# Simulating inequalities in social care provision during the Covid-19 pandemic: an agent-based model

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# Simulating inequalities in social care provision during the Covid-19 pandemic: an agent-based model

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## ABSTRACT

The Covid-19 pandemic is deeply affecting every aspect of people daily lives around the world, both through the effects of the virus itself and the related mitigation measures put into place by governments. However, the impact of the virus is not equal *within* each society, as an increasing number of empirical studies show that its effects at the individual level exhibit a *social gradient* of health, a phenomenon known to characterize many public health outcomes. In this paper, we present an agent-based computational model to investigate the effect of the pandemic and related mitigation policies on social care need and supply, using a proof-of-concept agent-based model (ABM). This ABM simulates agents' socioeconomic status, kinship networks, and heterogeneous behavioural responses to the pandemic. We propose that such models may help policymakers develop more effective policies to mitigate viral spread, that can take into account the unequal impact of the pandemic on individuals in different socioeconomic status groups. Through the use of these computational methods, we illustrate how policy solutions aimed at controlling the pandemic may have substantial effects on the level of unmet social care need.

## Introduction

Since its emergence in late 2019, SARS-CoV-2, more commonly known as Covid-19, has grown into a global pandemic, the most significant since the 1918 Spanish Flu. However, the impact of the pandemic has not been uniform throughout the global population; some sub-populations have significantly different risks of death due to Covid-19. The virus has affected vulnerable populations of older people and adults with disabilities particularly strongly. In the United Kingdom, for example, Office for National Statistics data shows that 65% of deaths due to Covid-19 between 12 February 2021 and 6 August 2021 were recorded in adults aged over 75[1]. Amongst adults with disabilities, the risk of death due to Covid-19 was 3.1 times greater for more-disabled men as compared to non-disabled men, and 3.5 times greater for more-disabled women[2].

The risk of death from Covid-19 also varies with ethnicity and the nature of one's occupation. In England and Wales, individuals of Black African ethnicity are significantly more likely to die of Covid-19 than individuals from white backgrounds (2.9 times higher risk for Black African males, 2.0 times higher for Black African females). Part of this additional risk is due to a higher likelihood that Black and Asian individuals work in occupations at greater risk of contracting Covid-19. These at-risk professions include those with a high degree of exposure to the public, including public transport and taxi drivers, security guards and medical staff. According to the Office for National Statistics, social care work was associated with significantly higher rates of death from Covid-19 than the general population, among both males and females[3].

Given the greatly increased risk of death due to Covid-19 among older age groups, and the risk the disease also presents to carers themselves, managing the pandemic in social care settings has become an issue of significant policy concern. Prior to the pandemic, social care in the UK was already under significant pressure, given the increasing elderly population and low birthrates[4]. The UK is dependent on informal carers to provide a significant portion of care supply; the National Audit Office estimated the value of informal care provision in the UK at £100 billion per annum in 2018.[5].

The pandemic has increased the pressure on informal carers significantly. Carers UK estimates that before the pandemic, the UK had 9.1 million unpaid carers, and that the impact of Covid-19 on vulnerable people generated an additional 4.5 million unpaid carers, for a total of 13.6 million[6]. Out of those already providing care before the arrival of the coronavirus, 81% report spending more time on care than they did previously[7]. Carers UK also estimates that carers had provided £135 billion of care between March and November 2020, representing a substantial increase over previous years.

In this paper we present an agent-based simulation model of social care in the United Kingdom, which includes a detailed model of the spread of Covid-19 and its impact on individuals. We use this simulation framework to investigate the impact of the pandemic and related mitigation measures on carers and care-receivers. While the simulation contains significant simplifications, we propose that this modelling framework can provide insight into the challenges faced by the social care system during this global crisis, and that simulations like these can be used to better prepare for future waves of Covid-19 and

its variants, or later outbreaks of a different novel pathogen.

### Previous works

Our model is composed of two main modules: a *social care provision* module and a *Covid-19 spread* module. The social care provision module adopted in this paper is the latest development of a modelling effort spanning the last decade[8–11], whose main features will be described in the next section.

The adoption of the agent-based methodology to model informal social care provision is quite recent and previous literature in this field is very sparse. One study related to the social care model used in this paper is a mixed micro-simulation/agent-based care supply and demand model, called DemoCare, recently proposed by Spijker et al[12]. This model takes into account fertility, mortality and marriage rates for cohorts born between 1908 and 1968 to estimate the amount of care available from partners and children for people aged 50 or over. The DemoCare model uses micro-simulation to generate kinship networks of 10,000 representative agents, based on the demographic characteristics of each cohort, limiting the network to spouse, children, children-in-law and grandchildren. Then, through ABM simulations, they estimate the demand for care of these representative agents and the amount of this need which can be satisfied by spouse and children, taking into account whether they are working, their state of health and the needs for care of the rest of the family (e.g child care needs).

The social care provision model we adopt in this paper is fully agent-based, unlike DemoCare, and this methodology allows us to account for the interactions *between* kinship networks (which occur when agents belong to more than one ego network). This interaction which is particularly important when enlarging the group of care suppliers beyond partners, children, children-in-law and grand-children to include brothers, nephews, aunts and uncles. Other important differences, such as a more extensive role for *social status* (which in the DemoCare model is represented by agents' educational levels) and the endogenous determination of *formal care* though the working agents' care-work choice, will be discussed in detail in the next section.

