiosyncratic income process.[37] The HM Treasury (2021) estimates imply progressivity in income drops, i.e. income drops were bigger for higher income deciles. This finding is consistent with existing evidence suggesting 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 translate the HM Treasury (2021) estimates of income losses to losses per socioeconomic group, we convert the per income decile drops to the groups we model using the pre-COVID-19 income distribution (see Appendix D). Although these are progressive in terms of net labour income and socioeconomic groups, when we express them in terms of total resources, the drop is only mildly regressive.

The third effect of $z_t = C$ takes the form of restrictions in consumption implied by measures to mitigate the spread of the disease. Evidence suggests that restrictions in consumption during the pandemic drive increased savings, with the effect being stronger for higher income groups (see Hacioglu-Hoke *et al.* (2021), Bank of England (2020), Tenreyro (2021) for the UK, Dossche and Zlatanos (2020) for the EU, and Miescu and Rossi (2021) for the US). In particular, evidence in Davenport *et al.* (2020) suggests that amongst the two highest income quintiles, consumption dropped approximately 25% in the first months of the crisis, with smaller changes for 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 follow the data patterns (see Appendix D).

Regarding periods of subsequent outbreaks, R, we assume that the increase in health risk is half of its increase in C and that losses in income 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 U, all idiosyncratic health and income processes are assumed to be the same as in state O; what distinguishes U from O is the transition probabilities to R and C.[38]

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

5 Inequality and risk exposure post-COVID-19

To study post-pandemic distributional dynamics, we numerically solve the households' problem described in Sections 3 and 4 using dynamic programming and compute the time

using the HM Treasury distributional analysis model.

[37] These transition matrices are denoted as Q^C_{pre} (for $s_t = \overline{s}_1$) and Q^C_{post} (for $s_t = \overline{s}_2, \overline{s}_3$) in the Appendix D.

[38] These transition matrices are denoted as Q^R_{pre}, Q^U_{pre}, Q^O_{pre} (for $s_t = \overline{s}_1$) and Q^R_{post}, Q^U_{post}, Q^O_{post} (for $s_t = \overline{s}_2, \overline{s}_3$) respectively in the Appendix D.

series of the cross-sectional distribution λ_t, across households, using methods we discuss in Appendix C. 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. In particular, conditional on initial values obtained from the pre-COVID-19 stationary distribution, households are surprised by the emergence of the pandemic in 2020 but form expectations about future outcomes that follow the impact shock in 2020 using the updated exogenous processes.

We compute statistics that summarize key properties of the distributions of health and wealth over time under uncertainty about outbreaks post-2020. To this end, we need to calculate the probability distribution of statistics regarding the cross-sectional distributions over possible paths of the aggregate state for all points in time. To obtain these distributions, we first simulate a panel of 5000 sequences of the evolution of the aggregate state, initializing each sequence from the invariant distribution λ^*, associated with Q^*, i.e. without pandemic risk. Then, we simulate the evolution of the distribution of all exogenous and endogenous variables, using the solution to the typical household's problem, and beginning from the distribution λ^*, for every path of aggregate state variables. The result of this Monte-Carlo 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. This procedure allows us to analyse possible distributional outcomes in terms of the probability that they will arise. For details of this Monte-Carlo procedure and how it is applied to generate the results shown in the figures and table in this Section, see Appendix C.

Our analysis of the results is organised as follows. We first summarize key characteristics of the increase in inequality. We then examine the factors contributing to the increase and analyse the implications of the form and scale of the increase in inequality for risk exposure and vulnerability to future shocks. Finally, we examine the effects of policy intervention to support those lacking means of self-insurance.

5.1 Scale and form of increase in inequality

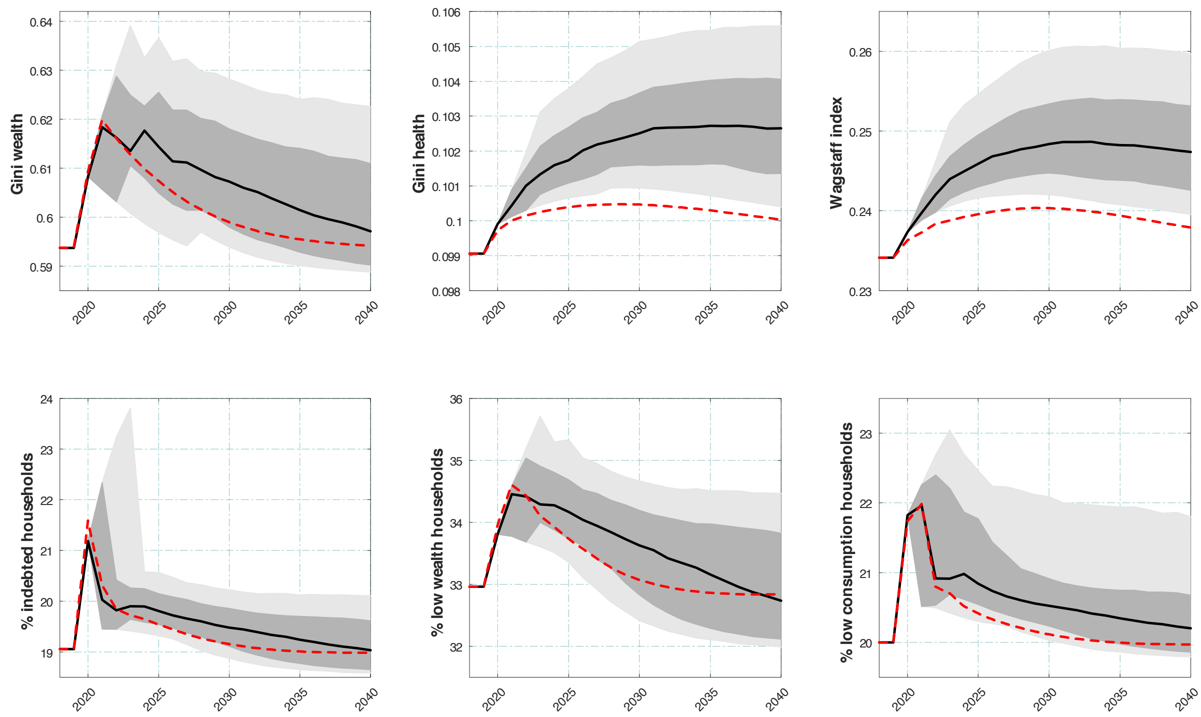
We show results for economy-wide statistics in Figure 2 and also by socioeconomic group in Figure 3. Figure 2 shows the Gini indices for wealth and health, the Wagstaff index of the relationship between health and wealth concentration, and the proportions of households in debt, with low assets and with low consumption. In Figure 3, we show mean wealth, wealth Gini index, and the share of indebted households for each of the four socioeconomic groups. In all cases, we plot the median value of these statistics across the distribution of their possible outcomes over realisations of the aggregate-pandemic state in each time period.[39] We also show the interquartile range (the 50% interval around the median) and the 80% interval around the median.

Dynamic paths of measures that capture relevant properties of the wealth distribution across the population are in Figure 2. *Following the 2020 shock, the wealth Gini index increases, remains at elevated levels for about a decade and declines slowly to pre-pandemic levels after a further decade.* Wealth inequality increases by more than 2.5 Gini points at the peak in half of the simulated post-pandemic paths. We also look more closely

[39] As explained previously, we have a distribution of 5000 descriptive statistics that relate to 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 relating to disease outbreaks.

at the low wealth part of the distribution, particularly the proportion of households in debt and those below a threshold for wealth, defined the maximum level of wealth of the bottom third of the pre-COVID-19 distribution of wealth.[40] We see that the proportions of low-wealth households also increase significantly, implying that *the increase in inequality is characterised by increases in the thickness of the left-tail of the wealth distribution.* Moreover, there is also a persistent increase in the proportion of households with low consumption, defined as households consuming less than the 20th percentile of the consumption distribution before pandemic. We analyse further the implications of the increase in inequality for different socioeconomic groups and pre-pandemic conditions below.

Figure 2: Post-pandemic inequality



Note: Simulated post-pandemic paths of measures of inequality. Median (solid black line), p25-p75 (dark shading) and p10-p90 intervals (light shading) are based on 5,000 random paths of disease outbreak states. One-off pandemic (dashed line) is obtained assuming that there is no disease outbreak risk after the main pandemic waves in 2020 and 2021. Low wealth (consumption) households are those that own wealth (consume) less than the 33rd (20th) percentile in the pre-pandemic distribution.

There are also *persistent increases in health inequality*, as can be seen by the increases in the health Gini and the increase in the Wagstaff index, implying a stronger association between health and wealth.[41] As analysed in Section 3.3 (see also Lemma 2 in Appendix B), household behaviour with two assets, wealth and health, implies that in response to

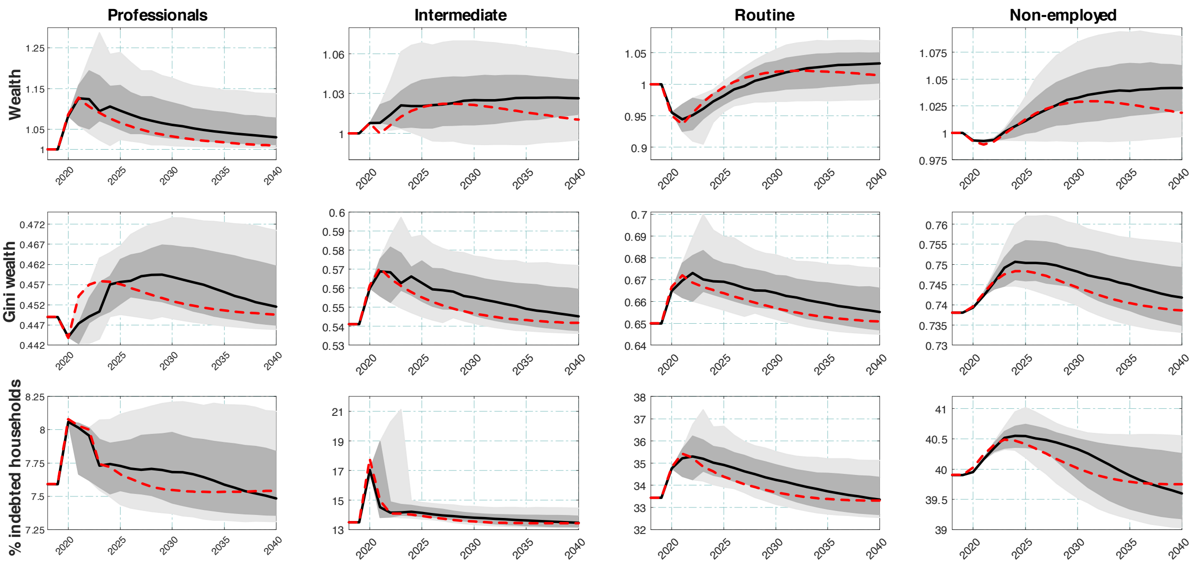
[40] This implies wealth less than about £9.2k in 2019, assuming a mean income of ∼£36,900 for the financial year ending in March 2020 (see O'Neill (2021)).

[41] Persistence of health inequality has been highlighted in the literature (e.g. Marmot (2004) and Font *et al.* (2011)).

disease outbreak shocks and the risk of future shocks, health and wealth are perceived as substitutes and thus need not move in the same direction. This substitutability can reduce the impact of the pandemic on the relationship between health and wealth concentration, and thus the extent of increases in health inequality measured in this way. However, the changes reported in Figure 2 in terms are comparable with changes we observe regarding the Wagstaff index of the relationship between net income and health in Understanding Society, which ranges between 0.085 and 0.091 in the ten years since 2009.

We next analyse in more detail wealth inequality between and within socioeconomic groups, based on Figure 3. We first examine mean wealth per socioeconomic group relative to the pre-COVID-19 stationary equilibrium and note stark differences in the changes between the groups. On average, professionals increase their wealth and maintain higher wealth levels for nearly two decades; intermediate professions are characterised by smaller increases in wealth, 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 non-employed group (inactive plus unemployed), we observe an increase in mean wealth.[42]

Figure 3: Post-pandemic inequality by socioeconomic group



Note: Simulated post-pandemic paths of measures of inequality. Median (solid black line), p25-p75 (dark shading) and p10-p90 intervals (light shading) are based on 5,000 random paths of disease outbreak states. One-off pandemic (dashed red line) is obtained assuming that there is no disease outbreak risk after the main pandemic waves in 2020 and 2021.

*Increased between-group inequality is accompanied by increases in within-group inequality, except for within-group inequality f*or professionals in the short-run after the pandemic, as the second row in Figure 3 suggests. The *increase in within-group inequal-*

[42]Since we assumed no change in the non-market income for this group (i.e. in benefits policies) during the pandemic, changes for this group reflect changes for the households in other groups that become non-employed, and, in this sense, reflect mainly the changes in wealth inequality already studied. We thus we do not discuss the group of non-employed further below.

ity is inversely related to the changes in mean wealth since higher (lower) wealth implies that the idiosyncratic income variation within each group is relatively less (more) important. Comparing, for example, professionals to routine households, the reduction in mean wealth (and thus in asset income) for the latter group implies that variation in labour income becomes a more important determinant of variation in wealth. The increase in within-group inequality is also manifested by an increase in the proportion of households in debt, shown in the last row of Figure 3. The plots in this row also demonstrate that the increase in the thickness of the left tail of the wealth distribution affects the socioeconomic groups with lower mean income and wealth more.

We examine the quantitative contribution of uncertainty about future outbreaks to inequality by comparing the results summarized in Figures 2-3 with those obtained from a one-off pandemic counterfactual, which is shown as the dashed red line in these figures. We define the one-off pandemic scenario as the hypothetical case where 2020 and 2021 are pandemic years with the same effects as those in the baseline simulations but assuming that the pandemic ends in 2021 without risk for further outbreaks.[43] The main patterns of inequality after the pandemic are the same without uncertainty about post-pandemic disease outbreaks. However, *when disease outbreak uncertainty is also considered, the inequality effects of the pandemic are generally more adverse, last longer, and can become particularly severe with a sizeable probability.* Indeed, the differences between the two scenarios become larger in the medium run, and especially when we examine worse paths of the aggregate state. For example, the 50th percentile of the wealth Gini under recurrent outbreaks differs from the one-off pandemic by about one Gini point in the decade that starts a few years after the pandemic, the 75th percentile differs by two and the 90th by three Gini points. *Under uncertainty about recurrent outbreaks, big increases in inequality remain plausible for at least a decade.*

We then examine changes in inequality from the perspective of households with different characteristics at the onset of the pandemic. We compute the changes in wealth and health after 2020 for groups of households that differ in their wealth in 2019 and the profession of the head of the household in 2019, on average across health and different future realisations of shocks to income and health.[44] Figure 4 plots the expected percentage deviation of wealth and health for these groups relative to a counterfactual situation where the pandemic never happened.

The plots in Figure 4 confirm the increase in inequality documented in the previous results and reveal its implications for households with low levels of wealth or who worked in occupations with lower mean earnings before the pandemic. In particular, Figure 4 reveals that while levels of wealth and health increase for households who were already in an advantageous position before the pandemic, for households with below-median level initial wealth, or in socioeconomic groups with lower wealth and health on average, there are persistent decreases in both wealth and health.[45] *These findings imply that the pandemic amplifies existing inequalities.* The reductions in wealth and health for households in percentiles below the median are substantial, up to about 10% of wealth on average for

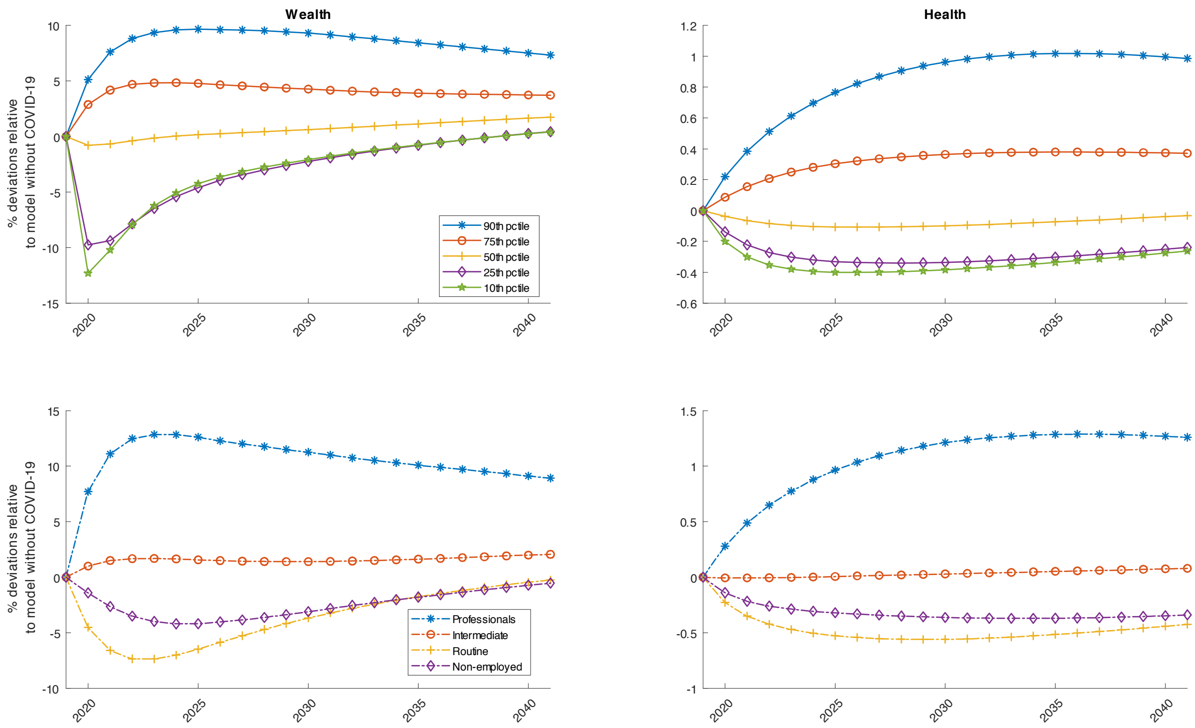
[43] See Appendix D for the aggregate-level transition matrix in this case.

[44] See Appendix C for more details on the computation of changes in inequality conditional on pre-pandemic characteristics.

[45] In Figure 4, we demonstrate an increase in the health gap between households that differ in terms of pre-pandemic wealth. Similar results are obtained for health between households that differ in terms of the combination of pre-pandemic health and wealth (see Appendix E for these results).

the 10th to 25th percentile, and about half a percent in terms of health. To contextualise an average fall in the health variable of about half a percent across households in the lower deciles, recall from the discussion of the UnSoc data in Section 4 that a severe health event (e.g. heart attack, stroke) implies a drop in household-level health of about 10% on average. Therefore, an average reduction of 0.5% is equivalent to the fall in health that would have been observed if 5% of households in these deciles had a member who experienced a severe health event.

