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Challenges of integrating economics into epidemiological analysis of and policy responses to emerging infectious diseases

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ABSTRACT

COVID-19 has shown that the consequences of a pandemic are wider-reaching than cases and deaths. Morbidity and mortality are important direct costs, but infectious diseases generate other direct and indirect benefits and costs as the economy responds to these shocks: some people lose, others gain and people modify their behaviours in ways that redistribute these benefits and costs. These additional effects feedback on health outcomes to create a complicated interdependent system of health and non-health outcomes. As a result, interventions primarily intended to reduce the burden of disease can have wider societal and economic effects and more complicated and unintended, but possibly not anticipable, system-level influences on the epidemiological dynamics themselves. Capturing these effects requires a systems approach that encompasses more direct health outcomes. Towards this end, in this article we discuss the importance of integrating epidemiology and economic models, setting out the key challenges which such a merging of epidemiology and economics presents. We conclude that understanding people's behaviour in the context of interventions is key to developing a more complete and integrated economic-epidemiological approach; and a wider perspective on the benefits and costs of interventions (and who these fall upon) will help society better understand how to respond to future pandemics.

1. Introduction

Pandemics do more than make people sick. Pandemics lead to changes in peoples' behaviour, changes in income, and changes in demand for household produced and public services amongst other impacts. Changes in economic and health incentives alter behaviour, which creates feedbacks to the infectious disease dynamics that make people sick and cost lives. For policy makers to identify better strategies to manage future pandemics, it is important to take into account these complex, often non-linear, interactions among different systems. Quantitative models help analysts keep track of interactions and feedbacks and provide decision makers with a more complete picture. This is why integrating economics into the analysis of epidemiological problems is of first-order importance to predict the effects of epidemics and epidemic policy (referred to as positive analysis), and to evaluate preferred strategies to tackle epidemics (known as normative analysis). This integration of economic behaviour into epidemiology, and then into models informing general economic policy, is critical. In this paper, we provide a partial summary of the insights that economics offers into how society might best respond to evolving and future pandemic, and outline some of the main challenges we see in deploying these tools in practice.

How the scope of an epidemic is defined by the analyst matters. Consider, as an illustration, how different possible behavioural (non-pharmaceutical) interventions such as social distancing, closing schools, and banning non-essential travel might affect health and economic outcomes during a pandemic. Both *direct* and *indirect* channels of influence need to be considered. The direct effects on health and economic

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outcomes might be captured by separate epidemiological and economic models: e.g., closure of schools reduces the disease transmission rate in an epidemiological model and restricts labour supply due to increased childcare burden in an economic model. But key indirect effects arise from the interdependence between health and economic outcomes: a health-carer or other critical worker may need to reduce the time spent on patient care or supply medical supplies or groceries to meet increased demands of childcare, and this affects health outcomes. These indirect effects can only be captured by integrating epidemiological models with economic models, as illustrated in Fig. 1. This is the challenge not just for positive analysis ("what will happen if we do x?"), but also for normative analysis of policy options ("is x the best choice of policy decisions?"). Normative economic analysis is concerned with how to evaluate these combinations of economic and health outcomes so as to assess which policy interventions should be undertaken. This requires giving consideration to values and preferences within society and the trade-offs revealed by the positive analysis.

In what follows, we discuss challenges in applying positive and normative approaches to understand the implications of alternative policy choices during a pandemic, aiming our discussion at an audience of non-economists. One such challenge in the positive analysis of policy is the "Lucas Critique": it is naïve to presume one can predict the future based on the stable past performance of 'parameters' of health and economic models used to assess policy interventions when they are highly aggregated, because these key parameters can change when a policy intervention occurs. Whilst a policy intervention affects current constraints on behaviour it also influences people's expectations about the future state of the world, so that the relation between individual behaviour and an intervention has a new and less predictable element: how the intervention affects expectations. A second exemplar challenge, this time in normative analysis, is how to compare what many may regard as incommensurable impacts. For example, how can we compare a life lost, with an increase in domestic violence, with a loss of earnings?