Agent-based modelling methodology has only recently been applied widely to the study of pandemics. The module presented in this paper shares some features with the work of Wilder et al.[13], who proposed an agent-based model of Covid-19 spread taking into account age and comorbidity distributions, age-stratified contact patterns and household structures. The model follows the standard SEIR agent classification, with four severity levels for infectious agents (asymptomatic, mild, severe and critical) and levels of infectiousness depending on the severity level (asymptomatic and symptomatic) and the stage of infection (before and after the onset of symptoms). In addition, agents are isolated if they are in the severe and critical severity levels while agents with mild symptoms become isolated after a number of days determined through a stochastic process. Agents can become exposed through in-household and out-of-household contacts, with the in-household contacts being more likely to transmit the virus. The out-of-household contacts are based on a country-specific contact matrix containing the mean number of daily contacts agents of an age group have with agents from each of the other age groups.

The model of Covid-19 spread we present in this paper includes significant differences compared to Wilder et al. First, because of the integration with a social care provision model, our pandemic model has an additional exposure setting, represented by the social care-related interaction between agents. Second, in our model the agents have additional attributes such as their homes' geographical location and the social status. These attributes have an important role in the generation of the contact networks (as we assume that agents close in location and social status are more likely to be part of the same contact network). Moreover, the agents' social status affects the probability they will develop conditions of different severity levels (according to the epidemiological phenomenon of the social gradient in health). Finally, our model includes a behavioural module representing the decision process determining the agents' degree of isolation, as a response to the various kinds of risks associated with Covid-19.

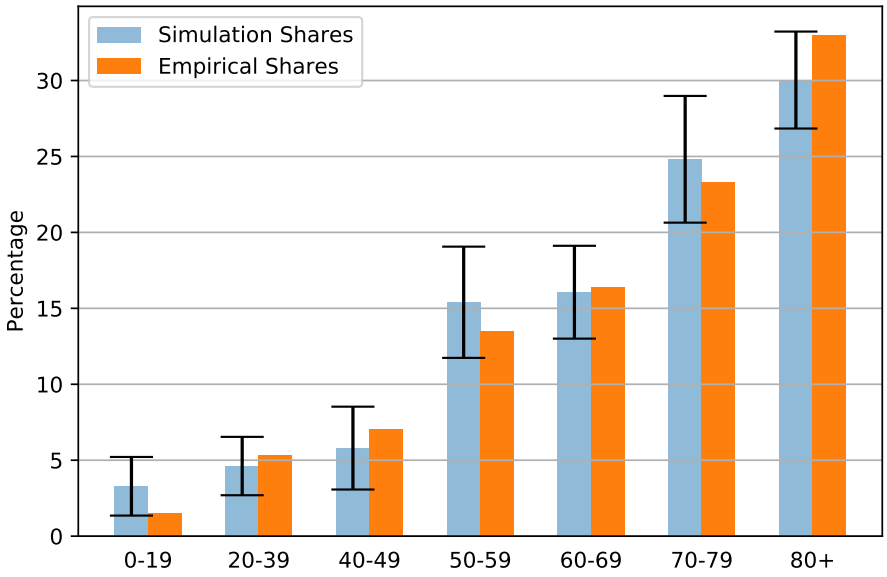
## Results

In this section, we present the simulations' results with a particular emphasis on the inequalities characterising both the pandemic and the social care outcomes.

The following graphs show, for each output, the mean across 20 repetitions, with 95% confidence intervals. Figure 1 demonstrates the model's capacity to approximate the distribution of people hospitalized by age group. We can see that, under a lockdown policy which allows freedom of movement for social care purposes (which is, among the policies we considered in these simulations, the one which most resemble the policy adopted by the UK government), the empirical shares of hospital admissions by age, as reported in[14], are within the 95% confidence interval for all the age groups, except for the 0-19 age group, which appears to be at the lower limit of the confidence interval (note, however, that there is a slight discrepancy between the grouping of[14], where the first age group is the 0-17 group, and the grouping of the simulations' outcomes, where the first age group is the 0-19 group. If we consider that the hospitalization rate increases with age, the empirical shares are higher for the 0-19 group and lower for the 20-39 group than they appear in Figure 1).

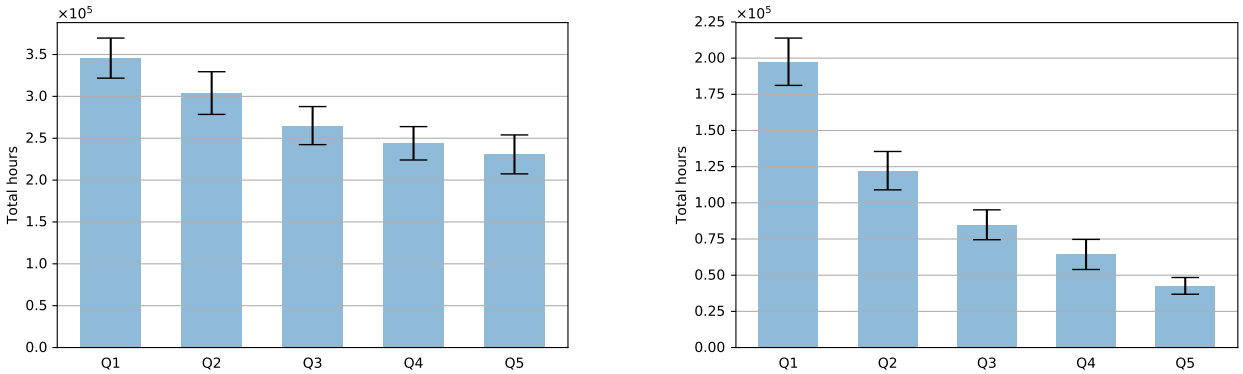
In the next two figures, we show the social gradients in social care provision. From Figure 2a we can see that social care need shows a clear social gradient, with the care need of the first quintile being around 20% higher than the care need of the

**Figure 1.** **Share of hospitalized by age group.**




fifth quintile. This results in the highly unequal distribution of the unmet care need we can see in Figure 2b, with the first quintile having four times the amount of unmet care need of the fifth quintile.