Figure 4: Post-pandemic inequality by initial conditions



Note: Expected percentage deviations of simulated paths under disease outbreak uncertainty versus simulated paths without Covid-19 and disease outbreak uncertainty. Lines in the top panels refer to households starting at the respective percentiles of the wealth distribution in 2019. Lines in the bottom panels refer to households of the respective socioeconomic groups in 2019.

5.2 Shock and risk as drivers of differential wealth accumulation

The differences in wealth accumulation after 2019 are driven by the differential response to the unexpected 2020 shock and by the differential response to the uncertainty associated with recurrent outbreak risk. We examine these factors by revisiting the theoretical analysis of household incentives for asset accumulation following unexpected shocks and increased income risk in Section 3.

The response to the 2020 shock incorporates two forces that have opposite effects on wealth accumulation. *First, the surprise fall in income creates consumption smoothing incentives that tend to reduce at least one of wealth and/or health. Second, a limit on consumption, which tends to increase at least one of the assets* (see the analysis in Section 3.3). Since all employed households lost income because of the pandemic, the incentives for consumption smoothing in 2020 characterise them all.[46] However, the limit on consumption spending has a smaller actual effect on increased savings potential for the households with lower resources, which are predominantly households that had low health and wealth and were in the socioeconomic groups with lower earnings prior to the pandemic, because these households do not typically have high consumption.[47] On the other hand, for the high income - high wealth households, the restrictions in consumption imply substantial drops in consumption, both according to empirical evidence and in the model, and thus substantial increases in asset accumulation. *For high income, high wealth households, the effects from the limit on consumption are stronger than the consumption smoothing incentive and drive the increases in wealth accumulation associated with the upper tail of the wealth distribution* seen in Figures 3-4. To demonstrate the importance of the consumption limit, we repeat the analysis in Section 5.1 without imposing the limit on consumption as an effect of the pandemic shocks and report the results in Appendix E. These confirm that the consumption limit is the key driver of increases in wealth for households with high initial wealth and/or in socioeconomic groups with higher mean earnings. *For the households below median initial wealth and/or in socioeconomic groups with lower mean earnings, consumption smoothing incentives are stronger and drive the reduction in wealth.* Indeed, as can be seen in Appendix E, the consumption limit matters less for the results for this group of households.

The precautionary response to increased risk also differs across households, as result of the different potential for self-insurance due to the initial effect of the pandemic shock. The increase in income risk, implied by the possibility of future disease outbreaks, creates incentives to increase the level of wealth or health to create buffers to smooth potential future shocks (see the analysis in Section 3.3). Households with high initial wealth and/or in socioeconomic groups with higher mean earnings have increased potential to accumulate wealth to serve as insurance because of the freeing up of resources due to the consumption limits, relative to households below median initial wealth and/or in socioeconomic groups with lower mean earnings. For the latter groups of households, the drops in wealth due to the direct pandemic effect in 2020 imply that they lack the resources to accumulate the required buffers. The implication is that due to precautionary incentives, wealth inequality increases and remains high because the first group of households retains increased wealth as a buffer for future shocks, while the second needs time to build the required buffers.

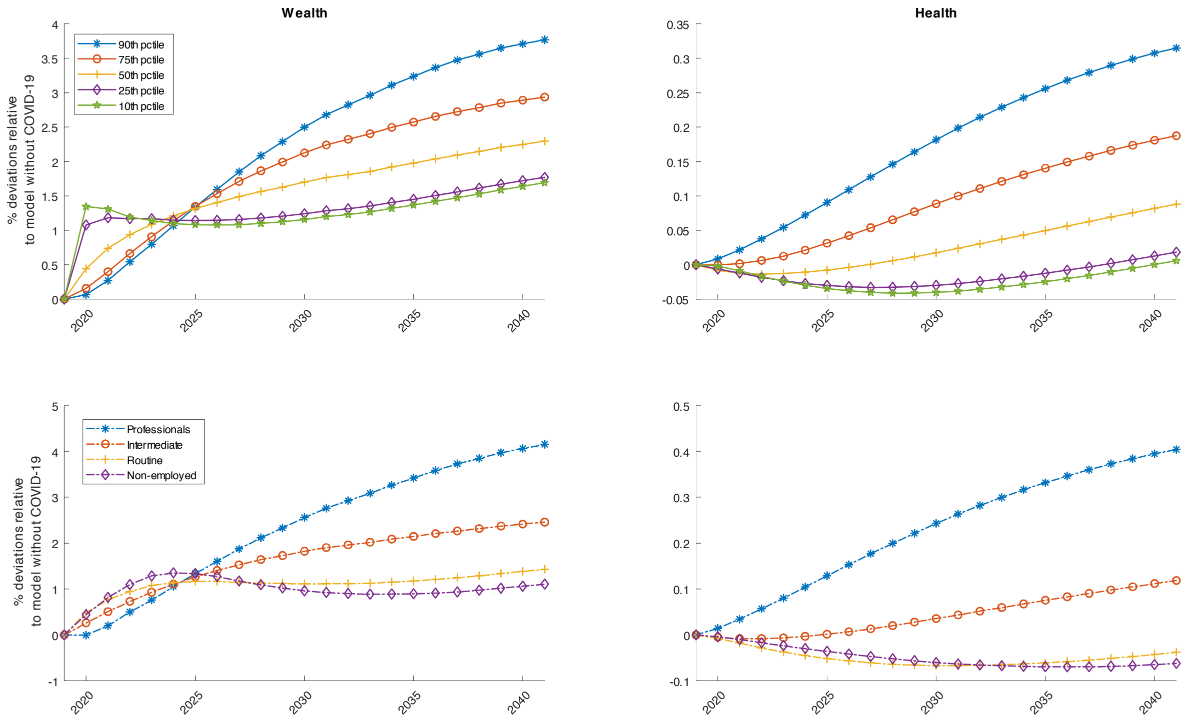
Precautionary incentives in response to disease outbreak risk amplify wealth inequality and increase its persistence over time when outbreak risk follows a regressive drop in wealth. To demonstrate this mechanism, we compute model outcomes from a counterfactual scenario where the pandemic did not directly affect households in 2020-21, but only implies post-2021 disease outbreak risk, modelled as in the baseline scenario. We plot model outcomes from this counterfactual in Figure 5, for the same quantities shown in Figure 4. Wealth accumulation under this counterfactual reflects the level of wealth accumulation that households would optimally want to achieve as a means of self-insurance given uncertainty about disease outbreaks and conditional on their pre-pandemic level of resources. By comparing results in Figures 4 and 5, we see that households below

[46] Note that some households may increase their income during the pandemic because of the idiosyncratic component of income shocks. However, the effect of the pandemic was calibrated to be negative for all households conditional on (n_t, l_t, s_t).

[47] As noted in Section 4, this model property is consistent with evidence on the effect of restrictions on consumption in, e.g. Davenport *et al.* (2020).

median initial wealth and/or in socioeconomic groups with lower mean earnings would have had higher wealth had they not lost a significant part of their wealth in an effort to smooth the implications of the 2020 shock. Therefore, without the regressive effects of the 2020-2021 shocks on wealth, increased disease outbreak risk would actually work to reduce inequality. Given that disease outbreaks affect mainly the households with lower wealth and income, it is optimally these households that would need to increase their wealth buffers more to self-insure against possible future income drops. In this respect, the persistent increase in inequality in the decade following the pandemic reflects a lack of opportunity for low income/low wealth households to respond optimally to changes in income risk.

Figure 5: Effects of disease outbreak risk by initial conditions



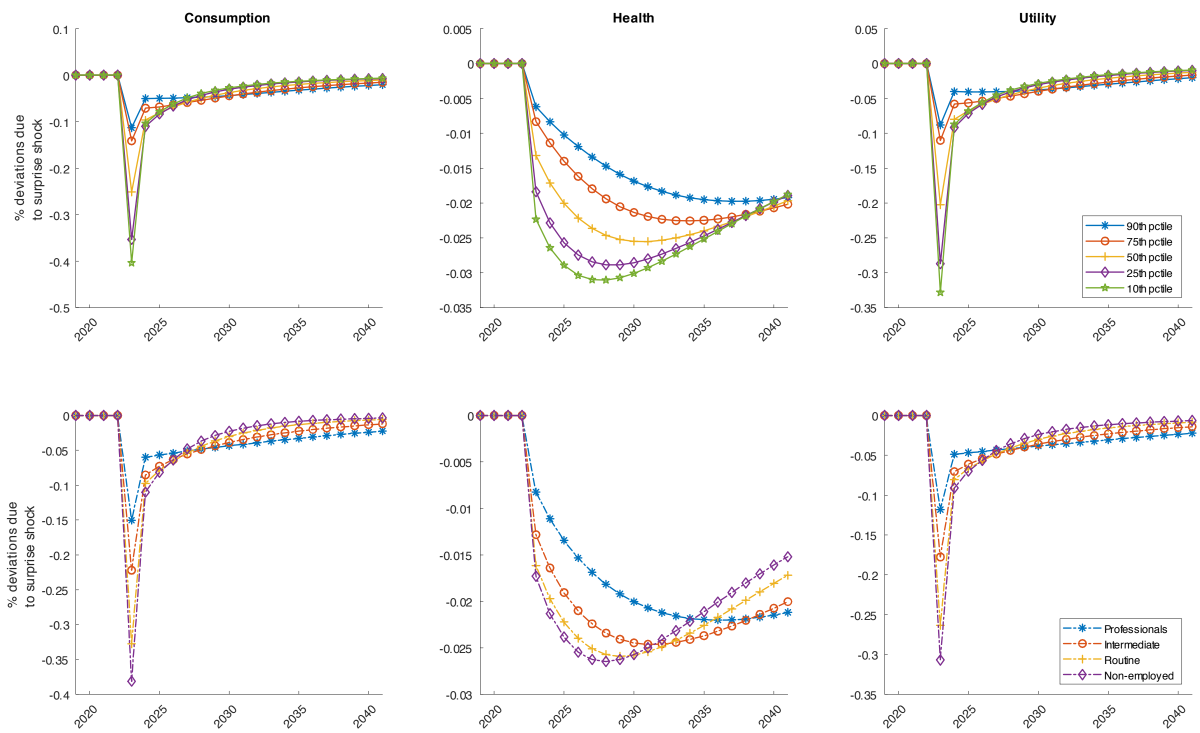
Note: Expected percentage deviations of simulated paths without Covid-19 under disease outbreak uncertainty versus simulated paths without Covid-19 and disease outbreak uncertainty. Lines in the left panels refer to households starting at the respective percentiles of the wealth distribution in 2019. Lines in the right panels refer to households of the respective socioeconomic groups in 2019.

As can also be seen in Figure 5, households in lower wealth quintiles, as well as in socioeconomic groups with lower mean income, decrease health while increasing wealth, in response to exogenous increases in income risk; households in higher wealth quintiles, as well as in socioeconomic groups with higher mean income, decrease health while increasing wealth. These changes reflect the substitutability between health and wealth in response to exogenous changes in the stochastic processes, analysed in Section 3. In particular, for households in lower wealth quintiles, or in socioeconomic groups with lower mean income, the budget constraint effects are stronger, since they have lower initial levels of assets and consumption, and thus dominate the complementarity incentives via the utility function.

On the contrary, for households in higher wealth quintiles, or in socioeconomic groups with higher mean income, the complementarity in consumption and health dominates and leads to an increase in both health and wealth.

5.3 Differential risk exposure and vulnerability

Figure 6: Effect of a surprise income shock



Note: Expected response of consumption and health to a uniform, one-time, unexpected household income shock of 1% that happens in 2023. Lines in the top panels refer to households starting at the respective percentiles of the wealth distributions in 2019. Lines in the bottom panels refer to households of the respective socioeconomic groups in 2019.

The post-pandemic increased variation in wealth accumulation for households with different characteristics implies differential changes in the exposure of these households to future exogenous reductions in income. In particular, households with high pre-pandemic wealth and/or in high-earnings socioeconomic groups at the onset of the pandemic or during the pandemic increase their wealth due to the impact effects of the pandemic shock; and they sustain the increased buffer levels for a prolonged period (Figures 3-5) as a result of recurrent outbreak risk. Conversely, as a result of the impact effects of the pandemic shock, households with low pre-pandemic wealth and/or in socioeconomic groups with lower mean earnings at the onset of the pandemic or during the pandemic decrease their wealth and are unable to accumulate wealth buffers to self-insure for a prolonged period (Figures 3-5). The implication is an increase in the inequality of risk exposure in the medium run following the pandemic.[48] Therefore, the first group of households is better prepared to absorb shocks to income without big drops in consumption, while the second

[48] Furthermore, there is an increase in the proportion of households with low or non-positive wealth following the pandemic (Figures 2-3).

group is worst insulated, and thus their consumption will drop more if there is a negative income shock.

We illustrate the inequality in post-pandemic income risk exposure in terms of drops in consumption, health and utility in response to a surprise income drop. To this end, we compute the paths of consumption and health for groups of households that differ in their wealth/health and the socioeconomic group at the onset of the pandemic, when there is an unexpected drop in income of 1% for all households three years after the main pandemic wave.[49] In Figure 6, we plot the percentage difference between paths where the income drop happens and paths where the income drop does not occur. The results in Figure 6 show *substantial inequality in income risk exposure after the pandemic, the effects of which are more severe for households that were already wealth poor prior to the pandemic.* In Table 7, we show the gap in the levels of consumption and health between the highest and lowest groups prior to the surprise shock, to which the drops in consumption and health following the income shock in Figure 6 apply. Together, Figure 6 and Table 7 reveal the *vulnerability of low wealth households to post-pandemic income risk: the substantial effects of the income shock are experienced by households with very low consumption prior to the surprise shock.* Indeed, vulnerability to income risk for low wealth households is reflected in the falls in utility following the surprise shock that are seen in Figure 6.

Table 7: Relative consumption and health in the year prior to the surprise shock

Percentiles	Relative Consumption	Relative Health	Soc. Groups	Relative Consumption	Relative Health
90th	1.25	1.20	Professional	1.27	1.15
75th	1.12	1.10	Intermediate	1.02	1.02
50th	0.95	1.00	Routine	0.79	0.91
25th	0.80	0.89	Non-employed	0.64	0.84
10th	0.76	0.83			

Notes: Consumption and health are relative to the median of pre-Covid-19 distribution, in 2019. Percentiles refer to households at the nth percentile of the wealth distribution in 2019. Socioeconomic groups refer to households of the respective socioeconomic group in 2019.

5.4 Social insurance

The vulnerability of consumption and health to post-pandemic negative shocks to income for low wealth households, especially because it reflects inability to implement household-level optimal self-insurance, implies that there is scope for policy intervention to mitigate income drops arising from exogenous shocks. Focusing on the effects of recurrent disease outbreaks, income support can mitigate the effect of income drops associated with disease outbreaks on household consumption and health, following the pandemic.

We assess a social insurance policy that provides income support to households to mitigate income drops that are caused by a recurrent outbreak, if they have wealth that is less than a critical level. Denote by $q^d(z_t) \equiv w(n_t, l_t, s_t; z_t = z^*) - w(n_t, l_t, s_t; z_t = C, R,)$, the drop in income for the household that is due to a pandemic outbreak relative to the pre-pandemic economy. This implies that $q^d(z_t) = 0$ when $z_t \neq R$ and $z_t \neq C$. For time period t that is greater than two years after the pandemic, the budget constraint of a

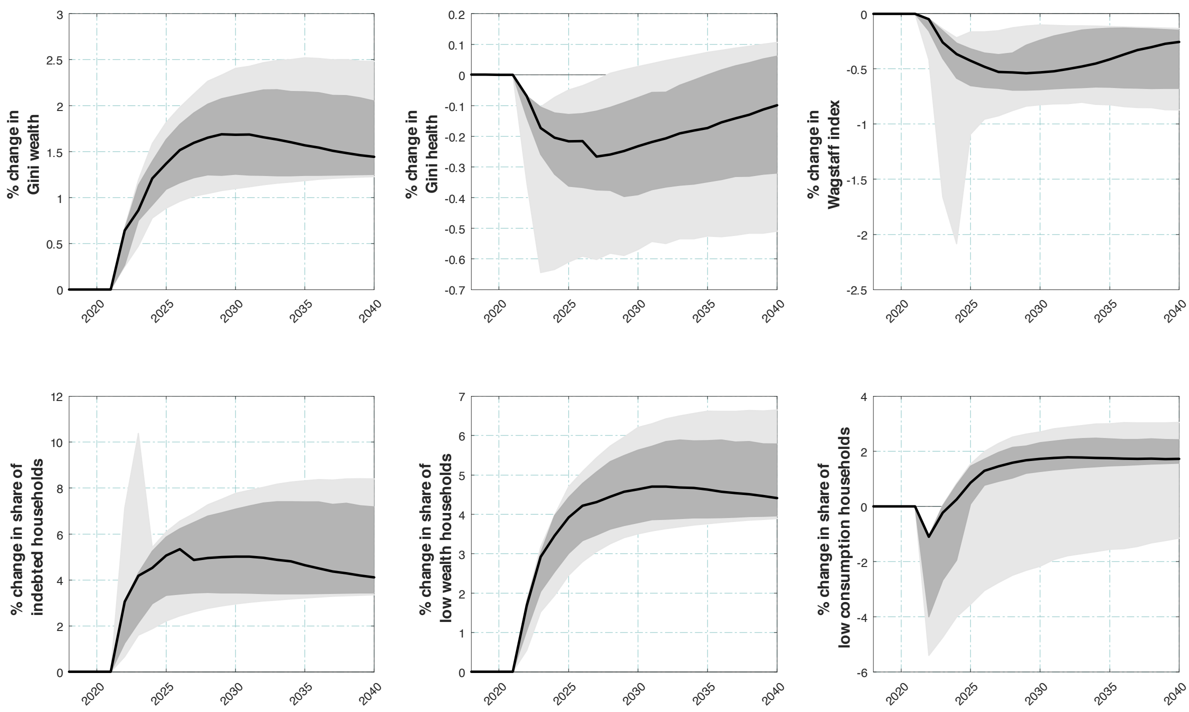
[49] See Appendix C for more details regarding the implementation of this counterfactual analysis.

household in (2) under this policy changes to:

$$
\begin{aligned}
&c_t + a_{t+1} + x_t = (1 + r(z_t))a_t + w(n_t, l_t, s_t, z_t) + q^s\left(a_t, z_t; \widetilde{a}\right), \\
&\quad q^s\left(a_t, z_t; \widetilde{a}\right) = \omega q^d\left(z_t\right), \text{ if } z_t = C, R \text{ and } a_t \leq \widetilde{a} \text{ and,} \\
&\quad q^s\left(a_t, z_t; \widetilde{a}\right) = 0, \text{ if } a_t > \widetilde{a},
\end{aligned}
$$

where $\omega \in (0,1)$ reflects the income replacement ratio and $\widetilde{a} \in A$ is a parameter that captures the coverage of the policy.