In the final section of the paper, we reflect on a different policy problem—the challenge associated with mitigating the risks of future pandemics. For example, how might society overcome a natural bias towards focusing resources on dealing with current problems such as traffic congestion, rather than those that might arise in the future such as the emergence of new zoonotic diseases? What would an economically sensible programme of investment in prevention of future diseases look like, given the increasing likelihood of new diseases arriving in the future?

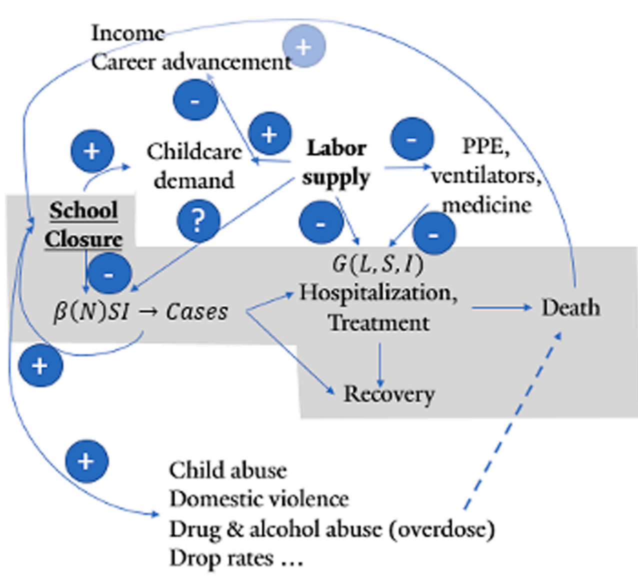

Fig. 1. Illustration of how economic processes are affected by and effect epidemiological outcomes for the example of school closure measures. We note that the indirect effects from school listed in this figure are from a high-income country and are not an exhaustive list. School closures may cause other indirect effects such as undernutrition, agricultural disruption etc, not represented here, since this figure is to illustrate the interplay between economic processes and epidemiological outcomes. The grey region is the domain of traditional epidemiological models and how these might analyse a school closure intervention.

2. Challenge 1: how to capture the range of impacts of an intervention when evaluating policy?

In the face of a novel pandemic, governments confront difficult policy decisions regarding how best to control and mitigate the impacts of a pandemic. Economists typically focus on "trying to achieve the most good for the most people" given constraints including infectious disease burdens, money and time – although this "discounted utilitarianism" is only one (albeit the most commonly-adopted) of the possible ethical underpinnings for normative economics (Hanley and Spash, 1994; Roughgarden, 2001). In contrast, epidemiologists are typically more narrowly focused on minimizing adverse health outcomes. Both approaches face challenges at the start of a novel pandemic as decisions need to be made quickly under great uncertainty about the short and long term impacts of the pathogen and about the availability and effectiveness of potential control measures. In the early phases of a pandemic, focus is typically on a single health outcome which is, at the time, deemed of primary concern. For example, in the case of COVID-19, the focus of many governments was to ensure health systems were not overwhelmed, whatever the societal or economic costs of achieving this.

In this section we consider how we might better evaluate policy decisions in the broader context, whilst noting that this may be difficult to achieve in the early phases of a pandemic due to the inherent constraints of real-time decision making under uncertainty.

Traditionally, (health) economists have used cost-effectiveness analysis to evaluate alternative health care interventions such as vaccination programmes. Cost effectiveness typically focusses on how to achieve a pre-defined target at least cost, or how to maximise the beneficial outcomes from a given budget. "Cost" here can be defined in many ways, for example including both transfer payments and resource costs, or as being from a private sector or a societal viewpoint. Use of a pre-specified target in cost-effectiveness analysis focusses attention away from the full range of benefits or costs of interventions. As a result, it can lead to the omission of many impacts which could be relevant for well-being – such as decreases in childrens' mental well-being due to missing school. Experience with the COVID-19 pandemic has illustrated that such side-benefits (and costs) can be extensive, which means they are important to take into consideration when evaluating policy decisions regarding interventions.

Cost benefit analysis (CBA) (also referred to as benefit-cost analysis) is a framework used by economists to consider the primary and secondary market impacts of an intervention throughout the economy. CBA asks: whether the sum of quantifiable benefits outweigh the sum of quantifiable costs? Unlike cost effectiveness analysis, CBA does not take as given the target that should be achieved. Instead it analyses how the full range of social benefits and costs change through a policy intervention.