**Figure 2.** **Social gradients of care.**




**(a)** Care needs by income quintile.

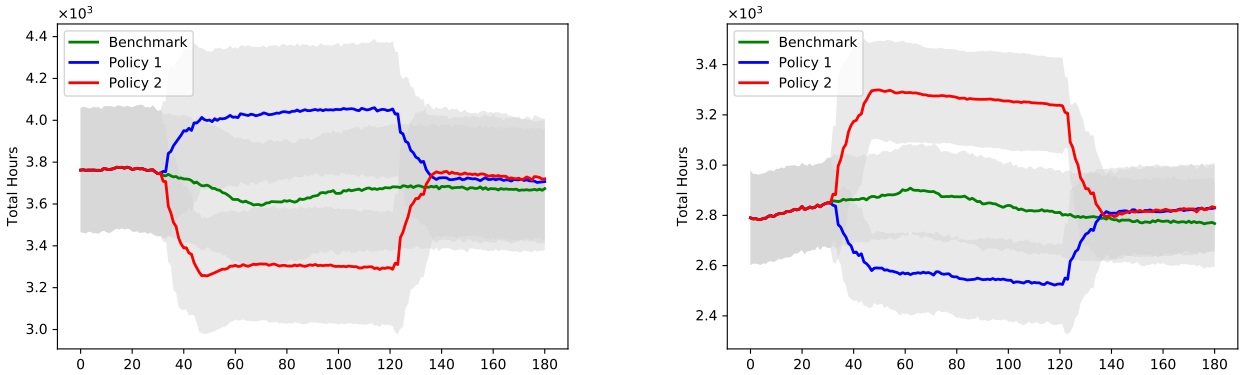
**(b)** Unmet care need by income quintile.

In the next set of figures, we compare the effects of two lockdown policies to the benchmark 'no-lockdown' scenario. In these figures, *Policy 1* refers to the partial lockdown policy, i.e. a lockdown which allows movement for social care purposes, while *Policy 2* refers to the 'full lockdown' policy. In both cases, the lockdown is imposed 3 days after the first death, and is lifted after 90 days.

The last four graphs show the effect of these two policies on social care provision. Figure 3a shows that the two policies have opposite effects on the amount of informal care provided: while total lockdown reduced the amount of informal care (as potential suppliers cannot provide care to people in need living in other households), partial lockdown increases the informal care provided, as under partial lockdown people have more time to allocate to social care (an effect which is consistent with empirical observations). The effect of this variations of care supply on unmet care need are shown in Figure 3b, where we can see an increase of unmet care need under Policy 1 and a decrease of it under Policy 2.

The following two figures show the differences between policies in terms of care provision and unmet care. From Figure 4a and Figure 4b we can see that the two policies have opposite effects on the amount of informal care and, therefore, unmet care need. While Policy 1 has a positive effect with regards to social care provision and unmet care need, the opposite is true for

**Figure 3. Policy comparison: care dynamics.**

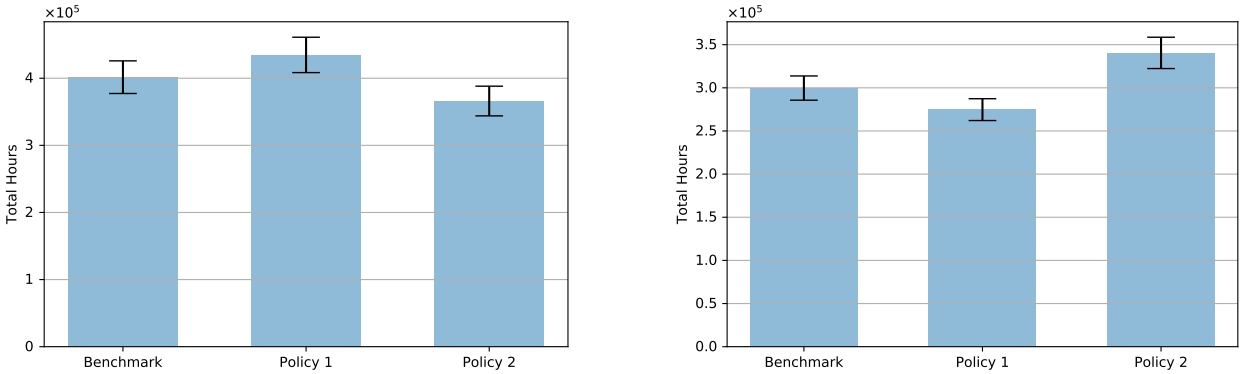



**(a)** Informal social care.

**(b)** Unmet care need.

Policy 2, with the level of unmet care need with this latter policy being more than 20% higher than the level of unmet care need under the former policy.