Figure 7: The effect of policy on post pandemic inequality



Note: Percentage change in measures of inequality with and without policy. Median (solid black line), p25-p75 (dark shading) and p10-p90 intervals (light shading) are based on 5,000 random paths of disease outbreak states. Low wealth (consumption) households are those that own wealth (consume) less than the 33rd (20th) percentile in the pre-pandemic distribution.

Our main finding is that there are trade-offs as a result of this policy, having both an intertemporal dimension and a health-wealth dimension. The emerging trade-offs do not depend on the generosity of the policy, measured by the parameters ω and $\widetilde{a}$, which determines the magnitude of the effects. Therefore, to illustrate the trade-offs we show in Figure 7 results that compare key outcomes under a policy that sets $\omega = 0.8$ and $\widetilde{a}$ to be equal to the wealth of the 33rd percentile of the pre-COVID-19 wealth distribution.[50] The cost of such a policy is, on average across the two post-pandemic decades, about 0.14% of aggregate income per year. Results for different ω and $\widetilde{a}$ are in Appendix E.

The plots in Figure 7 show that the policy intervention in effect is reducing the increase in the share of households with low consumption in the short run following the

[50] This is the threshold used in our analysis earlier to define low wealth households.

pandemic, thus helping more households smooth consumption after aggregate-level induced income drops in the first years that follow the pandemic. It also reduces health inequality compared to the baseline results without intervention, both by mitigating the increase in the health Gini and the Wagstaff indices. However, these positive effects come at the cost of increased wealth inequality (see wealth Gini), and in particular, an increase in the thickness of the left tail of the wealth distribution (see the percentage of households with negative or low wealth). In turn, the increased share of households with low wealth also implies an increased share of households that are vulnerable to income drops via reduced own self-insurance potential, leading to an increase in the share of households with low consumption in the medium run. The magnitude of the effects depends on the generosity of the policy, and as shown in Appendix E, they are stronger for policies that imply higher expenditure, albeit at a decreasing rate when the effects are normalized by the cost. However, the direction of the effects is robust when fiscal spending is accounted for, and different spending levels are considered.

The results suggest that intervention implies a trade-off between effective insurance from income drops in the short- and medium-run, and another trade-off between health and wealth inequality. The first trade-off arises because public insurance effectively crowds out household self-insurance by reducing household-level incentives to accumulate wealth for this purpose. The disincentives are stronger for households at higher risk, i.e. households with low wealth, which underlies the increase in wealth Gini and the increases in the shares of households with low wealth. In other words, the wealth distribution does not simply shift to the left, but the left tail becomes thicker as well. The second trade-off arises because of the substitutability in the use of health and wealth to respond to income drops and increases in income risk, which we analysed in Section 3, and given the aim of the policy intervention to mitigate income (as opposed to health) risk and its crowding-out effects on household wealth. In effect, therefore, public insurance policy against income risk crowds in investment in health. In particular, given that households with low health and wealth reduce wealth due to the reduction in income risk exposure, they instead invest a higher share of their resources in improving their health and thus being in a better position to mitigate health shocks. For example, the public insurance policy examined corrects about a quarter of the reduction in average health for households in the lowest quintile of the wealth and health distribution over the first 20 years of the policy. This implies that the health Gini is reduced, but also, by increasing health for low wealth households, there is a reduction in the health-wealth concentration captured by the Wagstaff index.

6 Conclusions

Pandemics, via their main waves and stochastic recurrent outbreaks, include a combination of shocks to income and health and increases in income and health risk, while policy intervention can restrict the potential for consumption, all of which are non-uniformly distributed across the population. These effects generate incentives for households to smooth consumption and create precautionary buffers under an altered set of constraints imposed on the household budget. These incentives and changes in constraints imply that either wealth and/or health can be used for consumption smoothing and precautionary choices, substituting one another in this process. The complexity of options afforded to households, which in addition face different types and sizes of shocks, and the dependence of household responses on the combination of initial health and wealth, imply that an assessment of likely changes in health and wealth inequality in the medium run following a pandemic requires quantitative analysis that incorporates all these features in an empirically relevant application.

Our analysis quantifies the scale and form of increases in wealth inequality that result from the COVID-19 pandemic in the UK and shows that it has severe implications. First, it amplifies existing and high wealth inequality, and in particular, it leads to a reduction in wealth for households that were already wealth poor prior to the pandemic. Second, it is accompanied by increases in health inequality, implying a deterioration in health for those with lower wealth and/or health, and strengthening the relationship between wealth and health, thus sowing the seeds for pervasive socioeconomic and health disparities. Third, recurrent outbreak risk following the main pandemic waves implies that, with a non-trivial probability, there can be a substantial divergence between median scenarios and substantially worse outcomes. Fourth, the reduction in wealth for the wealth-poor makes them particularly vulnerable to future adverse income shocks, as they lack the required means to self-insure. Fifth, the increase in vulnerability is socially troubling in addition to being economically painful because it reflects the inability to implement privately optimal self-insurance plans for those households exposed to post-pandemic risk, resulting from wealth reduction during the first waves of the pandemic. Sixth, the increase in inequality and vulnerability take place despite an extensive economic intervention to support income losses during the main pandemic waves. Seventh, public insurance interventions to mitigate post-pandemic vulnerability by supporting income losses for those with low wealth tend to crowd out private insurance by reducing own wealth accumulation, resulting in an intertemporal trade-off in the probability of low consumption.

Our results underline the difficult issues that societies face in the decades that follow a catastrophic event like a pandemic, an event that, as we find, casts a long shadow in terms of its distributional effects and their implications. Increased vulnerability, in particular, implies that there is strong potential for increased social pressure for intervention in the decades that follow the pandemic. Given the shortcomings of over-reliance on *ex post* intervention, policies to mitigate risk exposure should include a combination of measures to both strengthen income resilience *ex ante*, and provide support *ex post*.

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Supplementary material: https://github.com/maxschr90/2021-Angelopoulos-et-al.—Post-pandemic-Inequality.

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Appendix for "Pandemic-induced wealth and health inequality and risk exposure"

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Appendix A: Data

The UK Household Longitudinal Study - Understanding Society (UnSoc, ISER (2020)) is a large longitudinal survey that follows approximately 40,000 households (at Wave 1) in the UK. UnSoc covers a wide range of social, economic and behavioural factors, making it relevant to a wide range of researchers and policymakers. Data collection for each wave takes place over 24 months, and the first wave occurred between January 2009 and January 2011. Note that the periods of waves overlap, but the individual respondents are interviewed around the same time each year. Thus, no respondent is interviewed twice within a wave or a calendar year (see, e.g. Knies (2018)).

The Wealth and Assets Survey (WAS, ONS (2018)) started in July 2006, with the first wave of interviews carried out over two years to June 2008. The WAS interviewed approximately 30,500 households, including 53,300 adult household members in Wave 1. The same households were approached again for a Wave 2 interview between July 2008 and June 2010. In this wave, 20,170 households responded (around 70 percent of the initial sample), including 35,000 adult household members. Waves 3-5 covered the periods between July and June for 2010-12, 2012-14 and 2014-16, respectively. After Wave 2, due to sample attrition, the WAS started implementing boost samples in each wave to keep the number of interviewed households around 20,000 and 35,000-40,000 adult household members.

The WAS and UnSoc data sets employed in this paper refer to the free "End User Licence" versions of the datasets. In particular, we use the following datasets, WAS, SN-721,5 and UnSoc, SN-6614.

A.1 Demographics (UnSoc)

1. **Head of the Household**: The head of household is defined as the principal owner or renter of the property (w_hrpno, where the prefix w denotes wave), which coincides with the UnSoc definition of the head of the household and the ONS definition of the Household Reference Person. In cases where there is more than one head, the eldest takes precedence over the other heads.

2. **Household Members:** For each household, we retain the head of the household, and their spouse/partner if applicable (identified by the variable sppid).

3. **Socioeconomic Group:** We construct socioeconomic groups by first condensing the Eight Class NS-SEC (w_jbnssec8_dv), merging subclasses I-II, III-V and VI-VIII together. Then we generate a new classification by combining these three new classes with all those who do not have an applicable NS-SEC number (-8) into a 4 class classification. We label the resulting groups "Professionals", "Intermediate", "Routine" and "Non-employed" respectively. Those without an applicable 8 class NS-SEC are classed as non-employed. We also re-classify all those who describe their economic activity (w_jbstat) as "Unemployed", "Retired", "Family Care or Home Work", and "Long-term sick or disabled" as non-employed. We approximate the socioeconomic group of the household with the highest of the socioeconomic groups amongst either the household head or their spouse/partner if applicable.

A.2 Definitions of income (UnSoc)

Post policy labour income: For post-policy labour income, we use monthly net labour income in the current job (fimnlabnet_dv) and multiply by 12 to arrive at annual net labour income. To this, we add miscellaneous income (w_fimnmisc_dv), private benefit income (w_fimnprben_dv) and social benefit income (w_fimnsben_dv), all multiplied by 12 to generate annual estimates. All values are deflated using the annual Consumer Price Deflator for the UK (2015 = 100).

A.3 Definition of severe health events (UnSoc)

Respondents in the UnSoc survey are asked several health-related questions relating to the existence of several medical conditions. When the household enters the sample, they are asked about any prior existing condition, and after the initial wave, they are questioned on whether any new health condition has been diagnosed since the last interview. We select Congestive Heart Failure (w_hcondn3), Coronary Heart Disease (w_hcondn4), Heart attack or myocardial infarction (w_hcondn6), Stroke (w_hcondn7), Emphysema (w_hcondn8), Chronic Bronchitis (w_hcondn11) and Cancer or Malignancy (w_hcondn13) as examples of severe health events.[1] We consider the household as experiencing a severe health event if the household head or their spouse has experienced any of the health conditions mentioned above since the last interview.

These severe health events can have significant effects on the health of households (see Appendix D, Section 1). A potential worry regarding measuring these effects is that a proportion of individuals who receive these shocks die and never show up in our sample. UnSoc does include a follow-up question to indicate if a household member has died, but the information is not detailed enough to establish whether one of the specific health events was responsible for their passing. To the best of our knowledge cause of death cannot be established in the basic version of the Understanding Society data without linking further (confidential) medical data. Consequently, all our results regarding health shocks and health outcomes should be understood as being conditional on survival. However, quantitatively our calibration of the probability of severe health events should not be affected significantly by this. To examine this, we use the latest available data from the NHS Compendium of population health indicators (2016-2018) and collect the crude death rates for deaths from i) stroke, ii) all circulatory diseases, iii) all cancers & iv) bronchitis, emphysema and other COPD, amongst the age group of 15 to 64-year-olds, for England and Wales.[2] Across all four causes of death, the mortality rate per 100,000 people is 220, or 0.22% overall. There are $2,412$ reported severe health events within our sample, or one severe health event in 2.65% of all available observations. Applying the mortality rate of 0.22% would change the severe health event probability to 2.87%, an increase of less than 10%.

[1] Note that these variables are coded slightly differently in the initial wave since they capture the entire history prior to the first interview.

[2] The mortality data is reported in age bins, that fall outwith our sample. Therefore, we are likely overestimating mortality in this robustness check.

A.4 Definition of health measure (UnSoc)

We proxy the level of health by the SF-12 Physical Component Summary (PCS) which corresponds to the variable w_sf12pcs_dv in UnSoc. The PCS is a summary measure of health constructed from answers to 12 survey questions that are part of the SF-12 Health Survey. The result is a continuous score of physical fitness (for details, see Jenkinson and Layte (1997) and Ware *et al.* (2001)). In the first survey, respondents are walked through the components of the SF-12 Health Survey by the surveyor. In the following waves, the SF-12 is part of the self-completion questionnaire. The PCS in the UnSoc has been used to study, for example, the effect of job strain and late retirement on health (Carrino *et al.* (2020)), or the effect of sleep patterns on health and wellbeing (Tang *et al.* (2017)). We standardize the PCS on the interval $[0.1, 1]$ and average across the household head and their spouse/partner.

A.5 Sample selection (UnSoc)

Our primary sample consists of the General Population Sample, including the Northern Ireland sample and the Ethnic Minority boost samples. We drop those respondents who completed proxy interviews and all those where relevant information is missing. We restrict our sample to those households with heads aged 25 to 60, and further drop full-time students, apprentices, those in government training schemes, or working unpaid in family-owned businesses (w_jbstat). We also drop those that have a missing NS-SEC classification, even though they are classified as working.

Table A1: Household sample selection UnSoc

selection step	Total
1. Whole sample of households	229,510
2. Drop if household head cannot be identified	213,975
3. Drop if relevant information is missing	194,302
4. Drop proxy interviews	158,941
5. Drop full time students, apprenticeship, unpaid work in family business or unclear	156,058
6. Keep household with heads' aged between 25 and 60	90,916
Average number of household observations per wave	10,101.78

A.6 Sample coverage

The WAS does not cover Northern Ireland, while the UnSoc disproportionately samples from there. However, dropping Northern Ireland based households from the UnSoc sample, does not affect the descriptive statistics presented in Table 1 in the main text significantly. For comparison see below:

Table A2: Income, health & health risk by income quintile
and Socioeconomic Group

Socioeconomic Gr.	Relative Income	Relative Health	Gini Health	Severe Health cond.
Professionals	1.57	1.06	0.05	1.8 %
Intermediate	1.07	1.03	0.07	2.0 %
Routine	0.75	0.99	0.08	2.4 %
Non-employed	0.44	0.84	0.17	6.1 %
All	1	1	0.09	2.7 %

Note that Net Income includes taxes and transfers, but not investment income

Source: Pooled Sample UnSoc Waves 1-9; excluding Northern Ireland

A.7 Demographics (WAS)

1. **Head of the Household**: We define the head of household as the principal owner or renter of the property, and, when there is more than one head, the eldest takes precedence. This follows the ONS definition for the Household reference person (HRP) which is what the UnSoc follows as well. We use of the following variables: (HhldrW), (HiHNumW), (DVAGEw) and/or (DVAge17w).

2. **Socioeconomic Group:** We use the eight Class NS-SEC (NSSEC8W) and we follow the same steps as for Unsoc.

3. **Employment Status:** We use the variables for economic activity: (ecactw) for Waves 1-3 and (DVecactw) for Waves 4-5.

A.8 Definition of wealth (WAS)

1. **Net property wealth**: is the sum of all property values minus the value of all mortgages and amounts owed as a result of equity release. (HPROPWW).[3]

2. **Net financial wealth**: is the sum of the values of formal and informal financial assets, plus the value of certain assets held in the names of children, plus the value of endowments purchased to repay mortgages, less the value of non-mortgage debt. The informal financial assets exclude very small amounts (less than £250) and the financial liabilities are the sum of current account overdrafts plus amounts owed on credit cards, store cards, mail order, hire purchase and loans plus amounts owed in arrears. Finally, money held in Trusts, other than Child Trust Funds, is not included. (HFINWNTW_sum).

3. **Net Worth:** is the sum of the net property wealth and net financial wealth.

[3] All values are deflated using the annual Consumer Price Deflator for the UK (2015 = 100).

A.9 Sample selection (WAS)

We follow similar steps as in the sample selection for Understanding Society.

Table A3: Household sample selection WAS

selection step	Total
1. Whole sample of households	110,963
2. Drop households with mis-reported age variable	110,937
3. Drop households with duplicate hh grid numbers	110,910
4. Drop if NS-SEC is missing, either head or partner	109,820
5. Keep if heads' age between 25 and 60.	58,875
6. Drop if the head is student	58,218
Average net worth obs per wave	11,643.6

Appendix B: Theoretical results

B.1 Setup

The problem of the households is given by:

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

$$\text{where}$$

$$c\left(a_t, h_t, a_{t+1}, h_{t+1}\right) = (1 + r(z_t))a_t + w(e_t, z_t) - a_{t+1} - x(h_t, h_{t+1}),$$

$$e_t = (n_t, l_t, s_t)\,,\ h_{t+1} = \delta(e_t, z_t)h_t + m\left(x_t\right),$$

$$x_t \equiv x(h_t, h_{t+1}) = m^{-1}\left(h_{t+1} - \delta(e_t, z_t)h_t\right),$$

$$a_{t+1} \in A', \text{ and } h_{t+1} \in H', \text{ where } A' \text{ and } H'$$

$$\text{are defined to satisfy the constraints}$$

$$c_t, x_t \geq 0,\ a_{t+1} \geq a^{\min},\ h^{\min} \leq h_t \leq h^{\max},$$

$$\delta(e_t, z_t)h_t \leq h_{t+1} \leq h^{\max}$$

Assume that:

$$u_{c_t} > 0, u_{c_t c_t} < 0, \tag{1}$$

$$u_{h_{t+1}} > 0, u_{h_{t+1}h_{t+1}} < 0, \tag{2}$$

and that:

$$m_{x_t} > 0, m_{x_t x_t} < 0, \tag{3}$$

$$\lim_{x_t \to 0} m_{x_t} = +\infty, \tag{4}$$

$$-u_{c_t c_t} x_{h_{t+1}}(h_t, h_{t+1}) + u_{c_t h_{t+1}} > 0. \tag{5}$$

Note that:

$$\frac{\partial u_{c_t}\left(c\left(a_t,h_t,a_{t+1},h_{t+1}\right),h_{t+1}\right)}{\partial a_{t+1}} = u_{c_tc_t}c_{a_{t+1}}\left(a_t,h_t,a_{t+1},h_{t+1}\right) \tag{6}$$

$$\frac{\partial u_{c_{t+1}}\left(c\left(a_{t+1},h_{t+1},a_{t+2},h_{t+2}\right),h_{t+2}\right)}{\partial a_{t+1}} = u_{c_{t+1}c_{t+1}}c_{a_{t+1}}\left(a_{t+1},h_{t+1},a_{t+2},h_{t+2}\right) \tag{7}$$

$$\frac{\partial u_{h_{t+1}}\left(c\left(a_t,h_t,a_{t+1},h_{t+1}\right),h_{t+1}\right)}{\partial a_{t+1}} = u_{h_{t+1}c_t}c_{a_{t+1}}\left(a_t,h_t,a_{t+1},h_{t+1}\right) \tag{8}$$

$$\frac{\partial u_{c_t}\left(c\left(a_t,h_t,a_{t+1},h_{t+1}\right),h_{t+1}\right)}{\partial h_{t+1}} = u_{c_tc_t}c_{h_{t+1}}\left(a_t,h_t,a_{t+1},h_{t+1}\right) + u_{c_th_{t+1}} \tag{9}$$

$$\frac{\partial u_{c_{t+1}}\left(c\left(a_{t+1},h_{t+1},a_{t+2},h_{t+2}\right),h_{t+2}\right)}{\partial h_{t+1}} = u_{c_{t+1}c_{t+1}}c_{h_{t+1}}\left(a_{t+1},h_{t+1},a_{t+2},h_{t+2}\right) \tag{10}$$

$$\frac{\partial u_{h_{t+1}}\left(c\left(a_t,h_t,a_{t+1},h_{t+1}\right),h_{t+1}\right)}{\partial h_{t+1}} = u_{h_{t+1}c_t}c_{h_{t+1}}\left(a_t,h_t,a_{t+1},h_{t+1}\right) + u_{h_{t+1}h_{+1}}, \tag{11}$$

where:

$$x_{h_t}(h_t,h_{t+1}) < 0,\ \ x_{h_th_t}(h_t,h_{t+1}) > 0 \tag{12}$$

$$x_{h_{t+1}}(h_t,h_{t+1}) > 0,\ \ x_{h_{t+1}h_{t+1}}(h_t,h_{t+1}) > 0 \tag{13}$$

$$c_{a_t}\left(a_t,h_t,a_{t+1},h_{t+1}\right) = 1 + r(z_t) > 0 \tag{14}$$

$$c_{x_t}\left(a_t,h_t,a_{t+1},h_{t+1}\right) = -1 < 0 \tag{15}$$

$$c_{a_{t+1}}\left(a_t,h_t,a_{t+1},h_{t+1}\right) = -1 < 0 \tag{16}$$

$$c_{h_t}\left(a_t,h_t,a_{t+1},h_{t+1}\right) = -x_{h_t}(h_t,h_{t+1}) > 0 \tag{17}$$

$$c_{h_{t+1}}\left(a_t,h_t,a_{t+1},h_{t+1}\right) = -x_{h_{t+1}}(h_t,h_{t+1}) < 0. \tag{18}$$