CBA is used worldwide to evaluate public policies, including policies on public health and development (Hanley and Barbier, 2009).[1] Thunström et al. (2020) is an early example of using CBA to understand the trade-offs of social distancing to reduce COVID-19 risks. CBA identifies how an intervention (e.g. a lockdown) affects individuals, and the related repercussions of the intervention on firms' opportunities and decisions, market performance, government revenues and expenditures and environmental outcomes. Economy-wide benefits and costs of the intervention are quantified relative to a status quo (here, no lockdown).

[1] See, for example, https://sites.sph.harvard.edu/bcaguidelines/.

What counts as a benefit or cost within CBA is any positive or negative change in well-being for an individual, or in net benefits to a firm, whether these are valued by markets (for example, a rise in the price of electricity) or whether they are “non-market” (for example, a decrease in urban air pollution). If, from the perspective of society as a whole, the aggregate benefits exceed the aggregate costs (i.e., there are positive net benefits), the intervention is a potential improvement to overall well-being in the sense that, in principle with scope for compensations, there is the possibility to make some people better-off without making anyone worse-off. This is the so-called “Kaldor-Hicks Compensation Test”—do the winners win more than the losers lose?

The ‘potential’ qualification in the Kaldor-Hicks test is important for three reasons. Firstly, in practice, the benefit of an intervention may not exceed the cost for everyone. For example, suppose the key benefit of a lockdown is the prevention of COVID-19 deaths, while the costs are loss of income from the interruption to work. In broad brush terms, the benefits are largely enjoyed by the old who are more at risk, whereas the costs are mainly incurred by those who are younger and in the work force: i.e., the old gain but the young lose on this simple reckoning. However, when benefits exceed the costs in the aggregate, the policy maker knows that, in principle, those who gain (the old in this example) could compensate the losers (the young) and still be better-off than they would be without the intervention because benefits in the aggregate exceed the costs.

A second objection to the Kaldor-Hicks test is that governments may have no intention of actually compensating those who lose out, undermining the ethical basis of the Kaldor-Hicks test (Sen, 2000). Over time, this could lead to the accumulation of undesired impacts on income or wealth distribution that, in turn, require an explicit consideration of how concerns like equity are to be weighed against those of efficiency which are identified through CBA. Economists have had rather fewer useful or uncontroversial things to say about this weighing of equity and efficiency. Finally, some kinds of costs may be impossible to compensate for, even in principle.

Nevertheless, CBA provides a framework within which (a) all types of benefits and costs (market and non-market) associated with a policy intervention can be considered and (b) the distributional consequences of alternative actions can, in principle, be identified (e.g., is it really the old that gain from a lockdown and the young that lose once the full range of benefits and costs are considered? What are the differential impacts of lockdown on above-average income households compared to below-average income households?). The CBA framework allows policy makers to estimate whether a policy change will add to net social well-being; and provides a consistent structure and criterion that allows the implications of alternative policy interventions to be evaluated and ranked. True, profound conceptual issues have been identified with equating “passing the CBA test” with “adding to net social well-being over time” (e.g., Addicott et al., 2020), and in knowing how best to aggregate gains and losses to different parties over time. Yet CBA remains, in many economists’ eyes, a useful framework to help guide complex public policy appraisal (Hanley and Barbier, 2009; Carolus et al., 2018).

However, there are many challenges in the application of the CBA test to infection control interventions during a pandemic. First, relevant benefits and costs are broadly defined as any positive or negative impact, now and in the future, on individual well-being to any member of society. These must be rendered comparable in any calculation of a net-benefit, which requires a common unit of account for valuing the different benefits and costs. Today’s £s or $s are used for this purpose. If a person is willing to pay a particular price for something that is beneficial to the person in question, then this action is taken to reveal the minimum marginal benefit that a person attaches to that item. This makes it possible to calculate policy impacts on marketed goods and services because they have market prices. For non-market impacts such as changes in health, traffic noise and air pollution, or increases in anxiety, market values do not exist. However, economists have developed a variety of techniques to estimate the marginal costs or benefits of such impacts. We discuss one specific non-market value - the economic benefits of protecting lives – in detail below, as we consider in the specific challenges of applying CBA to infection control interventions during a pandemic.