**Figure 4. Policy comparison: care aggregate outcomes.**




**(a)** Total informal care.

**(b)** Total unmet care need.

To sum up, we can say that our simulations show that while Policy 1 has a positive effect on hospitalisations, intubations and unmet care need, in the case of Policy 2 the policy maker faces a trade-off posed by the even greater positive effect on the pandemic outcomes and an increase of about 13% of the level of unmet care need.

## Sensitivity Analysis

Typically, the results of ABM simulations depend on many parameters which are characterized by a high degree on uncertainty. In our model, in particular, there are parameters related to the agents' behaviour and the social networks which are not empirically determined and for which we must perform a sensitivity analysis in order to determine their importance in driving the simulations' outcomes. In this sensitivity analysis, we chose the number of hospitalisations as the main output of interest.

Table 1 shows the total effect on the outcome' variance for the eight parameters we included in the sensitivity analysis, the first four of which determine the agents' behaviour, while the last four affect the size and structure of the social networks. To determine the ranges, we halved (lower bound) and doubled (higher bound) the parameters' benchmark values.

We can see that the 'base' sensitivity to risk factors ($\mu$) and the effect of income ($\omega$) on the overall sensitivity are two of the most important parameters, with an effect on the overall variance of total hospitalizations of 35% and 27% respectively. The effect of the knowledge of infection on the behaviour within the household and during the care provision ($\phi$) is the second most important parameter, determining about 33% of the total variance of the outcome. The other-regarding preferences (affecting the behaviour of knowingly infected people) and the parameters affecting social network size and structure appear to have a marginal role in driving the outcome we considered.

**Table 1. Sensitivity analysis.**

| Parameter | Behaviour Affected | Range | Total Effect |
|---|---|---|---|
| $\phi$ | domestic/care prudence | [0.25, 1.0] | 2.0 |
| $\xi$ | other-regarding concern | [0.005, 0.02] | 33.04 |
| $\omega$ | 'income-effect' | [0.25, 1.0] | 2.28 |
| $\mu$ | 'base' sensitivity to outcomes | [20, 80] | 27.06 |
| $s$ | number of contacts | [0.05, 0.2] | 35.54 |
| $r$ | same-class contacts | [0.1, 0.4] | 0.68 |
| $h$ | same-area contacts | [0.001, 0.004] | 1.05 |
| $k$ | same-friends contacts | [0.05, 0.2] | 2.81 |

## Discussion

In this work, we presented a 'proof of concept' of an agent-based model of Covid-19 spread and the effect of the pandemic, and of the public health measures taken to contain it, on the provision of social care. We showed that the model could be used to evaluate the relative advantages and disadvantages of alternative policies, and can therefore represent an important decision-support tool for policy-making decisions in this complex and highly uncertain context.

The model results demonstrate that policy-makers have a trade-off to consider when imposing public health restrictions in these circumstances. When lighter restrictions are imposed, informal social care provision increases, as informal carers have more time available and are not restricted from providing care; however, under these conditions the negative outcomes of the pandemic are more modestly reduced. Conversely, under more severe restrictions informal social care between households becomes impossible, worsening care outcomes through a significant increase in unmet care need, while the effects of the pandemic are more effectively contained. Models like this one could be used to investigate the nature and extent of these public health trade-offs, so that policy-makers may make informed decisions based on the current state of the pandemic.

The results also reflect the social gradients of health and care present in these scenarios. Unmet social care need is distributed highly unequally, with the lowest income quintile having four times as much unmet care need as the highest quintile. The sensitivity analysis shows that the number of contacts is a significant factor driving these results, which suggests that the higher income quintiles benefit from having jobs with greater inherent flexibility, which enables them to work from home in larger numbers and take more time off work to provide informal care.

Agent behaviours are influenced by their other-regarding concern, and their base sensitivity to outcomes. Our sensitivity analysis shows that both these factors significantly impact the outcomes of the simulation. This demonstrates that our inclusion of a behavioural module captures an important element affecting pandemic outcomes, namely the role of individual perceptions of risk and the resultant behavioural responses.

In addition, apart from the practical insights which can be drawn from the simulations, the sensitivity analysis demonstrates the important role that such models can play in our theoretical understanding of the processes driving the outcomes' dynamics. While the high degree of uncertainty characterizing many parameters of the model prevents us from making 'point' predictions, an extensive sensitivity analysis allows us to identify the most important drivers of pandemic outcomes. These theoretical insights are also of great practical importance, as part of the effort to gather immediately useful data to inform a rapid pandemic response.

An advantage of the ABM approach is its flexibility, i.e., the possibility to adapt and improve the model according to stakeholders' needs. In fact, the proposed model can be expanded in many potentially useful ways. For example, the model could be modified to include a lower-level spatial element, and include local councils as independent policy-makers. Another extension could be the introduction of the evolutionary process through which the virus responds to selection pressure by changing its characteristics, such as infectivity and fatality rate. In addition, the pandemic module can be made more detailed, to model the effects of common interventions such as face coverings and the impact of the Covid-19 vaccines. In our future work we will continue to refine and extend this model to maximise its utility for public health policy-makers.

## Methods

This computational modelling study was carried out following all relevant guidelines; note that we only use publicly available population data, such as the Human Mortality Database[15], Eurostat[16] and the Office for National Statistics[17]. No human experiments were performed, nor was any human data collected during the course of this study.