To see (12) and (13), note that

$$\begin{aligned} x_{h_t}^{-1}(h_t,h_{t+1}) &= \left(m^{-1}\right)'\left(h_{t+1} - \delta(e_t,z_t)h_t\right) \\ \text{(Inv. Func. Theorem)} &= \frac{1}{\frac{dm}{dx}}\frac{d\left(h_{t+1} - \delta(e_t,z_t)h_t\right)}{dh_t} \\ &= \frac{1}{\underset{>0}{m_{x_t}}}(-\underset{<0}{\delta(e_t,z_t)}) < 0 \end{aligned}$$

$$\begin{aligned} x_{h_th_t}^{-1}(h_t,h_{t+1}) &= \left((m_{x_t})^{-1}\right)'(-\delta(e_t,z_t)) \\ &= \left(\left(m'(m^{-1}(h_{t+1} - \delta(e_t,z_t)h_t))\right)^{-1}\right)'(-\delta(e_t,z_t)) \\ \text{(Inv. Func. Theorem)} &= \underset{<0}{(-1)}\underset{<0}{m_{x_tx_t}}\frac{1}{\underset{>0}{m_{x_t}}}\underset{>0}{(m_{x_t})^{-2}}(\underset{>0}{-\delta(e_t,z_t))^2} > 0 \end{aligned}$$

$$
\begin{aligned}
x^{-1}_{h_{t+1}}(h_t,h_{t+1}) &= \left(m^{-1}\right)'(h_{t+1}-\delta(e_t,z_t)h_t) \\
\text{(Inv. Func. Theorem)} &= \frac{1}{\frac{dm}{dx}}\frac{d\left(h_{t+1}-\delta(e_t,z_t)h_t\right)}{dh_{t+1}} \\
&= \underbrace{\frac{1}{m_{x_t}}}_{>0}1<0
\end{aligned}
$$

$$
\begin{aligned}
x^{-1}_{h_{t+1}h_{t+1}}(h_t,h_{t+1}) &= \left((m_{x_t})^{-1}\right)' \\
&= \left(\left(m'(m^{-1}(h_{t+1}-\delta(e_t,z_t)h_t))\right)^{-1}\right)' \\
\text{(Inv. Func. Theorem)} &= \underbrace{(-1)}_{<0}\underbrace{m_{x_tx_t}}_{<0}\underbrace{\frac{1}{m_{x_t}}}_{>0}\underbrace{(m_{x_t})^{-2}}_{>0}>0
\end{aligned}
$$

The relationships in (14)-(18) are derived by using the budget constraint and (12)-(13).

B.2 Results

Assuming interior solutions, optimality requires that the two Euler conditions are satisfied:

$$
u_{c_t}=\beta E\left[u_{c_{t+1}}(1+r(z_{t+1})\right], \tag{19}
$$

and

$$
u_{c_t}x_{h_{t+1}}(h_t,h_{t+1})-u_{h_{t+1}}=\beta E\left[u_{c_{t+1}}\left(-x_{h_{t+1}}(h_{t+1},h_{t+2})\right)\right]. \tag{20}
$$

`Lemma 1`

Assume that (1) - (5) hold. Given a process (z_t), for any $(a_t,a_{t+2})\in A$, $(h_t,h_{t+2})\in\left(h^{\min},h^{\max}\right)$, and $e_t\in E$:

a) If a_{t+1} and h_{t+1} that satisfy (19) 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 (20) in period t is a downward slopping function. Moreover, when $h_{t+1}\to\delta(e_t,z_t)h_t$, higher values for a_{t+1} are required to satisfy (20), compared with (19).

b) A combination of a_{t+1} and h_{t+1} that is feasible and satisfies (19) and (20) simultaneously must be an intersection point of the downward slopping functions in a) that is within an area defined by vertical lines at $\delta(e_t,z_t)h_t$ and $\min\left\{\frac{h_{t+2}}{\delta(e_t,z_t)},h^{\max}\right\}$, a horizontal line at $a^{\min}$, and the function $a^{\max}_{t+1}=b\left(h_{t+1}\right)=(1+r(z_t))a_t+w(e_t,z_t)-x(h_t,h_{t+1})$.

`Proof`

Assuming interior solutions, the Euler equations are:

$$
F^{ea}\equiv u_{c_t}-\beta E\left[u_{c_{t+1}}(1+r(z_{t+1})\right]=0, \tag{21}
$$

and:

$$
F^{eh}\equiv u_{c_t}x_{h_{t+1}}(h_t,h_{t+1})-u_{h_{t+1}}-\beta E\left[u_{c_{t+1}}\left(-x_{h_{t+1}}(h_{t+1},h_{t+2})\right)\right]=0. \tag{22}
$$

a) Define the function f^{ea}, $a_{t+1} = f^{ea}(h_{t+1})$, giving the combinations of (a_{t+1}, h_{t+1}) such that $F^{ea} = 0$, i.e. the locus of solutions to (21)). Define the function f^{eh}, $a_{t+1} = f^{eh}(h_{t+1})$, giving the combinations of (a_{t+1}, h_{t+1}) such that $F^{eh} = 0$, i.e. the locus of solutions to (22)). Using (6)-(11) and (12)-(18), we have that:

$$F^{ea}_{a_{t+1}} = -u_{c_t c_t} - \beta E\left[u_{c_{t+1}c_{t+1}}(1 + r(z_{t+1})^2\right] > 0,$$

$$F^{ea}_{h_{t+1}} = -u_{c_t c_t} x_{h_{t+1}}(h_t, h_{t+1}) + u_{c_t h_{t+1}} - \beta E\left[u_{c_{t+1}c_{t+1}}\left(-x_{h_{t+1}}(h_{t+1}, h_{t+2})\right)(1 + r(z_{t+1})\right] > 0,$$

$$F^{eh}_{a_{t+1}} = -u_{c_t c_t} x_{h_{t+1}}(h_t, h_{t+1}) + u_{c_t h_{t+1}} - \beta E\left[u_{c_{t+1}c_{t+1}}\left(-x_{h_{t+1}}(h_{t+1}, h_{t+2})\right)(1 + r(z_{t+1})\right] > 0,$$

$$F^{eh}_{h_{t+1}} = \left\{\begin{array}{c} -u_{c_t c_t}\left(x_{h_{t+1}}(h_t, h_{t+1})\right)^2 + u_{c_t} x_{h_{t+1}h_{t+1}}(h_t, h_{t+1}) \\ +u_{h_{t+1}c_t} x_{h_{t+1}}(h_t, h_{t+1}) - u_{h_{t+1}h_{t+1}} \\ -\beta E\left[u_{c_{t+1}c_{t+1}}\left(-x^{-1}_{h_{t+1}}(h_{t+1}, h_{t+2})\right)\left(-x^{-1}_{h_{t+1}}(h_{t+1}, h_{t+2})\right)\right] \\ -\beta E\left[u_{c_{t+1}}\left(-x^{-1}_{h_{t+1}h_{t+1}}(h_{t+1}, h_{t+2})\right)\right] \end{array}\right\} > 0$$

Given monotonicity of (21) and (22), for any h_{t+1}, if there is a_{t+1} that satisfies (21), it will be unique, and if there is a_{t+1} that satisfies (22), it will be unique. Therefore, for the relevant domains where the mappings f^{ea} and f^{eh} are well defined, they are functions.

Given any combination (a_{t+1}, h_{t+1}) such that $F^{ea} = 0$ (i.e. any point in f^{ea}), a change in (a_{t+1}, h_{t+1}) such that the new combination remains on the f^{ea} function, requires that:

$$dF^{ea} = 0, \text{ or}$$
$$F^{ea}_{a_{t+1}} da_{t+1} + F^{ea}_{h_{t+1}} dh_{t+1} = 0,$$

which implies that

$$\frac{da_{t+1}}{dh_{t+1}} = -\frac{F^{ea}_{h_{t+1}}}{F^{ea}_{a_{t+1}}}.$$

Since $F^{ea}_{h_{t+1}}, F^{ea}_{a_{t+1}} > 0$, $\frac{da_{t+1}}{dh_{t+1}} < 0$. Therefore, the locus of combinations of (a_{t+1}, h_{t+1}) that define f^{ea} is downward slopping.

Given any combination (a_{t+1}, h_{t+1}) such that $F^{eh} = 0$ (i.e. any point in f^{eh}), changes in (a_{t+1}, h_{t+1}) that remain on the f^{eh} function, requires that:

$$dF^{eh} = 0, \text{ or}$$
$$F^{eh}_{a_{t+1}} da_{t+1} + F^{eh}_{h_{t+1}} dh_{t+1} = 0,$$

which implies that:

$$\frac{da_{t+1}}{dh_{t+1}} = -\frac{F^{eh}_{h_{t+1}}}{F^{eh}_{a_{t+1}}}.$$

Since $F^{eh}_{h_{t+1}}, F^{eh}_{a_{t+1}} > 0$, $\frac{da_{t+1}}{dh_{t+1}} < 0$. Therefore, the locus of combinations of (a_{t+1}, h_{t+1}) that define f^{eh} is downward slopping.

Next, denote $x(h_t, h_{t+1}) = m^{-1}(h_{t+1} - \delta(e_t, z_t)h_t)$ as $x(\bar{l}_t) = m^{-1}\left(\bar{l}_t\right)$, where $\bar{l}_t \equiv$

$h_{t+1} - \delta(e_t, z_t)h_t$. Note that $h_{t+1} \to \delta(e_t, z_t)h_t$ implies that $\bar{l}_t \to 0$. Since $x_{h_{t+1}}(h_t, h_{t+1}) = m_{\bar{l}_t}^{-1}\left(\bar{l}_t\right) = \frac{1}{m_{x_t}}$, and $\lim_{x_t \to 0} m_{x_t} = +\infty$, $\lim_{\bar{l}_t \to 0} m_{\bar{l}_t}^{-1}\left(\bar{l}_t\right) = 0$.

Consider the behaviour of $\left(F^{ea}, F^{eh}\right)$ when $h_{t+1} \to \delta(e_t, z_t)h_t$. Since

$$\lim_{h_{t+1} \to \delta(e_t, z_t)h_t} x_{h_{t+1}}(h_t, h_{t+1}) = \lim_{\bar{l}_t \to 0} m_{\bar{l}_t}^{-1}\left(\bar{l}_t\right) = 0,$$

(22) cannot be satisfied for any finite value of a_{t+1}. Therefore, a necessary condition for (22) to hold is that $a_{t+1} \to +\infty$. Hence, when $h_{t+1} \to \delta(e_t, z_t)h_t$, F^{eh} must imply higher values for a_{t+1} than F^{ea}.

b) The constraints for the household problem require that:

$$c_t, x_t \geq 0,\ a_{t+1} \geq a^{\min},\ h^{\min} \leq h_t \leq h^{\max}.$$

In turn, these imply that: (i) $x_t = h_{t+1} - \delta(e_t, z_t)h_{t+1} \geq 0$; (ii) $x_{t+1} = h_{t+2} - \delta(e_{t+1}, z_{t+1})h_t \geq 0$, and (iii) $h^{\min} \leq h_{t+1} \leq h^{\max}$, so that $\delta(e_t, z_t)h^{\min} \leq \delta(e_t, z_t)h_t \leq h_{t+1} \leq \{\min \frac{h_{t+2}}{\delta(e_t, z_t)}, h^{\max}\}$. Moreover, $c_t \geq 0$ implies that, to be feasible, combinations of (a_{t+1}, h_{t+1}) must be below the function $a_{t+1} = (1 + r(z_t))a_t + w(e_t, z_t) - x(h_t, h_{t+1})$, which in turn defines $a_{t+1}^{\max}$ as a function of h_{t+1}. Therefore, combinations of a_{t+1} and h_{t+1} that are feasible and satisfies (19) and (20) simultaneously must be an intersection point of the downward slopping functions f^{ea} and f^{eh} and be within an area defined by vertical lines at $\delta(e_t, z_t)h_t$ and $h^{\max}$, a horizontal line at $a^{\min}$, and the function $a_{t+1}^{\max} = b\left(h_{t+1}\right) = (1 + r(z_t))a_t + w(e_t, z_t) - x(h_t, h_{t+1})$. This is shown in Figure 1 in the main text. ■

`Lemma 2`

Given a process (z_t^s), assume that a household in period t 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 (19) and (20). Consider an aggregate-level stochastic process (z_t^p) which implies that in period t the *rhs* of (19) and (20) are higher (lower) relative to the *lhs* compared with (z_t^s), conditional on $(a_t, a_{t+2}) \in A$, and $(h_t, h_{t+2}) \in \left(h^{\min}, h^{\max}\right)$. Then:

a) The downward slopping f^{ea} and f^{eh} shift outwards (inwards), and at least one of a_{t+1} and h_{t+1} increase (decrease) relative to (a_{t+1}^s, h_{t+1}^s).

b) The change in a_{t+1} relative to a_{t+1}^s is a negative function of the change h_{t+1} relative to relative to h_{t+1}^s, and vice versa.

`Proof`

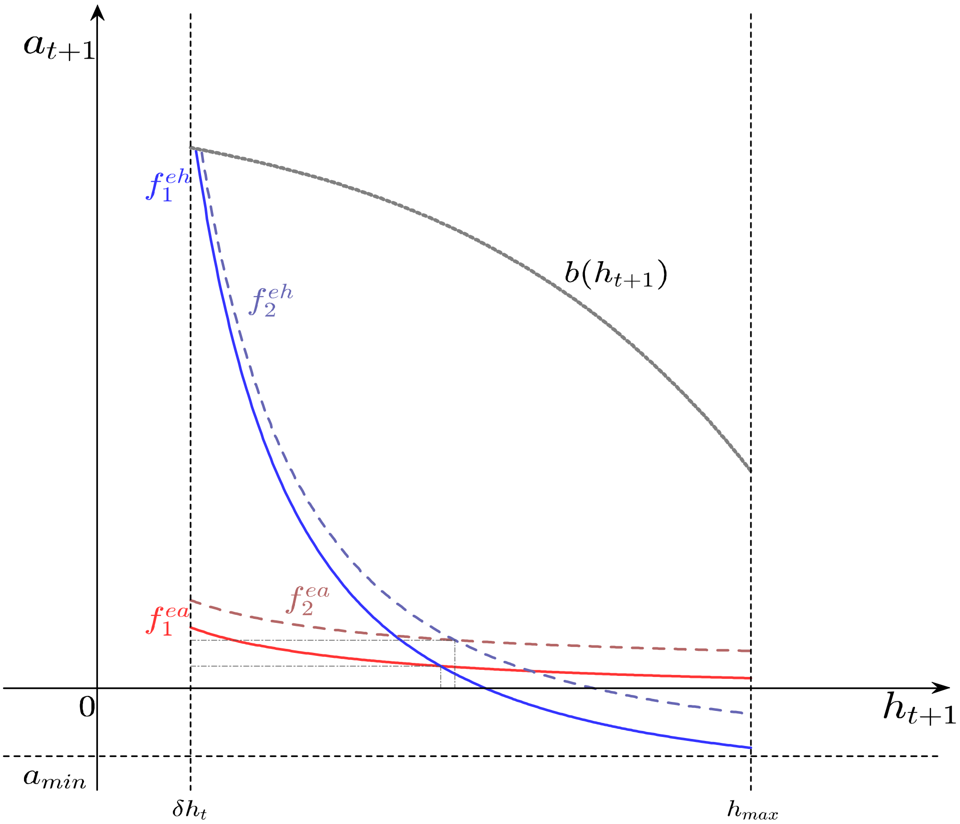
a) Using (6)-(11) and (12)-(18), the *rhs* of (21) and (22) are increasing functions of both a_{t+1} or h_{t+1}, while the *lhs* are decreasing functions of both a_{t+1} or h_{t+1}, for any $(a_t, a_{t+2}) \in A$, $(h_t, h_{t+2}) \in \left(h^{\min}, h^{\max}\right)$, and $e_t \in E$.

Consider the case where, under the change from (z_t^s) to (z_t^p), the *rhs* of (21) and (22) increase relative to the *lhs*. Assume that both a_{t+1} and h_{t+1} decrease. Then, the *rhs* of (21) and (22) increase more, while the *lhs* decrease more, hence such a change cannot be optimal. Therefore, at least one of a_{t+1} or h_{t+1} must increase.

Consider the case where, under the change from (z_t^s) to (z_t^p), the *rhs* of (21) and (22) decrease relative to the *lhs*. Assume that both a_{t+1} and h_{t+1} increase. Then the *rhs* of (21) and (22) decrease more, while the *lhs* increase more, hence such a change cannot be optimal. Therefore, at least one of a_{t+1} or h_{t+1} must decrease.

An increase (decrease) in the *rhs* of (21) relative to the *lhs* implies that, for any value of h_{t+1}, an increase in a_{t+1} is required; and, for any value of a_{t+1}, an increase in h_{t+1} is required. Therefore, f^{ea} shifts outwards (inwards). Similar arguments apply regarding changes to f^{eh}. The new equilibrium is found at the intersection of the two new functions, and thus must imply that at least one of a_{t+1} and h_{t+1} is higher. This is shown in Figure B1.