2.1. *Challenge 1a: measuring long term health and economic impacts in the face of uncertainty*

We begin with the costs to the economy in terms of foregone output resulting from imposition of a lockdown. These costs are in some ways the least problematic to value, in the sense that the goods and services that are not produced as a result of an intervention such as a lockdown have readily identifiable prices. However, a significant challenge arises because CBA requires all costs, present and *future*, to be entered into the calculation. For example, analysts have used macroeconomic estimates of expected GDP changes to quantify the economic costs of lockdown measures bought in to control the spread of COVID-19 (see Thunström et al., 2020; Miles et al., 2020). The longer/more intense the lockdown, the smaller is GDP now than it otherwise would have been. But how is future GDP affected by the duration/intensity of a lockdown implemented now? (Keogh-Brown et al., 2010; Bayham et al., 2020).

A further complication is that GDP is not a measure of net benefits to start with, it is better described as marketable production (Coyle, 2015; Stiglitz et al., 2010), with measurement of healthcare, education, public services, finance and insurance all highly problematic.[2] Moreover, GDP does not include changes to in-home services that might rise (e.g., childcare), carbon emissions that might be avoided, or innovations that are spurred by the change in people’s circumstances. Answering questions like these related to the long-term economic costs of interventions is difficult. This is in part because of the huge uncertainty, particularly at the start of a pandemic, in the properties of a novel virus, and how economic activity will respond to different control actions. Moreover, the highly non-linear nature of pandemics makes predicting future benefits and costs difficult, since it becomes hard to determine the effects of interventions on disease outcomes beyond the short run.

COVID-19 illustrates this problem well. At the start of the pandemic, scientific advice to the UK government presented two behaviour interventions: mitigation and suppression.[3] Mitigation focuses on slowing the spread of the disease and was deemed impractical because epidemiology models predicted health systems quickly would become overwhelmed. The only option considered was suppression. This involves the reversal of epidemic growth until a low level is maintained, possibly indefinitely until pharmaceutical interventions become available: either through an indefinite lockdown or intermittently through cycles of lockdown-relaxation-lockdown. The future GDP costs of a lockdown are uncertain because the duration of initial lockdown or the number of stop-go lockdown cycles depends on the date at which pharmaceutical interventions become available and the evolution of the virus, which are both uncertain. Innovations that occur in response to lockdowns (e.g., changes to home-working technologies) are also uncertain, which is problematic if such innovations affect benefits and costs.

The future uncertainty over how a pandemic will evolve is challenging when trying to quantify the future economic costs of interventions, and because of the problem of identifying which interventions to include within a CBA. For example, Gollier (2020) found that uncertainty about the rate of spread of the virus reduces the optimal intensity of a lockdown in the early (learning) phase of an

[2] GDP is good at measuring production of relatively homogeneous physical goods that do not experience rapid innovation. This was useful, particularly in the middle part of the 20th century (Coyle, 2015; Fenichel et al., 2020).

[3] Full details of evidence presented to Scientific Advisory Group for Emergencies (SAGE) in the UK available here https://www.imperial.ac.uk/mrc-global-infectious-disease-analysis/covid-19/report-9-impact-of-npis-on-covid-19/.

epidemic. In contrast, Giannitsarou et al. (2021) found that for diseases with waning immunity, the initial intensity of lockdowns should be higher than when immunity is permanent. Yet at early stages of a novel disease like COVID-19, it is difficult to ascertain whether immunity will eventually wane. Bayham et al. (2021) find that the arrival rate of vaccines has a large impact on optimal school closures.