The model is composed of three main modules. First, the *demographic module* creates a population on the UK with a realistic demographic structure, starting in the year 1860 and running until the year 2020 in one-year time steps. Then, from the beginning of the year 2020, a *social care module* and a *Covid-19 spread module* generate the social care provision process and

the epidemiological progression of the pandemic respectively. These process then proceed for 180 one-day time steps (i.e., we simulate the first 6 months of the pandemic).

## The demographic module

The initial population of couples is randomly distributed on a 8×12-cell grid approximating the geography of the United Kingdom. Agents live in houses which form towns, with the density of those houses varying in rough proportion to UK population density. The agent population is scaled down from real UK levels at a factor of roughly 1:10,000. The simulation begins in the year 1860, which allows sufficient time for the population dynamics to stabilise before 1951, at which point UK Census mortality and fertility data is incorporated into the simulation[15,17]. Agents form partnerships, have children, start working (and earn an income), relocate, retire and die, according to sub-modules the details of which have been described in previous works[8–11] and a summary of which is reported in the Supplementary Information.

## The social care module

The social care module simulates the social and child care provision processes, starting from the year 2020, for 180 days. In order to represent the complexities of care provision and receipt, we generate an agent population who are able to enter states of care need and are capable of providing care under certain circumstances. People in need may qualify for public social care. If they have residual need, they can receive informal care from other members of their household or relatives living in other households, and formal care, i.e., care from social workers paid with their wealth or their household' income. The details of these processes and related agent properties are explained below.

### *Health status and care need*

This module is based upon previous work on simulating child care provision[11]. Agents begin the simulation in a state of good health, and subsequently may develop care needs according to age-, gender- and SES-specific probabilities. Table 2 shows the five possible categories of care need, and the hours of care need required at each level. In line with the current understanding of care need progression, we assume that agents who develop a condition requiring care do not recover, but instead progress to higher levels of severity and care need over time. This progression through the care need levels depends on age, gender, SES, and the cumulative unmet care need experienced by that agent. We therefore assume that large amounts of unmet care need increase frailty..

**Table 2. Care need categories/levels and number of hours of care required.**

| Care need category | Care need level | Weekly hours of care required |
|---|---|---|
| None | 0 | 0 |
| Low | 1 | 8 |
| Moderate | 2 | 16 |
| Substantial | 3 | 36 |
| Critical | 4 | 84 |

### *Kinship Networks*

This subsection provides a brief summation of the kinship network mechanism in the simulation; for further details, we refer readers to our previous work[11]. Agents requiring care have kinship networks linking them to households with members having a consanguineous or affinal relationship with that agent. Within these networks we define 'degrees' of kinship, based on the distances between the agent and each household in the network. This kinship distance ranges from 0 for agents in the same household, to III (uncles and aunts, or nieces and nephews).

The supply of social care available to an agent is determined by the size of its kinship network, the kinship distances in that network, and the individual states of household members contained in that network. The hours of care supply that can be provided by each agent according to status and network distance are shown in Table 3.

In addition to kinship distance, physical distance also impacts care provision. In this model we assume that care receivers may only receive informal care if the provider is in the same town. We also assume that kinship distance restricts the provision of formal care; private paid-for care occurs only between members of the same household, or between parents and children.

### *Formal Care*

Formal care may be provided within the care receiver's household or by households with first-degree kinship relationships to the receiver. Income allocated for care may be used to buy private paid-for care, or to reduce hours spent at work in order to provide informal care (meaning that the income allocated in this case represents unearned income, rather than spent income).

**Table 3. Amount of care agents can provide depending on their status and kinship distance from the care receiver.**

| Agent status | Household (D 0) | D I | D II | D III |
|---|---|---|---|---|
| Teenager | 12 | 0 | 0 | 0 |
| Student | 16 | 8 | 4 | 0 |
| Employed* | 16 | 12 | 8 | 4 |
| Retired | 56 | 28 | 16 | 8 |

* Employed agents can provide additional care if they choose to reduce their working hours (i.e. in case it is more convenient than using income to pay for formal care. See the Formal Care section for details).

The care receiver may also purchase private care with their own wealth. The share of their wealth allocated to formal care is positively correlated to their overall financial wealth.

#### *Government-funded social care*

As outlined in previous work[11], agents with care needs may be eligible for publicly funded care, via a government-funded care scheme based upon the framework in place in England. In this scheme, all adults with care need levels of 'critical' and whose savings are below £23,250 receive public financial support. When their savings are less than £14,250 the government pays all social care expenses which the receiver cannot afford without reducing their income below £189 per week. Above this level of savings the government subsidy is reduced by £1 for every £250 in savings. This model does not distinguish between different types of care in this scheme (i.e., at-home care or care homes, etc.).

#### *Child Care*

Here we provide a brief summary of child care processes in the simulation; we refer the interested reader to our previous work[11] for further details on the child care allocation process. In this simulation all children, with the exception of newborns, have identical childcare need, requiring 10 hours of care each day. The net care need for each child agent varies by age, given the presence of child care and education policies targeted at specific age groups. Newborns have a much higher care need which must be provided by their mother, who in turn allocates all her care supply for the newborn.

There are two significant differences in our model between social and child care, which in turn affect how we model each type of care provision. First, parents are required by law to care for their children, and therefore we assume that child care always takes priority over the provision of adult social care. This means that in our allocation process, social care supply is only allocated after child care supply is allocated. Second, child care can be delivered on a many-to-one basis, whereas social care must be delivered on a one-to-one basis.