Figure B1: An example of curve shifting when the *rhs* increases relative to the *lhs*



b) Consider the case where, under the change from (z_t^s) to (z_t^p), the *rhs* of (21) and (22) increases relative to the *lhs*. Consider any two possible choices for h_{t+1}, h_{t+1}^1 and h_{t+1}^2, with $h_t < h_{t+1}^1 < h_{t+1}^2$. The increase in h_{t+1} tends to increase and decrease, respectively, the *lhs* and *rhs* of (21) and (22). The changes are larger for h_{t+1}^2 compared with h_{t+1}^1. Therefore, if an increase in a_{t+1} is required, it will be smaller for h_{t+1}^2 compared with h_{t+1}^1. Note that this is true for both (21) and (22). If a decrease is required it will be larger for h_{t+1}^2 compared with h_{t+1}^1. Similarly, if $h_{t+1}^1 < h_{t+1}^2 < h_t$, then an increase in a_{t+1} is required, and it will be smaller for h_{t+1}^2 compared with h_{t+1}^1. Finally, if $h_{t+1}^1 < h_t < h_{t+1}^2$, then a_{t+1} will need increase less for h_{t+1}^2 compared with h_{t+1}^1. Conversely, considering any two possible choices for a_{t+1}, a_{t+1}^1 and a_{t+1}^2, with $a_{t+1}^1 < a_{t+1}^2$, and working as above, we conclude that an increase in h_{t+1} will be smaller for a_{t+1}^2 compared with a_{t+1}^1, and a decrease larger for a_{t+1}^2 compared with a_{t+1}^1.

Consider the case where, under the change from (z_t^s) to (z_t), the *rhs* of (21) and (22) decreases relative to the *lhs*. Consider any two possible choices for h_{t+1}, h_{t+1}^1 and h_{t+1}^2, with $h_{t+1}^1 < h_{t+1}^2 < h_t$. The decrease in h_{t+1} tends to decrease and increase, respectively, the *lhs* and *rhs* of (21) and (22). The changes are larger for h_{t+1}^1 compared with h_{t+1}^2.

Therefore, if a decrease in a_{t+1} is required, it will be larger for h^2_{t+1} compared with h^1_{t+1}. Note that this is true for both (21) and (22). If an increase is required it will be smaller for h^2_{t+1} compared with h^1_{t+1}. Similarly, if $h_t < h^1_{t+1} < h^2_{t+1}$, then a decrease in a_{t+1} is required, and it will be larger for h^2_{t+1} compared with h^1_{t+1}. Finally, if $h^1_{t+1} < h_t < h^2_{t+1}$, then a_{t+1} will need decrease more for h^2_{t+1} compared with h^1_{t+1}. Conversely, considering any two possible choices for a_{t+1}, a^1_{t+1} and a^2_{t+1}, with $a^1_{t+1} < a^2_{t+1}$, and working as above, we conclude that a decrease in h_{t+1} will be larger for a^2_{t+1} compared with a^1_{t+1}, and an increase smaller for a^2_{t+1} compared with a^1_{t+1}.■

`Lemma 3`

Assume that a household in period t chooses $(a^s_{t+1}, h^s_{t+1}) \in \left(\left(a^{\min}, +\infty\right), \left(h^{\min}, h^{\max}\right)\right)$ that satisfy (19) and (20) for given $(a^s_t, a^s_{t+2}) \in A$, $\left(h^s_t, h^s_{t+2}\right) \in \left(h^{\min}, h^{\max}\right)$, and $e^s_t \in E$. Consider a change in (a^s_t, h^s_t) and/or in $\left(a^s_{t+2}, h^s_{t+2}\right)$ which increases (decreases) the *rhs* of (19) and (20) relative to the *lhs* in period t. Then, the downward slopping f^{ea} and f^{eh} shift outwards (inwards), and at least one of a_{t+1} and h_{t+1} increase (decrease) relative to (a^s_{t+1}, h^s_{t+1}).

`Proof`

The proof follows similar arguments to those in Lemma 2 a), for an increase (decrease) in the *rhs* of (19) and (20) relative to the *lhs* in period t. This change is also captured in Figure B1. ■

`Proposition 1`

Given a process (z^s_t), assume that a household in period t chooses $(a^s_{t+1}, h^s_{t+1}) \in \left(\left(a^{\min}, +\infty\right), \left(h^{\min}, h^{\max}\right)\right)$ that satisfy (19) and (20). Conditional on $(a_t, a_{t+2}) \in A$, and $(h_t, h_{t+2}) \in \left(h^{\min}, h^{\max}\right)$, a change in the aggregate-level stochastic process in period t from (z^s_t) to (z^p_t) implies that *ceteris paribus*:

a) 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 $h^p_{t+1} \leq h^s_{t+1}$).

b) 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 $c^p_t > c^l$.

c) 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 $h^p_{t+1} \geq h^s_{t+1}$).

d) 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 $h^p_{t+1} \leq h^s_{t+1}$).

`Proof`

a) A decrease in $w(z^p_t; e^p_t)$ or in $r(z^p_t)$ implies a decrease in c^p_t and thus, given concavity of the utility function, an increase in u_{c_t}. Assuming no effects on neither $w(z^p_{t+1}; e^p_{t+1})$ nor $r(z^p_{t+1})$, these changes do not affect the *rhs* of (19) and (20), and thus tend to decrease the *rhs* in (19) and (20) relative to the *lhs*. Given Lemma 2, at least one of a_{t+1} and h_{t+1} must decrease.

b) The introduction of the consumption limit implies that u_{c_t} drops to zero from a positive number for the subset of households for which (a^p_{t+1}, h^p_{t+1}) implies $c^p_t > c^l$, implying a reduction in the *lhs* of (19) and (20) for these households. Given Lemma 2, at least one of a_{t+1} and h_{t+1} must increase.

c) A decrease in $w(z^p_{t+1}; e^p_{t+1})$ in any state of z^p_{t+1} implies a decrease in c^p_{t+1} in that state of z^p_{t+1} and thus, given concavity of the utility function, an increase in $u_{c_{t+1}}$ in the state z^p_{t+1}. Because the expectation operator preserves monotonicity, this implies that the *rhs* of (19) and (20) increase. Assuming no effects on $w(z^p_t; e^p_t)$, these changes do not affect the *lhs* of (19) and (20), and thus tend to increase the *rhs* in (19) and (20) relative to the *lhs.* Given Lemma 2, at least one of a_{t+1} and h_{t+1} must increase.

d) A limit on consumption c^l in future periods that binds for specific states of z^p_{t+1} and when $c^p_{t+1} > c^l$ introduces a discontinuity in $u_{c_{t+1}}$, which, for the exogenous states including the limit, becomes zero for a^p_{t+1} and h^p_{t+1} for which $c^p_{t+1} > c^l$. In other words, the introduction of the consumption limit implies that the state space includes states where $u_{c_{t+1}}$ drops to zero from a positive number, implying a reduction in the *rhs* of (19) and (20) relative to the *lhs.* Given Lemma 2, at least one of a_{t+1} and h_{t+1} must decrease. ■

Appendix C: Computation

This appendix provides explanations about the computational and mathematical techniques used to obtain the computational results in the main text.

C.1 Computation of the benchmark model

The solution of the benchmark model requires two main steps: i) the solution of the household problem to obtain the policy functions for the next period assets and next period health; and ii) the calculation of the cross-sectional distribution.

C.1.1 Solving the household's problem

We compute 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:

$$V(a_t, h_t, y_t) = \max_{c_t, a_{t+1}, x_t, h_{t+1}} \{u(c_t, h_{t+1}) + \beta E[V(a_{t+1}, h_{t+1}, y_{t+1})|y_t]\}, \tag{23}$$

$$\begin{aligned} &\text{subject to} \\ c_t + a_{t+1} + x_t &= (1 + r(z_t) + \pi(\mathbf{1}_{a_t<0}))a_t + w(y_t), \\ h_{t+1} &= \delta(y_t)h_t + m(x_t), \\ \delta(y_t)h_t \le h_{t+1} &\le h^{\max},\ 0 \le c_t \le c^l(z_t), \\ x_t \ge 0,\ a_{t+1} &\ge a^{\min}, \text{ and } h^{\min} \le h_t \le h^{\max}, \end{aligned} \tag{24}$$

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 $y_t \equiv (n_t, l_t, s_t, z_t)$ and $\mathbf{1}_{a_t<0}$ is an indicator function taking the value one when the household has negative wealth. Note that the representation in (23) - (24) includes a potential consumption limit, $c^l(z_t)$, as a function of the aggregate state and a penalty paid on borrowing, π, which, as explained in Section 4, reflect relevant empirical properties. 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 $x_t = g^x(a_t, h_t, e_t; z_t)$. For ease of notation, we drop the explicit dependence of e_t on z_t, i.e. $e_t(z_t)$.

We solve the household's problem using Value Function Iteration with interpolation on the recursive problem presented in section 3. The solution method requires the discretization of the state space. For the assets we let $a^{\min} = -0.0059$ and $a^{\max} = 20$ and following Maliar *et al.* (2010) we discretise the space of household assets $\left[a^{\min}, a^{\max}\right]$ by allowing for $\widetilde{a} = 100$ points with the following formula:

$$a_j = a^{\min} + (a^{\max} - a^{\min})(\frac{j-1}{100-1})^2, \; \forall j = 1, ..., 100$$

For health, we let $h^{\min} = 0.1$ and $h^{\max} = 1$ and we discretise the space of household assets $\left[h^{\min}, h^{\max}\right]$ by allowing for $\widetilde{h} = 25$ points with the following formula:

$$h_q = h^{\min} + (h^{\max} - h^{\min})(\frac{q-1}{25-1}), \; \forall q = 1, ..., 25.$$

The solution method requires interpolation of the value function because we allow the choice variables, a' and h', to be off the grid when we maximise the Bellman equation. In this respect, we use a 7th order polynomial approximation of the value function over the endogenous state variables interacted with all exogenous states (see e.g. Maliar and Maliar (2014)).[4] Let $y \in Y = N^z \times \Lambda^z \times S^z \times Z$ and let the values on this grid to be $Y \equiv \{\overline{y}_\varsigma\}_{\varsigma=1}^{\widetilde{y}}$ where each $\overline{y}_\varsigma$ is a vector containing a unique combination of n, l, s and z. Then, let $\hat{V}(a, h, y)$ be the approximated value function for given values of a, h and y :

$$\hat{V}(a, h, y) = \begin{array}{c} \alpha_{0,\varsigma} + \alpha_{1,\varsigma} a + \alpha_{2,\varsigma} h + \alpha_{3,\varsigma} ah + ... \\ +\alpha_{34,\varsigma} a^7 + \alpha_{35,\varsigma} h^7 + \alpha_{36,\varsigma} a^7 h^7 \end{array}$$

To obtain the set of coefficients $\alpha = \left[[\alpha_{\kappa,\varsigma}]_{\kappa=1}^{36}\right]_{\varsigma=1}^{\widetilde{y}}$ for each $\overline{y}_\varsigma$ we run linear regressions of the type

$$Vech\left[V(A, H, y = \overline{y}_\varsigma)\right] = \begin{array}{c} \alpha_{0,\varsigma} + \alpha_{1,\varsigma} Vech\left[A \otimes J_{N^h}\right] \\ +\alpha_{2,\varsigma} Vech\left[J_{N^a} \otimes H\right] + \alpha_{3,\varsigma} Vech\left[A \times H\right] + ... \\ +\alpha_{34,\varsigma} Vech\left[A \otimes J_{N^h}\right]^7 + \alpha_{35,\varsigma}^7 Vech\left[J_{N^a} \otimes H\right] \\ +\alpha_{36,\varsigma}^7 Vech\left[A \otimes J_{N^h}\right]^7 \circ Vech\left[J_{N^a} \otimes H\right]^7 \end{array}$$

where $Vech$ denotes the vectorisation operator, $\otimes$ denotes the Kronecker product and $\circ$ element-wise multiplication. We measure the convergence over the Value Function and we set the convergence criterion to 10^{-8}.

`Algorithm 1: solving the household problem`

1. Set up the grid for the state variables and choose a stopping criterion $\varepsilon > 0$.
2. Given a guess V_i obtain the initial set of coefficients α_i via linear regression.

[4] The approximation provides a balance between accuracy of the solution and speed. Chebychev polynomials proved to be numerically unstable, while piecewise polynomial approximations are infeasible given the dimensionality of the problem.

3. For each point on the grid, (a, h, y), numerically solve the maximisation problem

$$V_{i+1}(a,h,y) = \max_{c,x,a'} \left\{ u(c,h') + \beta \sum_{y \in Y} \pi(y'|y) \hat{V}_i(a'(a,h,y), h'(a,h,y), y') \right\}$$

$$\begin{aligned} & s.t \\ c + a' + x &= (1 + r(z) + \pi(\mathbf{1}_{a<0}))a + w(y) \\ h' &= \delta(y)h + m(x) \\ h^{\max} &\geq h' \geq h^{\min},\ c^l(z) \geq c \geq 0, \\ x &\geq 0,\ a^{\max} \geq a\prime \geq a^{\min} \end{aligned}$$

   Obtain $a' = g^a(a,h,y)$, $c = g^c(a,h,y)$, $x = g^x(a,h,y)$ and $h' = g^h(a,h,y)$ from the solution.

4. Use $V_{i+1}(a,h,y)$ to calculate the set of coefficients α_{i+1} via a linear regression.

5. If $\|V_{i+1} - V_i\|_\infty < \varepsilon$ stop, otherwise set $V_i = V_{i+1}$ and go back to step 3.

C.1.2 Simulating the distribution

We follow Young (2010) and Heer and Maussner (2009) in computing the stationary distribution. In particular, we simulate the evolution of the stationary distribution of all exogenous and endogenous variables using a nonstochastic simulation method. The basic strategy of this method is as follows. We need first to form the histogram of the joint distribution assigning a probability mass $\lambda(x,u) \geq 0$ (where x denotes the endogenous state variables and u the exogenous state variables) to every point $(x,u) \in [X \times U]$, so that the resulting histogram λ has a total probability mass of 1. Then we use the policy functions and the conditional probabilities of the exogenous process to compute the distribution over the state space $X \times U$ that will hold at the end of the period. Since the policy functions do not have to lie on the grid, we need to redistribute the current mass on a point using linear interpolation to generate approximate decision rules.

The algorithm above has been used extensively in the literature of heterogeneous agents incomplete markets models but usually for one endogenous state variable. Here, we extend this approach to two endogenous state variables, i.e. the state space here is $(a,h,e) \in [A \times H \times E]$. Below we explain the computational algorithm analytically.

`Algorithm 2: computing the cross sectional distribution`

1. Draw a random series of aggregate states, $\{z_t\}_{t=1}^T$, starting from a pandemic i.e. $z_1 = C$.

2. For each z, compute weights for each $j = 1, ..., \widetilde{a}$ and $(a,h,e) \in A \times H \times E$ such that:

   - For all $j = 2, ..., \widetilde{a} - 1$

$$\varrho_j^a(a,h,e;z) = \begin{cases} 1 - \frac{g^a(a,h,e;z) - a^j}{a^{j+1} - a^j} & \text{if } a^{j-1} \leq g^a(a,h,e;z) \leq a^j \\ \frac{g^a(a,h,e;z) - a^j}{a^{j+1} - a^j} & \text{if } a^j \leq g^a(a,h,e;z) \leq a^{j+1} \\ 0 & \text{otherwise} \end{cases}$$

- For $j = 1$

$$\varrho_1^a(a,h,e;z) = \begin{cases} 1 - \frac{g^a(a,h,e;z)-a^j}{a^{j+1}-a^j} & \text{if } a^1 \leq g^a(a,h,e;z) \leq a^2 \\ 1 & \text{if } g^a(a,h,e;z) < a^1 \\ 0 & \text{otherwise} \end{cases}$$

- For $j = \widetilde{a}$

$$\varrho_{\widetilde{a}}^a(a,h,e;z) = \begin{cases} 1 & \text{if } g^a(a,h,e;z) > a^{\widetilde{a}} \\ \frac{g^a(a,h,e;z)-a^j}{a^{j+1}-a^j} & \text{if } a^{\widetilde{a}-1} \leq g^a(a,h,e;z) \leq a^{\widetilde{a}} \\ 0 & \text{otherwise} \end{cases}$$

3. Compute weights for each $q = 1, ..., \widetilde{h}$ and $(a,h,e) \in A \times H \times E$ such that:

- For all $q = 2, ..., \widetilde{h} - 1$

$$\varrho_q^h(a,h,e;z) = \begin{cases} 1 - \frac{g^h(a,h,e;z)-h^j}{h^{j+1}-h^j} & \text{if } h^{j-1} \leq g^h(a,h,e;z_t) \leq h^j \\ \frac{g^h(a,h,e;z)-h^j}{h^{j+1}-h^j} & \text{if } h^j \leq g^h(a,h,e;z) \leq h^{j+1} \\ 0 & \text{otherwise} \end{cases}$$

- For $q = 1$

$$\varrho_1^h(a,h,e;z) = \begin{cases} 1 - \frac{g^h(a,h,e;z)-h^j}{h^{j+1}-h^j} & \text{if } h^1 \leq g^h(a,h,e;z) \leq h^2 \\ 1 & \text{if } g^h(a,h,e;z) < h^1 \\ 0 & \text{otherwise} \end{cases}$$

- For $q = \widetilde{h}$

$$\varrho_{\widetilde{h}}^h(a,h,e;z) = \begin{cases} 1 & \text{if } g^h(a,h,e;z) > h^{\widetilde{h}} \\ \frac{g^h(a,h,e;z)-h^j}{h^{j+1}-h^j} & \text{if } h^{\widetilde{h}-1} \leq g^h(a,h,e;z) \leq h^{\widetilde{h}} \\ 0 & \text{otherwise} \end{cases}$$

4. Set the initial cross-sectional distribution to be the stationary cross-sectional distribution i.e. $\lambda_0 = \lambda^*(a,h,e)$. Then we can calculate the cross-sectional distribution at time $t = 1$, by using the distribution function

$$\lambda_1(a^j, h^q, e'; z' = C) = \sum_e \pi^C(e'|e) \sum_{a \in A} \sum_{h \in H} \varrho_j^a(a,h,e) \varrho_q^h(a,h,e) \lambda^*(a,h,e).$$

where $\varrho_j^a(a,h,e)$ and $\varrho_q^h(a,h,e)$ are constructed working as in Step 3, but by using the policy functions of the stationary model.

5. For $t > 1$, given the distribution function $\lambda_t(a,h,e;z)$, update the distribution using the realisation of $z_t = \overline{z}$ and the transition function for all $j = 1, ..., \widetilde{a}$ and $q = 1, ..., \widetilde{h}$,

$$\lambda_{t+1}(a^j, h^q, e'; z') = \sum_e \pi^{z'}(e'|e) \sum_{a \in A} \sum_{h \in H} \varrho_j^a(a,h,e;z) \varrho_q^h(a,h,e;z) \lambda_t(a,h,e;z).$$

6. Stop when $t > T$.

We simulate the economy for a long time series of $\{z_t\}_{t=1}^{10100}$, discarding the first 100 periods, and find that the model aggregates, mean assets and mean health, exhibit bounded fluctuatins indicating long-run stationarity.