In the UK and much of Europe, the focus at the start of the COVID-19 pandemic was on mitigation or suppression with little discussion of a third behavioural intervention strategy: elimination. This is probably because elimination is seldom economically optimal (Barrett and Hoel, 2007). For example, at the start of the pandemic, COVID-19 was treated by some as a flu-like pandemic (Lee et al., 2021) for which evidence suggests elimination is difficult and expensive (Ferguson, 2006; Inglesby et al., 2006). Elimination was discounted as a potential strategy (for further discussions on the elimination versus endemicity strategy see the challenges paper on this topic also in this series, Metcalf et al., 2021). While the initial costs of an elimination strategy may be high, it was not considered whether these may be less than the long-term costs from multiple lockdowns needed under a suppression strategy. The point is that, with a new virus, it is difficult to know what longer term health-wealth trajectories might be available through different policy strategies, because these depend on the character of the virus which is poorly understood at the onset of a pandemic. A similar set of knowledge difficulties also attach to the detailed effects of specific elements in any lockdown strategy (e.g., social distancing, school closures, and the like), making the application of CBA more difficult.

2.2. Challenge 1b: quantifying the wider social and health costs of interventions for COVID-19

Typically, the cost of health interventions focuses on the direct economic costs, for example the cost of a vaccine or the loss to GDP from a lockdown. The experience of the COVID-19 pandemic, however, has shown that interventions themselves can have negative effects on the health system and wider society. Like the economic costs discussed above, the knowledge difficulties are again significant for these wider social and health costs (see Roy et al., 2021).

What are these wider costs? They can include:

- The rise in domestic violence due to lock-down (Boserup et al., 2020; Hisham et al., 2020). Domestic violence, like any other crime, imposes serious costs on the sufferer, but can such impacts be expressed in monetary terms to allow them to be included within a CBA? Domestic violence will reduce well-being, and there are well-founded approaches which link changes in self-reported (subjective) well-being (SWB) to monetary values (Ferreira and Moro, 2010), essentially by calculating the trade-off rates between those determinants that are positively related to well-being such as income to negative determinants (Mahuteau and Zhu, 2016).
- Mental health effects of isolation (Rossi, 2020) and fear of unemployment; as Hisham et al. (2020) say "…epidemics such as SARS and COVID-19 adversely affect mental health in a multitude of ways, permeating at individual, communal and societal levels". The effects of declines in mental well-being due to COVID-19 on SWB have been estimated for 1500 respondents in Germany, for example, although the authors do not then convert this into economic costs (Rudolph and Zacher, 2020).
- Disruption of education (school closures) also leads to lower mental well-being amongst school-children, for example due to the reduction of regular contacts with their friends. Subjective well-being approaches have been successfully applied with children which link SWB to mental health indicators and to contacts with school friends (e.g., Moore et al., 2018). In principle, such linkages could again be used to generate economic cost estimates for use in a CBA of pandemic control options.
- School closures can contribute to reduced future earnings due to disruption of education. The discounted lifetime earnings approach (Jorgensen and Fraumeni, 1992) can be used to estimate these costs due, for example, to lower university entrance, since we know that university degrees are associated on average with higher earnings (Dickson and Harmon, 2011). School closures can also reduce the hours that health care (or other) workers are able to supply: Bayham and Fenichel (2020) found a potential 15% decline in labour supply of healthcare workers due to child care needs associated with school closures in the US, if other options were not made available. This would reduce the quality of treatment outcomes for COVID-19 patients. Women have seen greater wage losses than men related to COVID-19 related distruption (Alon et al., 2020).
- Impacts on non-COVID-19 medical outcomes (e.g. delay in cancer screening) of the re-allocation of health care resources: cost-of-illness or Willingness To Pay-based approaches can be used to value increases in morbidity or mortality for non-COVID-19 diseases which are attributable to the diverting of health care resources to COVID-19 care.

2.3. Challenge 1c: determining the economic value of lives saved

The valuation of lives (or life years or quality adjusted life years) is the key driver of any pandemic benefit calculation (see for example Robinson et al., 2021; Evans and Taylor, 2020; Hall et al., 2020). There is a variety of ways in which economists impute a monetary value to a life saved. The most common in many policy contexts (e.g., pollution interventions) involves determining how people trade off higher wages for riskier jobs, or by asking (or imputing the answer from behaviour) to people questions like 'how much would you pay for an environmental intervention that reduces your chances of dying from air pollution by 3 in 100,000 to 2 in 100,000?'.[4] Suppose the average answer were $30, then in a population of 100,000 in which 1 life is saved through the intervention, the value that is placed on this one statistical life (what economists call the Value of a Statistical Life, or VSL) is $3m (i.e., 100,000 × $30). This is the baseline figure recommended by the OECD in more usual policy evaluations in which lives are affected (e.g., air pollution reductions). Some estimate for the VSL must be used if different interventions with different profiles of costs and benefits are to be compared.