Social care is significantly more expensive to provide than child care, with prices between three to four times higher. Within our model we assume that households will therefore prefer to allocate their *income* to provide formal child care, and their own *time* to provide informal social care, as this is the most economically viable option in most cases.

#### *Care allocation process*

In this model we adopt the care allocation process developed in our previous work[11]. We simulate care allocation as a negotiation taking place across agent kinship networks. The allocation process has two stages: 1) the available care supply (available time/income for care) is allocated to child care need; 2) remaining resources are provided to social care needs.

In both stages the allocation process randomly samples one care-receiving unit (which is an individual in the case of social care, or a household in the case of child care), with a probability proportional the unmet care need of that unit. The care receiver is then linked with a care-providing household in the receiver's kinship network; potential care-giving households are sampled with a probability proportional to that household's care supply.

After the care supplier has been chosen, a 2-hour unit of care is provided from one member of that household with available supply to the care receiver. If the supplying household is at distance I, then that household may choose to provide either time (in the form of informal care) or income (in the form of formal care).

When choosing between providing assistance in the form of income or time, the choice is made depending on the hourly wage of the worker in the supplying household with the lowest wage. If the price of formal care is higher than that wage, then the supplying agent will prefer to take time off work to provide informal care; if the price of formal care is lower, then the agent will prefer to purchase that care and remain in work.

### The Covid-19 spread module

Building on the framework underlying our previous social care models, we introduce a model of Covid-19 spread which takes into account UK demographic structure, income distribution, age- and income-specific social mixing patterns, household structure and social care provision networks.

As in the standard SEIR model, the agents can be in one of four states: *susceptible*, *exposed*, *infectious* or *removed* (i.e. recovered or deceased). As for the conditions of the infected agents after the virus incubation period, we distinguish between: *asymptomatic*, *mild symptomatic* (i.e., not hospitalized), *severe* (i.e., hospitalized but not in intensive care) and *critical* (i.e., in intensive care).

An infected agent is given a *viral load*, which is sampled from a standard uniform distribution. The viral load determines the agent's *contagiousness* and, together with their age and income quintile, the severity of their symptoms (which we call the agent's *symptoms severity index* ($\pi$)). The severity index affects both the agent's mobility (which is equal to 0 for those hospitalized) and the probability that it takes a test to determine whether it is infected.

The main features characterizing our model of the pandemic are:

- the inclusion of a *behavioural module* determining the agents' behavioural response to the risks of being infected or infect others.
- a multi-setting exposure process, composed of: a *social setting*, a *domestic setting*, and a *social care setting*;
- age-, income- and gender-specific probabilities of developing different *virus infection courses*.

### *Behavioural module*

In this model, the agents react to the risks posed by the pandemic by reducing their social and work activities – by self-isolating. We assume that the agents can be concerned about two kinds of risk:

- the risk of being infected, if susceptible or if unknowingly infected (e.g. asymptomatic agents);
- the risk of infecting others, if knowingly infectious.

Infected agents become aware of their infection status if they take a test, which is taken with a probability that depends on the severity of their symptoms.

As for susceptible agents, who will be concerned about the risk of being infected, the factor by which they reduce their social and work activity (the *mobility reduction rate* ($m$)) depends on their sensitivity to the virus spread. The variable measuring the spread ($\rho$) is represented by the weighted moving average of the number of *new cases*, relative to the size of population. Formally, the mobility reduction rate is given by:

$$m_b = \frac{1}{e^{g\rho}} \tag{1}$$

where $g$ represents the susceptible agent's overall *sensitivity* to the risk of being infected, which depends fundamentally on two parameters of the behavioural model:

- the *infection fatality rate* ($f$). It is a characteristic of the virus, and it is constant as during the simulation the virus does not evolve. For the agents, it represents the expected 'cost' of being infected and it depends on the agents' age, income and gender.
- the 'base' sensitivity to infection's outcomes ($\mu$). It is a behavioural parameter representing the 'strength' of the agents' reaction to a unit increase of the infection fatality rate.

For a not-working agent (e.g., a retired agent), the degree of isolation does not affect its income and the occupational factor is not relevant, so the agent's sensitivity to risk becomes:

$$g_u^s = f\mu \tag{2}$$

In case the agent is working, their sensitivity to the risk of being infected depends also on:

- the agent's *income* factor ($\omega$)
- the agent's *occupation* factor ($\sigma$)

If the agent is working, indeed, reducing its mobility may mean reducing its working hours and therefore its income. Agents with a relatively high income can afford a higher reduction of their working hours compared to agents with a low income. Finally, agents with different kinds of occupations differ in their capacity to work from home. In line with empirical observations[18], we assume that people of low social status have jobs with less inherent flexibility and are less able to work from home, compared to the jobs of people of high social status. The agent's income quintile is used as a proxy for its social status. Formally, the agent's sensitivity to the risk of being infected for a working agent is given by:

$$g_w^s = f\mu\omega\sigma \tag{3}$$

where $g$ is a proportionality parameter and $\omega$ is an increasing function of the agents' income quintile.

For the reasons mentioned above, therefore, we should expect old people of high social status to be the most sensitive to the risk of being infected, and young people of low social status to be the least sensitive; in other words, we should expect agents of the former category to adopt a stricter isolation regime compared to the latter, for a given increase in case numbers.