C.2 Stationary model

To obtain the dynamic programming formulation of the household's problem in the stationary environment where $z_t \equiv z^*$, $\forall t$, we use the joint distribution $e_t = (n_t, l_t, s_t)$ (with the appropriate Markov chain associated with transition matrix Q^*; see Appendix D for details), and let $v^{st}(a_t, h_t, e_t)$ denote the optimal value of the objective function starting from state (a_t, h_t, e_t). The Bellman equation is:

$$v^{st}(a_t, h_t, e_t) = \max_{c_t, a_{t+1}, x_t} \left\{ u(c_t, h_{t+1}) + \beta E[v^{st}(a_{t+1}, h_{t+1}, e_{t+1})|e_t] \right\} \tag{25}$$

$$\begin{aligned} & s.t. \\ c_t + a_{t+1} + x_t &= (1 + r(z^*) + \pi(\mathbf{1}_{a<0}))a_t + w(e_t) \\ h_{t+1} &= \delta(e_t)h_t + m(x_t) \\ h^{\max} &\geq h' \geq h^{\min},\ c_t \geq 0,\ x_t \geq 0,\ a_{t+1} \geq a^{\min} \end{aligned} \tag{26}$$

and the policy functions that solve (25) are $a_{t+1} = q^a(a_t, h_t, e_t)$, $c_t = q^c(a_t, h_t, e_t)$, $h_{t+1} = q^h(a_t, h_t, e_t)$ and $x_t = q^x(a_t, h_t, e_t)$. We use $a_{t+1} = q^a(a_t, h_t, e_t)$, $h_{t+1} = q^h(a_t, h_t, e_t)$ and the Markov chain e_t to calculate the invariant cross-sectional distribution $\lambda^*(A \times H \times E)$.

A *Stationary Recursive Equilibrium* is a set of policy functions q^a, q^h, q^c and q^x, and a stationary distribution λ^* of (a_t, h_t, e_t) on $A \times H \times E$, such that: for each household the policy functions q^a, q^h, q^c, q^x and the value functions $v^{st}(a_t, h_t, e_t)$ solve the households' optimum problems in (25).

C.2.1 Computation of the stationary model

The computation is almost identical to the benchmark model with the only differences being that the exogenous process is $e \in E = N \times L \times S$ instead of $y \in Y = N \times L \times S \times Z$ and λ_0 is an arbitrary initial distribution. To find the stationary cross-sectional distribution we iterate the distribution until it converges, using a convergence criterion of 10^{-8}.

C.3 Generating the figures

We apply the methods outlined above to generate the results summarised in different figures as follows.

Figures 2 & 3 To generate the results from the benchmark model in figures 2 and 3 follow the algorithm below:

`Algorithm 3: computing the transition dynamics and theirs bands`

1. Solve the problem of the household for the stationary world and calculate the stationary distribution λ^* as described in C.2.1.

2. Solve the problem of the household for the world with pandemic risk using Algorithm 1.

3. Draw 5000 random sequences of aggregate states, $\{z_t^b\}_{t=1}^T$, starting always from a pandemic i.e. $z_1 = C$.

4. For each sequence $\{z_t^b\}_{t=1}^T$, simulate the distribution forward for $t = 1, ..., T$ to calculate a series of cross-sectional distributions $\{\lambda_t^b\}_{t=1}^T$ as described in Algorithm 2.

5. For each sequence $\{z_t^b\}_{t=1}^T$, calculate the aggregate variables and statistics of interest (e.g. Gini) by using $\{\lambda_t^b\}_{t=1}^T$, the policy functions $\{g^a(a_t, h_t, e_t; z_t)\}_{t=1}^T$, $\{g^h(a_t, h_t, e_t; z_t)\}_{t=1}^T$, $\{g^c(a_t, h_t, e_t; z_t)\}_{t=1}^T$ and $\{g^x(a_t, h_t, e_t; z_t)\}_{t=1}^T$ and the value functions $\{v(a_t, h_t, e_t; z_t)\}_{t=1}^T$.

6. For each period t, we calculate various percentiles of the aggregate variables and other statistics over interest to create confidence-interval like bands.

To obtain the path of the one-off pandemic counterfactual, solve the model using the modified aggregate transition matrix, described in Appendix D. Follow the steps above, but note that since there is no aggregate uncertainty in this counterfactual it is sufficient to simulate a single economy.

Figures 4 & 5 To create figures 4 and 5 follow the algorithm below:

`Algorithm 4: computing the transition dynamics of households starting from different initial conditions`

1. Calculate the desired percentile of a_t (a_t^{pct}) using the stationary distribution $\lambda^*(a, h, e)$ and the policy function $q^a(a, h, e)$.

2. Generate the initial distribution λ^+, by setting all mass located at points other than a_t^{pct} to 0 and renormalising λ^+ to have total mass 1.[5]

3. Follow the steps 2-5 of Algorithm 3 above to obtain the dynamics under uncertainty of households starting with wealth a_t^{pct}. For each sequence $\{z_t^b\}_{t=1}^T$ and for each period calculate the average health and wealth.

4. Average across all simulations to obtain the unconditional expectation of the evolution of wealth and health for the selected subset of households.

5. Repeat step 3, but instead of using the policy functions and aggregate transition matrix under aggregate uncertainty, impose that the economy remains in $z_t \equiv z^*$ for ever and the household use the stationary equilibrium policy functions $q^a(a_t, h_t, e_t)$ to make decisions. As there is no aggregate uncertainty in this case, only one simulation is needed (for the sequence $\{z^*\}_{t=1}^T$).

6. Calculate the percentage deviation between the values in step 4 from those in step 5.

[5] To obtain the distribution by socioeconomic group simply replace a_t^{pct} with the desired exogenous state.

Figure 6 To create figure 6 follow the algorithm below:

`Algorithm 5: computing the transition dynamics of households starting from different initial conditions with surprise income shock`

1. Solve the problem of the household with pandemic risk using Algorithm 1.

2. Using the value function obtained in step 1, solve a one period optimization problem, where the desired income drop is imposed and the continuation value is the same as in step 1. Save the decision rules from this problem.

3. Choose a time t^s for when the surprise shock is going to hit the economy.

4. Simulate the distribution as explained in Algorithm 2 substituting the policy functions at time t^s with those obtained in step 2. Average across all simulations to obtain the unconditional expectation of the evolution of wealth and health for the selected subset of households.

5. Follow the steps 2-5 of Algorithm 3 above to obtain the dynamics under uncertainty of households starting with wealth a_t^{pct}. For each sequence $\left\{z_t^b\right\}_{t=1}^T$ and for each period calculate the average health and wealth. Average across all simulations to obtain the unconditional expectation of the evolution of wealth and health for the selected subset of households.

6. Calculate the percentage deviation between the values in step 4 from those in step 5.

Appendix D: Calibration

D.1 Health

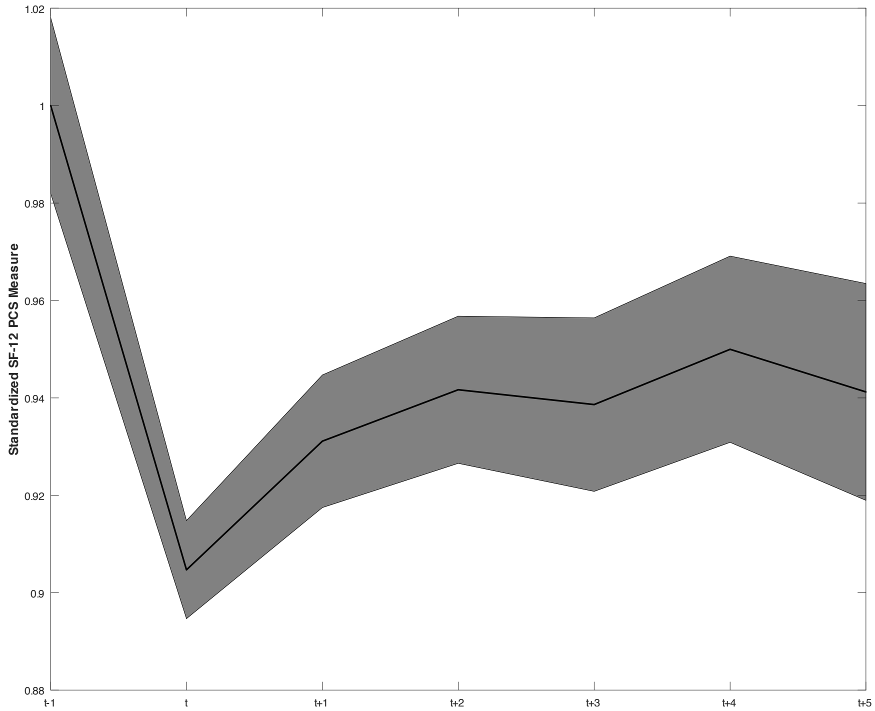
D.1.1 Effects of severe health events

Using the SF-12 PCS measure[6] of self-reported health, we find that individuals report much lower physical functioning scores after experiencing a severe health event, reflecting the impairment suffered from the shock. Figure D1 below plots the evolution of the PCS measure[7] for households who experience a severe health shock at time t. There is a stark drop of almost 10% in reported health at the household level when at least one household member experiences a severe health shock. In the periods following the shock, household health recovers moderately, to around 95% of its original level, but the effects of these large shocks seem to be very persistent, and households do not appear to fully recover, as long as we can observe them in our sample. Even five years after the shock, self-reported health is around 5% lower than before the shock.

[6] See Appendix A for details.

[7] For convenience, we standardize the measure to have mean 1 in the period before the health shock is experienced. The shaded areas denote 95% confidence intervals.

Figure D1: Relative change in the SF-12 PCS measure following a severe health shock.



Source: Pooled Sample UnSoc Waves 1-9

We use this observation to motivate our modelling decision of the three health states $\overline{s}_1, \overline{s}_2$ and $\overline{s}_3$, since there is a clear distinction between the time before and after the shock and between the year in which the shock is experienced and subsequent years. Specifically, we interpret $\overline{s}_3$ as the period, where the initial short-run effects of the shock have already been absorbed, but the household is still suffering from long-run after effects.

D.1.2 Robustness

Individuals that experience severe health events are likely very different from those that do not. They are likely to be older and also more likely to suffer from pre-existing conditions. To assess the robustness of our findings in Figure D1, we run a Mincer type regression of the SF-12 PCS measure on several observable characteristics and information on the households' medical history available from UnSoc.

$$h_{i,t} = \beta_0 + \beta_1 D_{i,t} + \beta_2 M_{i,t} + \varepsilon_{i,t} \tag{27}$$

where $D_{i,t}$ contains demographic information about the household:

1. An indicator for the sex of the respondent household member (w_sex_dv).
2. A third order polynomial of mean household age, calculated over all household members (calculated from w_age_dv).
3. A dummy for each of the 12 UK government office regions (w_gor_dv).

4. A dummy for the year of the interview (w_intdaty_dv).
5. The natural logarithm of household size (calculated from w_hhsize).

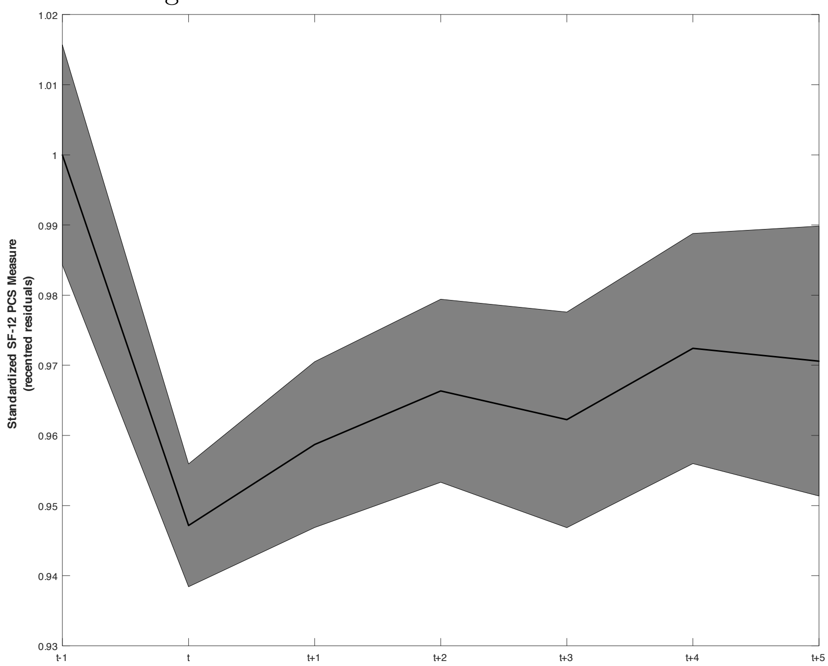
And $M_{i,t}$ contains information about the households medical history:

1. An indicator, if anyone in the household ever suffered from any of the following conditions: Asthma (derived from w_hcondn1), Arthritis (derived from w_hcondn2), Angina (derived from w_hcondn5), Hyperthyroidism (derived from w_hcondn9), Hypothyroidism (derived from w_hcondn10), Diabetes (derived from w_hcondn14), a liver condition (derived from w_hcondn12), Epilepsy (derived from w_hcondn15), or high blood pressure (derived from w_hcondn16).
2. An indicator, of whether any of the household members father or mother died before the household member was aged 14 (w_paju & w_maju).

We then obtain the residuals $\varepsilon_{i,t}$ and standardize them around the unconditional mean of our original health measure. Figure E2 again plots the evolution of health of a household before and after a severe health shock, where health now is measured by the recentred residuals from the regression (27). Again, values have been standardized to be mean 1 in the period before the shock for convenience.

After purging several potential confounding factors from our health measure, we still find a qualitatively similar pattern. The health measure drops by around 6% in the period directly following the health shock and then recovers moderately in the following periods. Again the household does not recover fully but remains around 3% below its pre-shock level.

Figure D2: Relative change in the mincerian residuals of the SF-12 PCS measure following a severe health shock.



Source: Pooled Sample UnSoc Waves 1-9

D.2 Income and Earnings

D.2.1 Mincerian Regression

This subsection details the mincerian regression in section 4.1. First, we drop all those households who report zero post policy labour income;[8] then we trim the top and bottom 0.5% of values in every wave. In order to partial out the observable components, we run a regression of the natural logarithm of household post policy labour income $\ln(\underline{w}_{i,t})$ on a number of variables:

$$\ln(\underline{w}_{i,t}) = \beta_0 + \beta_1 D_{i,t} + \epsilon_{i,t}, \tag{28}$$

where $D_{i,t}$ contains demographic information about the household:

1. An indicator for the sex of the respondent household member (w_sex_dv).
2. A third order polynomial of mean household age (calculated from w_age_dv).
3. A dummy for each of the 12 UK government office regions (w_gor_dv).
4. A dummy for the year of the interview (w_intdaty_dv).
5. The natural logarithm of household size (calculated from w_hhsize).
6. An indicator term that captures the households socioeconomic group as discussed in Appendix A.

We collect the residuals $\epsilon_{i,t}$ and re-centre them around the group specific conditional mean.

D.3 Concentration indices

Concentration indices have become an established way of measuring socioeconomic inequalities in health (see, for example, Wagstaff and van Doorslaer (2000)). Given two variables, one measuring a quantity of interest and the other establishing a ranking of the observations relating to the former, one can establish a concentration curve which can be used to map the cumulative distribution function of the variable of interest across the population ranking defined by the ranking variable. Thus, the concentration curve illustrates inequality for the variable of interest across the dimension specified by the ranking variable. A concentration index is then a specific transformation of a concentration curve into a single number. An example is the Gini index, a concentration index of the Lorenz curve as the associated concentration curve, in the special case, where the variable of interest and the ranking variable are the same.

[8] As the definition of net income here includes transfers, we consider zeros to be examples of erroneous reporting.

D.4 State spaces and transitions - stationary environment

The following details the transition matrix Q^*, estimated from UnSoc. To preserve space, we present the socioeconomic groups transitions separately from the health status transitions. Tables D1 describes the probability of a household member experiencing a severe health shock in a given year, conditional on having not experienced a severe health event before, by socioeconomic group.

Table D1: Health Shock Probabilities

Socioeconomic group	$\Pr(s_{t+1} = \overline{s}_2 \| s_t = \overline{s}_1)$
Professionals	0.0102
Intermediate	0.0092
Routine	0.0116
Non-employed	0.0248

Source: Pooled Sample UnSoc (Wave 1-9)

We denote $\Pr(s_{t+1} = \overline{s}_2|s_t = \overline{s}_1)$ as P_s (4×1 vector) and $\Pr(s_{t+1} = \overline{s}_3|s_t = \overline{s}_2)$= 0.0895 as p^r (scalar).

$$Q^* = \begin{bmatrix} \left[(\underset{4\times1}{\mathbf{I}} - \underset{4\times1}{P_s}) \otimes \underset{3\times12}{\mathbf{I}}\right] \circ \underset{12\times12}{Q^*_{pre}} & \left[\underset{4\times1}{P_s} \otimes \underset{3\times12}{\mathbf{I}}\right] \circ \underset{12\times12}{Q^*_{post}} & \underset{12\times12}{\mathbf{0}} \\ \underset{12\times12}{\mathbf{0}} & \underset{12\times12}{\mathbf{0}} & \underset{12\times12}{\mathbf{I}} \circ \underset{12\times12}{Q^*_{post}} \\ \left[\underset{12\times12}{\mathbf{I}} p^r\right] \circ \underset{12\times12}{Q^*_{pre}} & \underset{12\times12}{\mathbf{0}} & \left[\underset{12\times12}{\mathbf{I}}(1-p^r)\right] \circ \underset{12\times12}{Q^*_{post}} \end{bmatrix}$$

Q^*_{pre}, Q^*_{post} denote the transition matrices from n_t, l_t to n_{t+1}, l_{t+1}, pre and post a health shock occurs. We employ the UnSoc data to calculate these using the socioeconomic group information n_t and the residuals $\epsilon_{i,t}$ from equation (28) as explained in the main text.

Table D2 describes the calibrated net labour income states $w_t(n_t, l_t)$ for the pre-COVID-19 stationary world. To obtain the productivity states for other realisations of the aggregate state z_t, we follow the adjustments described in Section 4.