The problem, however, with the use of VSL calculations for a pandemic is that the standard questions used to elicit values are too focused on the individual's own chances of death. Yet people care about how an intervention also affects the chances of *other* people dying. For example, an individual may not only care about how a lockdown affects their own chances of dying from COVID-19, but also that the lockdown influences their chances of transmitting the virus to an elderly relative. Of course, a selfish person will not be concerned about this difference, but anyone who cares about others will be; and the elicitation question should allow for this possibility (Gersovitz, 2011; Geoffard and Philipson, 1996). When it does, estimates of the VSL appear to be much higher (see Hargreaves Heap et al., 2020).

One might argue that there are other reasons why contemporaneous elicitations of VSL may lead to extraordinarily high values and should perhaps be downplayed or even ignored by policy makers. For example, it is well known that people are more likely to take out earthquake insurance after a major earthquake has been in the news, and it is difficult

[4] In the US and UK, the VSL has been estimated using a combination of revealed preference (e.g., hedonic wage risk studies) and stated preference methods. See for example Visicusi (2018) for detailed discussion on how the VSL is created using either or both preference elicitation methods and then used in policy work. In the specific CBA analyses of COVID interventions, the value of QALYs has often been used because the demographic incidence of death os skewed towards certain groups (e.g. see. Miles et al., 2020).

to see why this temporary psychological sensitivity to recent events should guide policy making, especially when policies have long run effects. However, even some part of the high COVID-19 VSLs cannot easily be ignored for this reason. This is because there is evidence that people are more likely to comply with policies that they agree with. Naturally, a positive net benefit may not be the only way that people come to agree with a lockdown policy, but in so far, for example, as a high VSL counts against an early relaxation of a lockdown, then it is possible that when the effects of such a relaxation are modelled the modellers will have to take account of the way any diminished agreement with the relaxation will impair compliance. Suddenly, a high COVID-19 VSL not only complicates CBA, it also complicates modelling of disease control. The modelling and the evaluation of a policy can no longer be treated as separate exercises.

2.4. Challenge 1d: valuing the indirect benefits from interventions

Health-focused lockdown benefits comprise deaths avoided, lower incidence of non-lethal health impacts like 'long-COVID', and the reduction in anxiety that comes from reducing the threats of COVID-19 to those who are not yet infected. With a new virus like COVID-19, the modelling of lives saved and occurrence of non-lethal health outcomes involves obvious challenges because data are emerging as policy is being enacted. For example, it only became apparent in the course of the pandemic that the incidence of death was concentrated among the old and those with co-morbidities, so that the years of life lost were smaller than would have been the case had the incidence of death been uniformly distributed across the population (Hanlon et al., 2020).

However, ancillary benefits from lockdowns such as reductions in urban air pollution and noise, reduced vehicle collisions, and reductions in influenza are also potentially important. These can be valued using a range of non-market valuation approaches (Hanley and Barbier, 2009). There is now a great deal of research on what these Willingness to Pay values look like for many different measures of air pollution, for instance, using techniques such as contingent valuation and hedonic pricing; whilst the Subjective Well-Being approach can also be used to value changes in air pollution (Dolan and Laffan, 2016).

3. Challenge 2: interactions between health risks and economic behaviour

Health risks impact behaviour; behaviour affects health risks. Understanding these impacts and feedback loops between health and economic systems is critical for better predictions about the likely health and economic risks posed by a pandemic like COVID-19. Furthermore, understanding these feedbacks is important for understanding the likelihood that a given intervention will alter the course of the epidemic in a particular manner. Integrating insights from epidemiology and economics into one coherent framework provides a way to understand these feedbacks between the two systems.