As for the knowingly infectious agents, who will be concerned about the risk of infecting others, we assume that their mobility reduction depends on their sensitivity to the share of the susceptible population $S$:

$$m_b = \frac{1}{e^{gS}} \tag{4}$$

For working agents, once again the sensitivity depends on the income and occupation, but differently from the susceptible agents, we assume that it depends on the *general* infection fatality rate, $F$, (as opposed to the agent-specific infection fatality rate) as it is the variable measuring the virus fatality among the population. Formally, the infectious agents' sensitivity to the share of susceptible is given by:

$$g_w^i = \mu\xi F\omega\sigma \tag{5}$$

and for unemployed agents:

$$g_u^i = \mu\xi F \tag{6}$$

where $\xi$ is a parameter representing the 'strength' of the agents' social (or other-regarding) preferences (i.e., how much they care about others' well-being).

Apart from behavioural reactions to pandemic risks, the mobility of infected agents who are not asymptomatic may be reduced because of the debilitating effect of the virus. We assume that the extent to which the infected agent's mobility is reduced depends on its symptoms severity index, $\pi$, according to the formula:

$$m_v = (1-\pi)^\eta \tag{7}$$

where $\eta$ is a parameter determining how the mobility decreases as the severity of the agent's symptoms increase. Therefore, the overall agent's mobility reduction rate $m$, will be given by:

$$m = min(m_b, m_v) \tag{8}$$

### *Exposure settings*

A susceptible agent can become exposed in three settings: social interaction, by meeting people who are part of its social network (e.g. friends and colleagues); through contacts within its households; or through the social care process(either as a receiver or a supplier of care).

**Between-household social care provision –** As described in the previous sections, agents with social care needs can receive care supply from relatives living in other households, and our model accounts for this between-household care-based interaction as a process through which the virus may spread.

We assume that the probability of being infected by the care receiver or the care supplier depends on the contagiousness of the infected agent, on the duration of the interaction and, if the person carrying the virus is the care receiver, on whether the person knows about their infection status. If the receiver knows they are infectious, we assume that both the care receiver and the care supplier adopt a prudent behaviour which reduces the risk of contagion by a certain factor $\phi$ which is a parameter of the model. When the care supplier is infectious and aware of their status, we assume instead that they do not provide any care supply.

**Domestic interaction –** Agents can be infected through interactions within their household. The capacity of an infected household member to transmit the virus to a susceptible agent depends on their contagiousness (their viral load) and whether the infected agent knows they are infected. If the agent knows they are infected, we assume that households adopt a prudent behaviour reducing the risk of contagion by a certain factor $\phi$ which is a parameter of the model.

**Social interaction –** Each agent is the focal node of an *ego network*, for which the size (i.e. the number of contacts) and distribution of contacts by age group depends on the agent's age group, according to empirical findings on social mixing patterns ([19–21]). In line with findings of empirical studies of the effect of social status on social networks[22], we assume that the network size increases with the agents' social status (represented by their income quintile), according to a factor $s$ which is a parameter of the model. The probability that two agents are part of the same network depends negatively on the geographical and social status distances and positively on the number of common friends, with the 'strength' of these three factors being regulated by three parameters of the model (indicated in the sensitivity analysis below as, respectively, $h$, $r$ and $k$). Once a link is created between two agents, a *weight* is assigned to the link equal to the probability of its creation, so that the interaction between pairs of agents is more 'intense' the closer they are geographically and socially, and the higher the number of common friends.

During each simulated day, a list of daily contacts is drawn for each agent based on its ego network as follows. For each agent, the *mean* number of contacts by age group associated with the agent's age group is determined (from the empirical data). The *actual* number of contacts for each agent is then determined through a random draw from a Poisson distribution with parameter $\lambda$ equal to the mean number of contacts for that agent's age group. Then, the list of daily contacts is created by randomly drawing the actual number of contacts from the agent's ego network with probabilities proportional to the links' weights.

Because of the physiological effect of the virus (for infected agents with symptoms) and the agents' behavioural reaction to the risks posed by the pandemic (see the previous sub-section), during the pandemic the capacity and availability of the agents to engage in social interactions may be reduced by a certain factor, which we call the agent's *isolation rate* ($i$). The values of $i$ can go from 0 to 1 for hospitalized agents. The isolation rate affects the size and the composition of the list of the agent's daily contacts. First, the mean number of contacts for an agent is reduced by a factor equal to the product of that agent's isolation rate and the weighted average of its contacts' isolation rates (with the weights being the strength of the network's links); second, the weights of the links are reduced by the contacts' isolation rates (so that the agent is less likely to meet people with higher isolation rates).

On any given day, the probability that a given agent becomes exposed, depends on three indexes representing the *intensity* of the interaction in the three settings mentioned above, and the interactions' *contagiousness*, which is 0 for interactions with susceptible or exposed (i.e. infected but not yet contagious) agents. Formally, an agent's probability of becoming exposed $p_e$ is given by:

$$p_e = \frac{e^r - 1}{e^r} \tag{9}$$

where $r$ is the *total risk of infection*, which is given by:

$$r = \alpha s + \beta d + \gamma c \tag{10}$$

with $s$ being the risk of exposure by social contact, $d$ the risk of domestic exposure and $c$ the risk of being infected through the social care process (multiplied by the respective proportionality factors, which are parameters of the model).

The risk of exposure by social contact, in turn, is given by:

$$s = n\bar{v} \tag{11}$$

where $n$ is the number of daily contacts and $\bar{v}$ is the contacts' average contagiousness.