Table D2: Productivity States

Socioeconomic group	$l = 1$	$l = 2$	$l = 3$
Professionals	2.17	1.40	0.87
Intermediate	1.57	0.96	0.57
Routine	1.05	0.68	0.43
Non-employed	0.73	0.45	0.24

Source: Understanding Society (Wave 1-9)

D.5 Calibration of remaining parameters

We set the remaining parameters $\theta = (a^{\min}, q, \gamma, \phi, \delta(\overline{s}_2), \delta(\overline{s}_3))$ to match a number of targets, which are motivated by empirical evidence, using a minimum distance procedure: i) the mean health of households across all three health states $(0.688, 0.577, 0.603)$; ii) the overall variance of health (0.014); iii) the share of households with (less than) zero wealth

(19%) from WAS iv) the share of private expenditure relating to health in household consumption (8.9%).

To obtain a target for private health expenditure, we work as follows. As a lower bound, we consider the share of private health spending in household consumption. Empirical evidence in, e.g. Stoye (2017), suggests that private health spending accounts for roughly 21% of total health spending, which in turn accounts for 9.8% of GDP. Noting that household consumption is around two thirds of GDP, we arrive at $0.21*0.098/(\frac{2}{3}) = 3.09\%$. However, direct expenditure on private healthcare is only part of the expenditure that improves health. For example, expenditure on healthier food, exercise, and even housing arguably contains a component of health investment. We do not have data to decompose such expenditure into a part providing consumption utility benefits, and another which improves utility via improving health. We take total health spending, i.e. private plus public health spending, to be a proxy of an upper bound of what individuals might be willing to spend to improve their health. As a share of GDP, this expenditure is $0.098/(\frac{2}{3}) = 14.7\%$. Based on these estimates, we select the midpoint between these two values (8.9%).

We define $\tilde{m}$ as the vector of the data targets described above, and $\hat{m}(\theta)$ as the corresponding vector of targets when the model is solved and evaluated at the parameters θ. We choose θ to minimize the squared percentage deviation:

$$\hat{\theta} = \arg\min_{\theta} \sum \left(\frac{\hat{m}(\theta) - \tilde{m}}{\tilde{m}} \right)^2 \tag{29}$$

We use a global, non derivative based solver to find $\hat{\theta}$.

Table D3: Calibration fit

Target	Target Value	Outcome Value	Percentage Deviation
$\bar{h}_{t+1}(\bar{s}_1)$	0.688	0.689	0.176%
$\bar{h}_{t+1}(\bar{s}_2)$	0.577	0.578	0.162%
$\bar{h}_{t+1}(\bar{s}_3)$	0.603	0.602	-0.100%
$var(h_{t+1})$	0.014	0.014	-0.244%
$\frac{\sum x_t}{\sum c_t}$	0.089	0.089	0.042%
$\sum_{a_i<=0} i$	0.190	0.196	0.302%
$SSM = 2.1947e-05$			

D.6 State spaces and transitions - dynamic environment

D.6.1 Markov regime-switching model

This subsection contains the details of the Markov-Regime-Switching model, underlying the analysis in Sections 4 in the main text regarding the calibration of the aggregate state transition matrix Q_Z. Our aim is to to estimate the probability of a pandemic period starting (i.e. a pandemic happening) and the probability of exiting the period of post-pandemic period of increased risk of disease outbreaks. We assume that annual mortality rates d_t follow a log-normal distribution[9]

$$\log(d_t) \sim N(\mu_r, \sigma_r^2) \tag{30}$$

where the mean and variance of the underlying distribution is allowed to vary between the two distinct regimes of periods of low and high disease outbreak risk, $r = \{1, 2\}$. Markov-Regime-Switching models have been used to analyse business cycle behaviour (Hamilton (1989), Doornik (2013)) and also in the detection of infectious disease outbreaks (Martínez-Beneito et al. (2008), Unkel et al. (2012)).

We estimate the model using data for the UK from Schroeder *et al.* (2021). We test the assumption of two regimes versus a single regime, by performing a quasi-likelihood test for regime-switching models based on Bostwick and Steigerwald (2014) and reject at the 1% level the null hypothesis that the variation in the data is explained by only one regime. Table D4 below shows the results from estimating the Markov-Switching model with two regimes and Table D5 shows the implied properties of each mortality regime in each case.

Table D4: Two disease outbreak regimes

UK 1895 - 1950			
	Coefficient	Std. Error	95% Confidence Interval
μ_1	4.91	0.099	[4.713, 5.102]
μ_2	5.85	0.229	[5.404, 6.302]
σ_1	0.55	0.066	[0.435, 0.695]
σ_2	0.79	0.137	[0.566, 1.112]
p_{11}	0.973	0.029	[0.803, 0.996]
p_{21}	0.079	0.067	[0.013, 0.345]

Log Likelihood -58.07, 1% critical value: 7.85, value of test statistic: 14.24

Table D5: Characteristics of mortality regimes

UK 1895 - 1950			
	$E(d_t)$	$Std(d_t)$	exp. duration
Regime I	157.79	94	37.04
Regime II	474.40	442	12.66

Expectation and standard deviation of mortality rates based on point estimates in Table D1.

D.6.2 Transition matrix Q

The following section describes how to obtain the transition matrix Q for the model version with aggregate uncertainty. The construction is similar to the case of the transition matrix Q^* of the stationary environment as described above but includes an extra step that incorporates the transitions of the aggregate state. For convenience, we present the construction of Q backwards, beginning first with the construction of Q out of the state-specific idiosyncratic transition matrices, then moving on to show how to construct the idiosyncratic transition matrices for each realization of the aggregate state. Again, we denote $\Pr(s_{t+1} = \bar{s}_2 | s_t = \bar{s}_1)$ as P_s (4×1 vector) and $\Pr(s_{t+1} = \bar{s}_3 | s_t = \bar{s}_2)$= 0.0895 as p^r

[9]The log-normal has a long right tail which makes it suitable to approximate the distribution of mortality from infectious diseases.

(scalar). Further, $\varpi^C = 1.5$ and $\varpi^R = 1.25$. Q_Z is the transition matrix of the aggregate state described in section 5.

$$
\begin{aligned}
Q &= \text{probability of transition from state } (n_t, \ell_t, s_t, z_t) \text{ to } (n_{t+1}, \ell_{t+1}, s_{t+1}, z,) \\
&= \begin{bmatrix}
Q_Z(1,1)\circ Q^C & Q_Z(1,2)\circ Q^R & Q_Z(1,3)\circ Q^U & Q_Z(1,4)\circ Q^O \\
Q_Z(2,1)\circ Q^C & Q_Z(2,2)\circ Q^R & Q_Z(2,3)\circ Q^U & Q_Z(2,4)\circ Q^O \\
Q_Z(3,1)\circ Q^C & Q_Z(3,2)\circ Q^R & Q_Z(3,3)\circ Q^U & Q_Z(3,4)\circ Q^O \\
Q_Z(4,1)\circ Q^C & Q_Z(4,2)\circ Q^R & Q_Z(4,3)\circ Q^U & Q_Z(4,4)\circ Q^O
\end{bmatrix}
\end{aligned}
$$

$$
Q^C = \begin{bmatrix}
\left[(\underset{4\times1}{\mathbf{I}} - \varpi^C \underset{4\times1}{P_s}) \otimes \underset{3\times12}{\mathbf{I}}\right] \circ \underset{12\times12}{Q^C_{pre}} & \left[\varpi^C \underset{4\times1}{P_s} \otimes \underset{3\times12}{\mathbf{I}}\right] \circ \underset{12\times12}{Q^C_{post}} & \underset{12\times12}{\mathbf{0}} \\
\underset{12\times12}{\mathbf{0}} & \underset{12\times12}{\mathbf{0}} & \underset{12\times12}{\mathbf{I}} \circ \underset{12\times12}{Q^C_{post}} \\
\left[\underset{12\times12}{\mathbf{I}} p^r\right] \circ \underset{12\times12}{Q^C_{pre}} & \underset{12\times12}{\mathbf{0}} & \left[\underset{12\times12}{\mathbf{I}}(1-p^r)\right] \circ \underset{12\times12}{Q^C_{post}}
\end{bmatrix}
$$

$$
Q^R = \begin{bmatrix}
\left[(\underset{4\times1}{\mathbf{I}} - \varpi^R \underset{4\times1}{P_s}) \otimes \underset{3\times12}{\mathbf{I}}\right] \circ \underset{12\times12}{Q^R_{pre}} & \left[\varpi^R \underset{4\times1}{P_s} \otimes \underset{3\times12}{\mathbf{I}}\right] \circ \underset{12\times12}{Q^R_{post}} & \underset{12\times12}{\mathbf{0}} \\
\underset{12\times12}{\mathbf{0}} & \underset{12\times12}{\mathbf{0}} & \underset{12\times12}{\mathbf{I}} \circ \underset{12\times12}{Q^R_{post}} \\
\left[\underset{12\times12}{\mathbf{I}} p^r\right] \circ \underset{12\times12}{Q^R_{pre}} & \underset{12\times12}{\mathbf{0}} & \left[\underset{12\times12}{\mathbf{I}}(1-p^r)\right] \circ \underset{12\times12}{Q^R_{post}}
\end{bmatrix}
$$

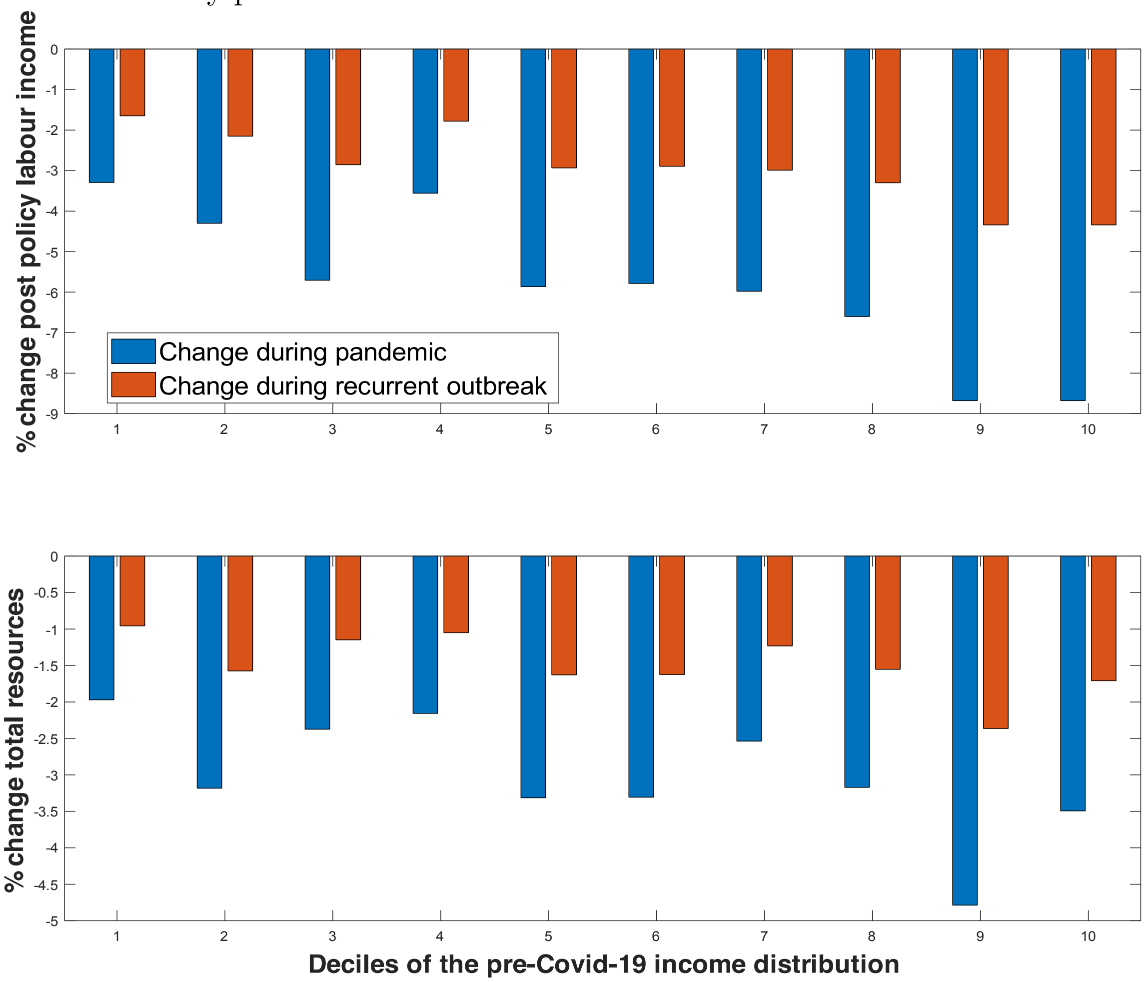
$$
Q^U = \begin{bmatrix}
\left[(\underset{4\times1}{\mathbf{I}} - \underset{4\times1}{P_s}) \otimes \underset{3\times12}{\mathbf{I}}\right] \circ \underset{12\times12}{Q^U_{pre}} & \left[\varpi \underset{4\times1}{P_s} \otimes \underset{3\times12}{\mathbf{I}}\right] \circ \underset{12\times12}{Q^U_{post}} & \underset{12\times12}{\mathbf{0}} \\
\underset{12\times12}{\mathbf{0}} & \underset{12\times12}{\mathbf{0}} & \underset{12\times12}{\mathbf{I}} \circ \underset{12\times12}{Q^U_{post}} \\
\left[\underset{12\times12}{\mathbf{I}} p^r\right] \circ \underset{12\times12}{Q^U_{pre}} & \underset{12\times12}{\mathbf{0}} & \left[\underset{12\times12}{\mathbf{I}}(1-p^r)\right] \circ \underset{12\times12}{Q^U_{post}}
\end{bmatrix}
$$

$$
Q^O = \begin{bmatrix}
\left[(\underset{4\times1}{\mathbf{I}} - \underset{4\times1}{P_s}) \otimes \underset{3\times12}{\mathbf{I}}\right] \circ \underset{12\times12}{Q^O_{pre}} & \left[\underset{4\times1}{P_s} \otimes \underset{3\times12}{\mathbf{I}}\right] \circ \underset{12\times12}{Q^O_{post}} & \underset{12\times12}{\mathbf{0}} \\
\underset{12\times12}{\mathbf{0}} & \underset{12\times12}{\mathbf{0}} & \underset{12\times12}{\mathbf{I}} \circ \underset{12\times12}{Q^O_{post}} \\
\left[\underset{12\times12}{\mathbf{I}} p^r\right] \circ \underset{12\times12}{Q^O_{pre}} & \underset{12\times12}{\mathbf{0}} & \left[\underset{12\times12}{\mathbf{I}}(1-p^r)\right] \circ \underset{12\times12}{Q^O_{post}}
\end{bmatrix}
$$

The Q^C_{pre}, Q^C_{post}, Q^R_{pre}, Q^R_{post}, Q^U_{pre}, Q^U_{post}, Q^O_{pre}, Q^O_{post} denote the transition matrices from (n_t, l_t) to (n_{t+1}, l_{t+1}) per state z_t, *pre* and *post* a health shock occurs. We employ the UnSoc data to calculate these using the socioeconomic group information n_t and the residuals $\epsilon_{i,t}$ from equation (28) as explained in the main text.

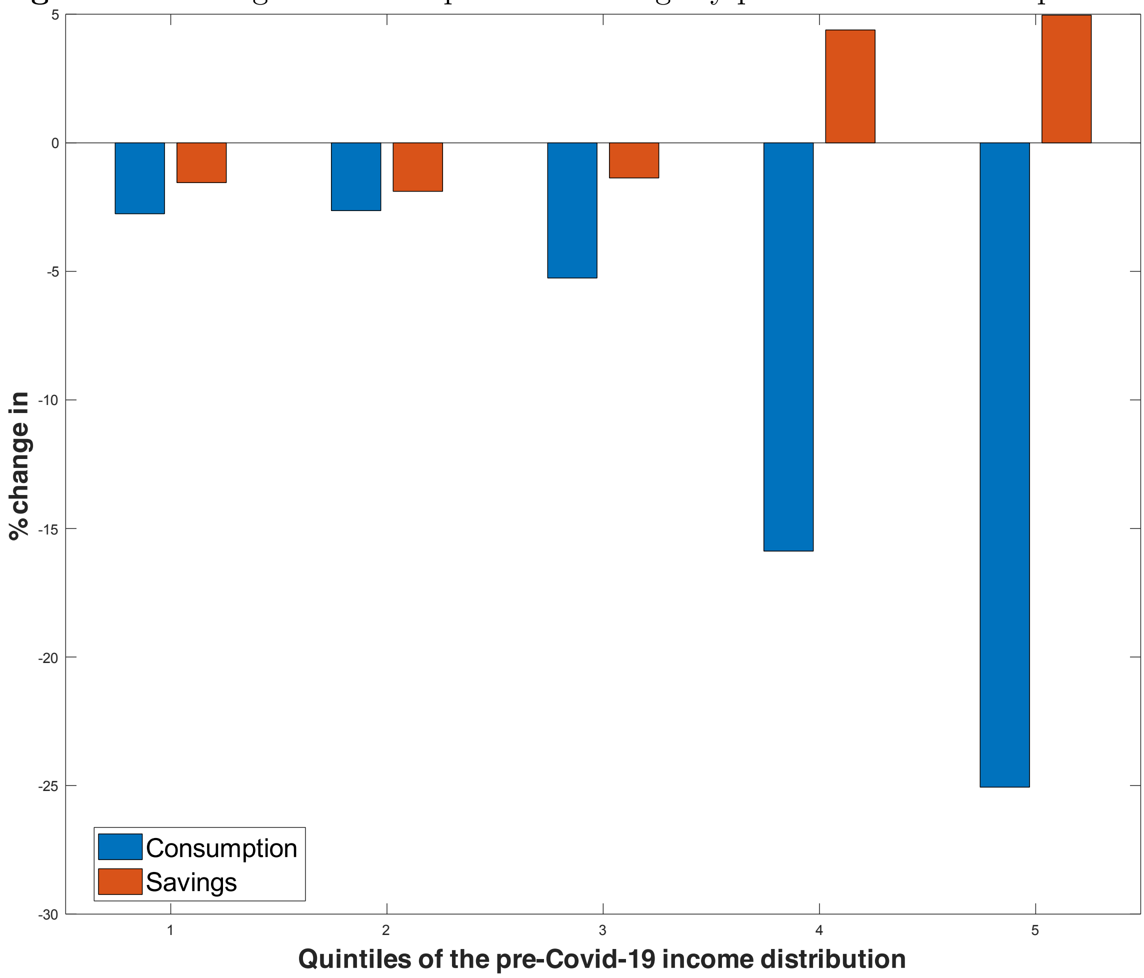
D.6.3 Additional figures

Figure D3: Calibrated changes in post policy labour income and total resources by pre-Covid-19 income deciles.



Changes are relative to pre-COVID-19.

Figure D4: Changes in consumption and savings by pre-Covid-19 income quintiles.



Changes are relative to pre-COVID-19.