There is ample empirical evidence that people respond to infectious pathogen risk by changing their behaviours (Bayham et al., 2015; Fenichel et al., 2013; Malik et al., 2020; Villas-Boas et al., 2020; Yan et al., 2021a). This has led to numerous calls and some efforts to create behavioural epidemic models (Funk et al., 2015, 2010; Kremer, 1996; Manfredi and D'Onofrio, 2013; Perrings et al., 2014). Most attention has focused on the transmission function or the propensity to vaccinate (Francis, 1997; Chen and Toxvaerd, 2014; Ward, 2014). Fenichel et al. (2011) argue in favour of embedding a model of utility maximisation based on adaptive expectations, in which a representative individual maximises the private net present value of utility flows from contacting others to provide a description of behavioural adaption. Using this approach one of the key parameter was found to be the elasticity of behavioural response to prevalence (Philipson, 2000; Fenichel, 2013). Although we note that perception and/or motivational related behaviour rather than prevalence itself may also be important.

To illustrate this, we briefly discuss how the transmission term in an epidemiology model can be altered to include behaviour directly into the modelling framework. The transmission term in a standard epidemiology model takes the following form $C(\cdot)\beta(\cdot)SI/N$, where the number of contacts is independent of population size (N), as is typically the case for human infectious diseases (frequency-dependent transmission), $C(\cdot)$ is the rate that susceptibles contact other individuals, and $C(\cdot)I/N$ is the rate at which susceptible individuals contact infectious individuals, and $\beta(\cdot)$ represents the likelihood that contact with an infectious individual results in transmission. Traditionally, analysts have treated β as fixed and driven by host-pathogen biology. However, it is increasingly clear that β must also capture "the quality" or intensity of the contact, which can be modulated by choices such as physical distancing and mask wearing (Jarvis et al., 2020; Stutt et al., 2020). Moreover, β could also change over time as the pathogen evolves, e.g., as new variants emerge. In Fenichel et al. (2011) the contact function $C(\cdot)$ is a function of the choices of susceptible, infectious, and recovered individuals.[5] These choices are modelled based on economic theory so that they adapt to the state of the world leading $C(\cdot)$ to be time varying. Each class or compartment of like individuals solves a class-specific expected utility maximisation problem, where location, mixing choices and health outcomes matter to the decision maker, but the decision maker does not have lexicographic preferences for health. The representative agents solve their respective problems, use the first period solution, and iterate forward (the adaptive expectations assumption). Fenichel (2013) used this approach to consider the optimal sequence of contacts for each group that minimises social welfare losses from an epidemic. Other algorithms and expectations models are possible (Acemoglu et al., 2020; Fenichel, 2013; Fenichel and Wang, 2013). Recent extensions have mapped contacts into economic transactions or consumption and avoiding welfare losses from expected infection (e.g., Acemoglu et al., 2020, Toxvaerd, 2020). Others, using similar economic-epidemiology principles, have moved from traditional mean-field analyses to network-based analyses (Akbarpour et al., 2020).

Incorporating behaviour directly into models is important to understand the potential unintended consequences of an intervention. For example, Bayham and Fenichel (2020) show that while school closures could reduce contacts and cases, they can potentially *increase* disease-induced mortality per infection by reducing the health care labour force due to childcare responsibilities of healthcare workers in the absence of schools or alternative child care. Aadland et al. (2013) demonstrate the difficulty in managing the spread of an infectious disease in the face of heterogeneous populations. While low activity individuals react to the risk of infection and attenuate the oscillations of a disease through the population, high activity individuals react to the risk in the opposite direction and exacerbate the oscillations. Further unintended consequences are found in Aadland et al. (2020) who make the point that when merging epidemiological details into economic modelling, nonconvexities are introduced into human decision rules. Policies that lower the transmission probability (e.g., preventative therapies) or policies that raise quality-of-life following infection (e.g., curative therapies) may push endemic equilibria from being stable to exhibiting instability or indeterminacy, which can contribute to the volatility and unpredictability of the system. Toxvaerd (2019) considers the possibility that policies backfire due to behavioural disinhibition. In particular, the introduction of pre-exposure prophylaxis, which reduces

[5] If $C = 1$, we have frequency dependent transmission; if $C = N$, we have density dependent transmission; there are many variations in between since C is a function of all individuals in society including mixing patterns (see McCallum et al., 2001 for further generalised forms of $C(\cdot)$). There has been substantial work expanding health states as vectors of observable characteristics (e.g., age, gender, income, household size). There has been considerable work using various data sources, e.g., surveys, administrative data, and smart device data to measure and parameterised behavioural responses.

the probability of disease transmission for each unprotected contact between infected and at-risk individuals, may increase overall contacts in the population and thereby increase aggregate disease transmission and make everyone worse off. Yan et al. (2021b) found a similar empirical effect that led individuals to spend more time out of the house following face mask mandates.