The risk of domestic exposure, is given by:

$$d = \sum_{i=1}^{h} v_i \theta \tag{12}$$

where $h$ is the size of the household, $v_i$ is the contagiousness of household member $i$ and $\theta$ is a prudential behaviour, risk-reducing factor, which is equal to 1 if the agents are not infected or are infected but are unaware of this fact, while $\theta < 1$ otherwise.

Finally the risk of exposure through social care is given by:

$$c = \sum_{i=1}^{k} (t_i \theta)^{\phi} v_i \tag{13}$$

where $k$ is the number of social care interactions (the number of people met to receive or provide for care), $t_i$ is the number of hours of care in interaction $i$, $\theta$ is the test-dependent, risk-reducing factor, $\phi$ is a parameter determining how the risk grows with the time of care (in our simulations, $\phi < 1$, meaning that the risk grows with time but at a decreasing speed) and $v_i$ is the contagiousness of the agent met in interaction $i$.

#### *Virus infection courses*

Once an agent has become exposed through one of the three spread settings described above, it is assigned one *infection course* over four possible courses, listed below in order of growing severity:

- asymptomatic
- mild conditions (symptomatic not hospitalized)
- severe conditions (hospitalized not in intensive care)
- critical conditions (in intensive care)

In accordance with empirical studies, we assume that the probabilities through which each exposed agent is assigned one of these conditions depends on the agent's age, social status (income quintile) and gender, with the probability of developing more serious conditions growing with age, decreasing with social status and being higher for males than for females[23–29].

Upon exposure, the agent is also assigned an *incubation period*, which, in line with empirical observations[30,31], is drawn from a log-normal distribution with mean of about 5 days, and a *recovery period*, whose length depends on the severity level assigned to the agent (in line with the empirical findings, we assume that the more severe the infection the longer the recovery period), in order to reproduce a log-normal distribution of the recovery period with mean of about 12 days at the population level. The exposed agent is also assigned a *viral load*, $\varepsilon$, which is drawn from a standard uniform distribution.

After the incubation period, the agent starts to develop symptoms (if not asymptomatic) and, in line with empirical observations[32], we assume that the exposed agent becomes infectious 2 days before the emergence of symptoms (therefore, 3 days after exposure, on average). We assume that the agent's contagiousness $v$ is a growing function of its viral load:

$$v = \varepsilon^{\delta} \tag{14}$$

with $\delta$ being a parameter regulating the relationship between viral load and contagiousness.

We differentiate the conditions of symptomatic agents by assigning them a *symptoms severity index*, between 0 and 1 exclusive, with the probability of the agent being assigned a higher value increasing with its viral load and its age, decreasing with its income quintile and being higher for males than for females. The closer to 1 the symptoms severity index, the more severe are the symptoms, the greater is the reduction of the agent's mobility and the higher the probability that the agent will take a test.

After the recovery period, some agents will die, with a probability that also depends on age, social class and gender. All other agents recover and we assume that they are immune to Covid-19 thereafter.

## The pandemic-social care interaction

The pandemic and the social care provision process affect each other, and one of our main goals in this paper is to investigate this complex relationship, especially in terms of unmet social care need inequalities across social classes.

In the previous subsection, we have already seen that the social care provision process affects the dynamics of the pandemic as the care-related interactions represent a channel through which the pandemic spreads. On the other hand, the pandemic affects both the demand and the supply of social care.

On the demand side, agents who are hospitalized receive all the care they need in hospitals, and therefore these parts of social care demand are reduced to 0 for the duration of the hospitalization period. On the other hand, we assume that infected

people may develop symptoms that, although not severe enough to require hospitalization, are sufficiently debilitating that they generate additional social care needs (other than reducing the capacity to provide for social care to nil, if the agents were normally care suppliers). Further, we assume that in infected children with symptom severity above a certain threshold, though below hospitalisation level, are not able to attend school and therefore increase the child care load of their household.

On the supply side, symptomatic agents who are not hospitalized have their care supply reduced to nil if the severity of their symptoms exceeds a certain threshold or if they become aware of their infected status. If the symptom severity of non-hospitalized agents remains below the threshold, the social care they can normally supply is reduced by a certain factor which depends on their symptom severity.

Besides the pandemic's direct effects on social care provision, the model we present is a useful tool to investigate the effects of policies implemented to prevent the spread of Covid-19, such as *lockdowns*. In the Results section below, after presenting the results for the 'No-lockdown' benchmark scenario, we will show the effects of two lockdown policies: a 'full lockdown' policy, under which the agents are not allowed to visit other households, and a 'partial lockdown' policy, under which people can visit other households for social care purposes. In the latter case, we expect the total care supply to increases as we assume that the normally occupied agent (i.e. workers or students) will have more time available for social care provision, given their reduced level of 'pre-pandemic' activity. The effect of 'full lockdown' case on social care supply will be more complex as, if on one hand the normally occupied agents will have more time for social care, on the other, under this policy, people are not allowed to visit other households, so there will be a decrease of carer as people in need can only count on the carers within their household. In both cases, the simulations allow us to assess the *extent* to which social care supply is affected and to take into account these effects in the assessment of the overall desirability of these policy, in comparison to other policies.

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## Author contributions statement

UG prepared the simulation and analysed the results, ES contributed to simulation development, and both ES and UG contributed to the preparation of the manuscript.

## Additional information

**Accession codes:** Not applicable. **Competing interests:** The authors declare no competing interests.

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