D.7 Transitions of the aggregate state

D.7.1 Transition matrix for the one-off pandemic counterfactual

Below we present the aggregate state transition matrix for the "one-off pandemic" counterfactual. Note that in this case the transitions are not stochastic, but instead z follows a deterministic sequence : $\{C_{t=1}, C_{t=2}, U_{t=3}, O_{t=4}, O_{t=5}, ...O_{t=T}\}\,_{t=1}^{T}$. Since $Q_{one-off}$ is known to the households, when solving their optimisation problem, the decision rules reflect the households' knowledge of the transition path of the aggregate state.

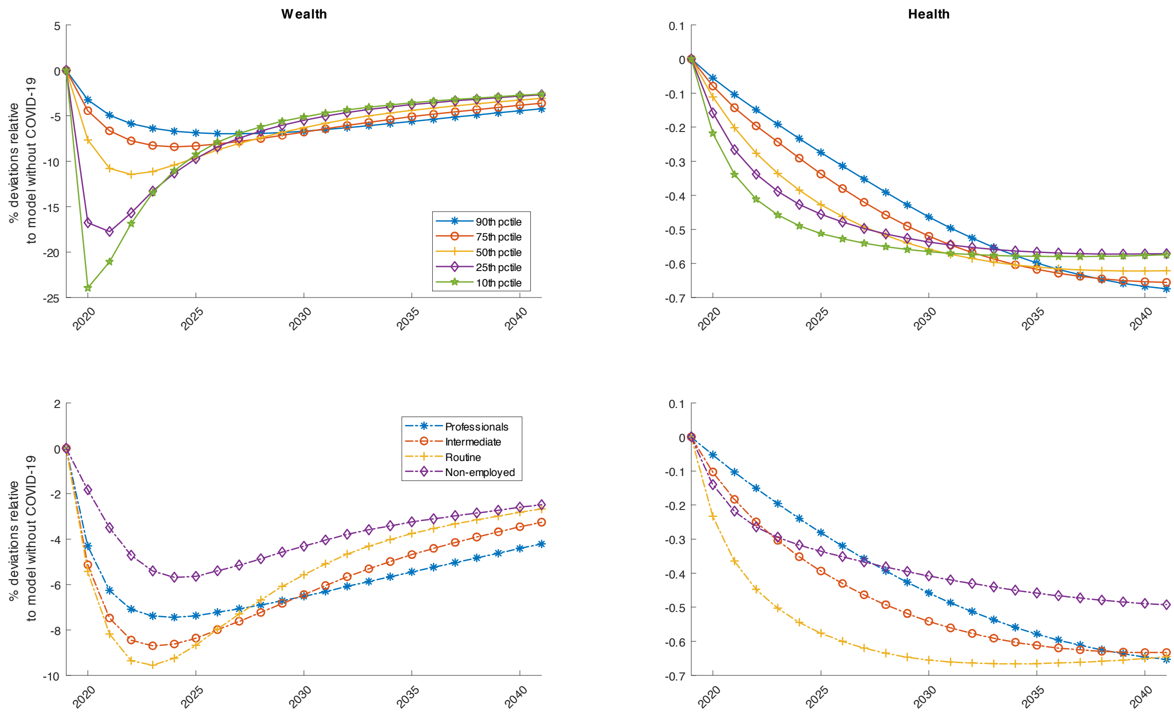
$$Q_{one-off}: \begin{array}{ccccc} z_t \backslash z_{t+1} & C & C & U & O \\ C & 0 & 1 & 0 & 0 \\ C & 0 & 0 & 1 & 0 \\ U & 0 & 0 & 0 & 1 \\ O & 0 & 0 & 0 & 1 \end{array}.$$

Appendix E: Additional results

E.1 Results without consumption cap

Figure E1 reproduces Figure 4 in the main text, without imposing the consumption limit.

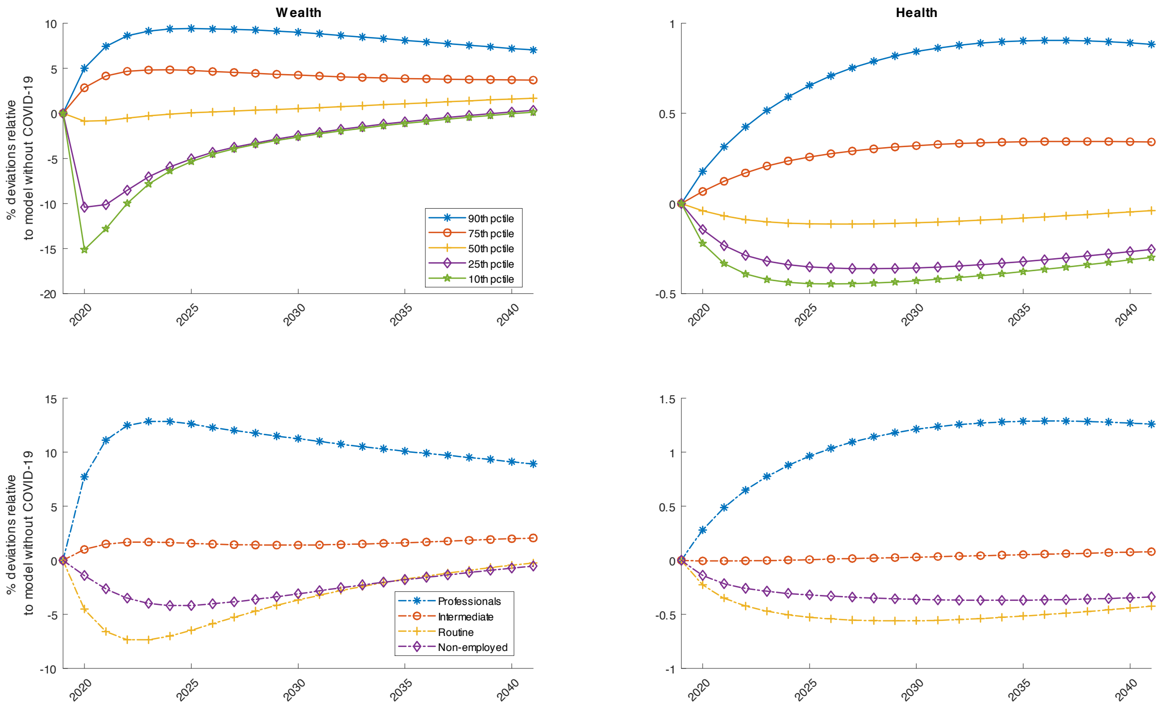
Figure E1: Post-pandemic inequality by initial conditions without consumption limit



Note: Expected percentage deviations of simulated paths under disease outbreak uncertainty versus simulated paths without Covid-19 and disease outbreak uncertainty. Lines in the top panels refer to households starting at the respective percentiles of the wealth distribution in 2019. Lines in the bottom panels refer to households of the respective socioeconomic groups in 2019.

Figure E2 reproduces **Figure 4** in the main text, using initial conditions of the health and wealth distribution.

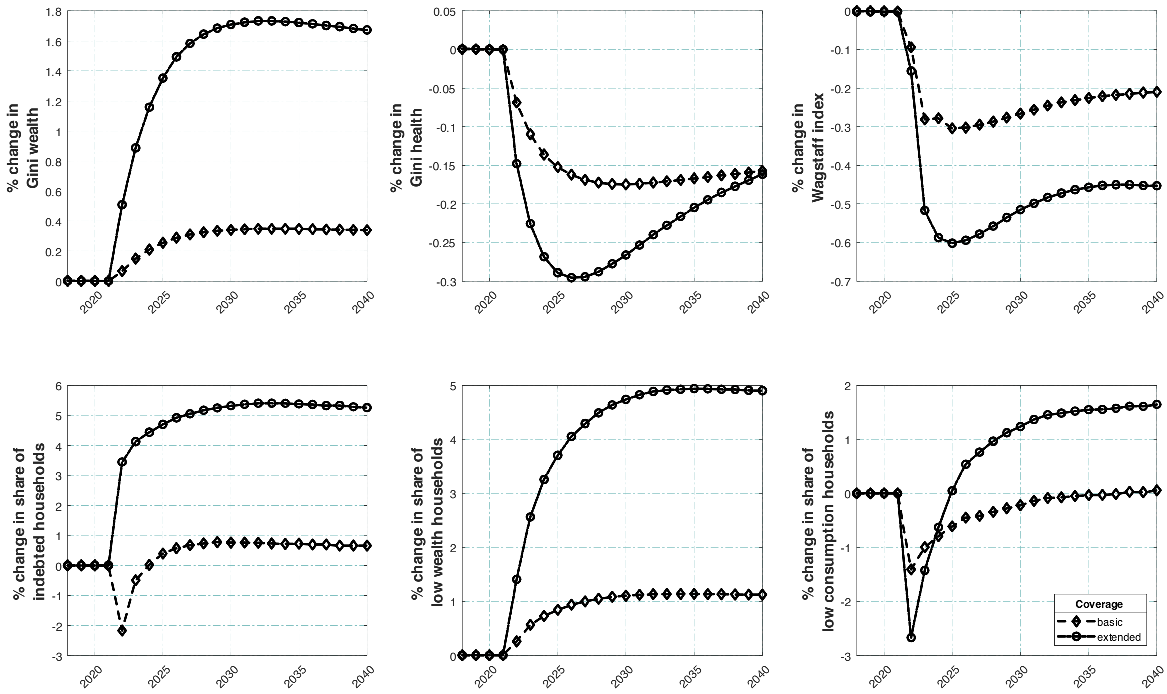
Figure E2: Post-pandemic inequality by initial conditions (wealth and health)



Note: Expected percentage deviations of simulated paths under disease outbreak uncertainty versus simulated paths without Covid-19 and disease outbreak uncertainty. Lines in the top panels refer to households starting at the respective percentiles of the wealth and health distribution in 2019. Lines in the bottom panels refer to households of the respective socioeconomic groups in 2019.

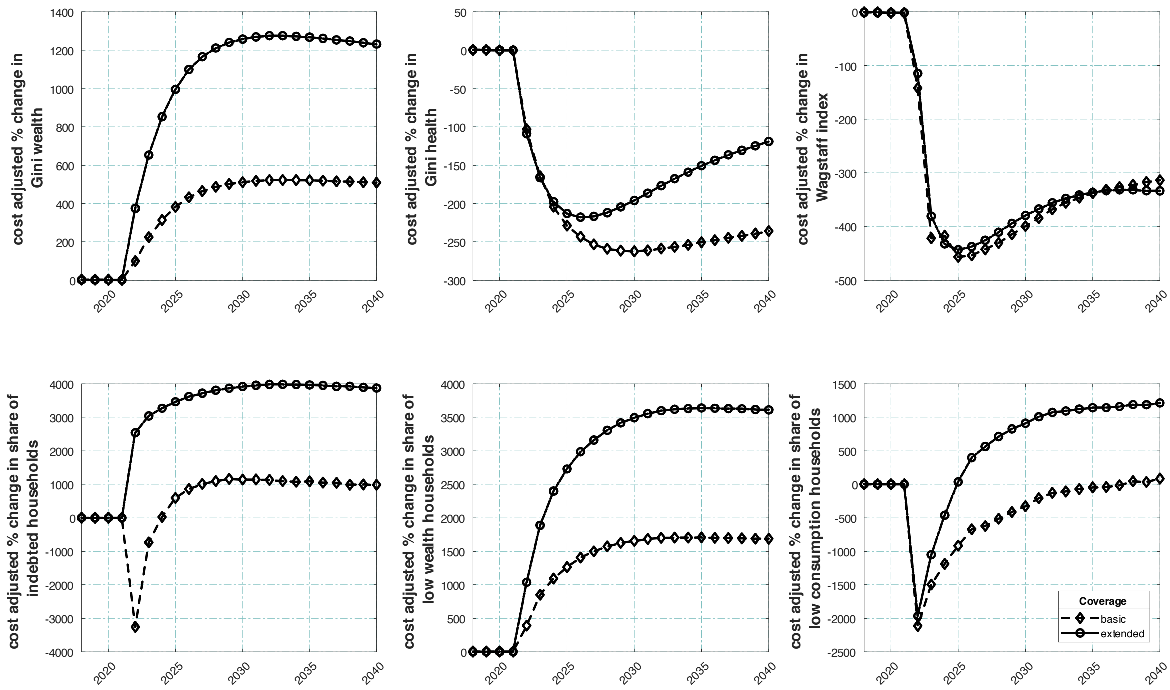
E.2 Additional policy results

Figure E3: Comparison of policy effectiveness across different coverage groups



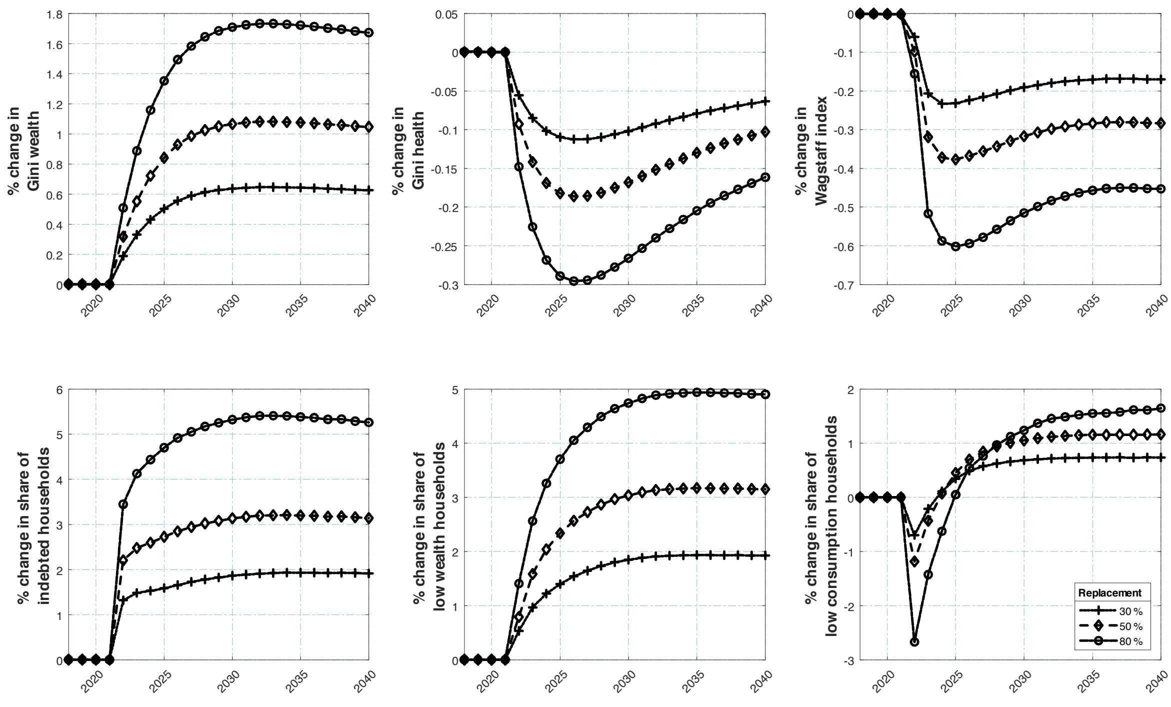
Note: Expected percentage change in measures of inequality with and without policy. Basic coverage applies the policy to all households that have less than zero wealth. Extended coverage includes all households with wealth less than the 33rd percentile of the pre-COVID-19 distribution ($\sim \pounds 9,200$ in £2015).

Figure E4: Comparison of policy efficiency across different coverage groups



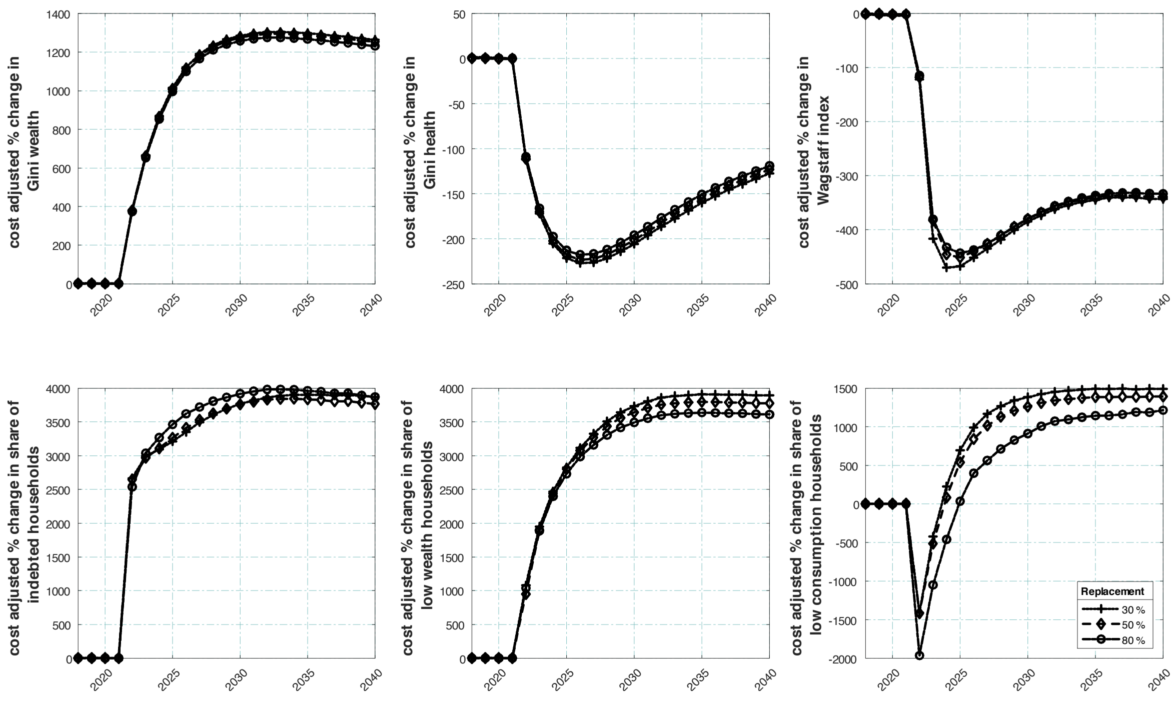
Note: Cost adjusted expected percentage change in measures of inequality with and without policy. Basic coverage applies the policy to all households that have less than zero wealth. Extended coverage includes all households with wealth less than the 33rd percentile of the pre-COVID-19 distribution ($\sim \pounds 9,200$ in £2015). Effects of policies are standardised by expected average costs of policy over the first 20 years.

Figure E5: Comparison of policy effectiveness across different replacement rates



Note: Expected percentage change in measures of inequality with and without policy.
Coverage includes all households with wealth less than the 33rd percentile of the pre-COVID-19 distribution ($\sim$ £9,200 in £2015).

Figure E6: Comparison of policy efficiency across different replacement rates



Note: Cost adjusted expected percentage change in measures of inequality with and without policy. Coverage includes all households with wealth less than the 33rd percentile of the pre-COVID-19 distribution ($\sim \pounds 9,200$ in £2015). Effects of policies are standardised by expected average costs of policy over the first 20 years.

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