We now examine six key challenges to this "bio-economic" modelling of interventions.

3.1. Challenge 2a: utility functions

First, utility functions, constraints, and expectations models must be specified in a way that avoids the time varying problem that leads to the Lucas critique. This is important for making projections under novel conditions. As a first step, this means that expected utility must be a function of the probability of future health states. The approach above is strictly selfish-utilitarian, in which the representative individual only has preferences over his or her own contacts and health, but it is possible to specify functions with a degree of preferences over the state of the system, the health of others, and other intrinsic motivations (see e.g., Fehr and Schmidt, 1999; Bénabou and Tirole, 2006).

3.2. Challenge 2b: constraints

Second, constraints that influence behaviour also need to be a function of future health outcomes, economic states, and considerations such as income, policies and associated penalties for violating regulations. For example, the contact choice may be a function of income and savings, employment opportunities, and child care demands (Bayham et al., 2021). Furthermore, social distancing policy that is not enforceable creates different behavioural responses than policies that have strong enforcement mechanisms (Becker, 1968).

3.3. Challenge 2c: modelling the formation of expectations

Fenichel and Wang (2013) discuss three approaches to modelling people's expectations: adaptive expectations, which assume the world will stay as it is but update continuously, scientific expectations, which are an extension of adaptive expectations that use a forecasting model to predict future states but update continuously as new information arrives, and rational expectations that result from solving the dynamic equilibrium. Yet, COVID-19 has illustrated that the role of information provision is critical in this process, implying that explicit information processing models may be important to develop appropriate behavioural epidemiological models. Expectation models can lead to caution or fatalism, so understanding how people form expectations is critical (Kremer, 1996).

3.4. Challenge 2d: behavioural departures from rationality

COVID-19 poses risks to private health. These risks are defined by the combination of (a) the probability that a person becomes infected/ill, and (b) the severity of the illness if realised. Like nuclear power and environmental accidents, these pandemic health risks fall into the classic category of a low-probability/high-consequence event, e.g., small chance of a highly adverse outcome such as death. If people reacted rationally to these low probability/high consequence risks, their decisions would account for the expected damages associated with different actions. They would invest resources either to reduce the odds that they will get ill or to reducing the severity if they become ill, or both. But herein lies the challenge—experience tells people little about how to react to these low-probability, high-consequence risks. People who have low odds of confronting a catastrophe seek information to help them judge the likelihood that a bad event will actually occur (see, e.g., Viscusi, 1998; Shogren and Taylor, 2008). This information can be vague or ambiguous. Behavioural studies reveal that under these circumstances, people do not react rationally to the expected damages; rather they tend to have a bimodal response—people either ignore these risks completely or overestimate the chance that they might suffer from such a risk. Both reactions could render policy ineffective if it were designed presuming that citizens would respond rationally to health risks. Policymakers must presume that people will react to the risk, but they could benefit from more guidance on the nature of the distribution of the likely reactions of their citizens—they need information on how many would do nothing relative to those who would over-invest in protection. Incorporating this information on how people react to risk into the epi-econ models is a challenge that if mastered, would help better define their predictions.

3.5. Challenge 2e: time-invariant parameters

Estimating the time-invariant parameters associated with utility functions, expectation formation, and constraints is a non-trivial challenge. This is made more difficult because parameters that could have been taken as non-time varying outside an epidemic such as the prices of personal protective equipment, the probability of becoming unemployed, or mean household size, may shift as a result of interventions and/or the progress of the outbreak. For some policy questions, behavioural epidemic models may need to consider these general equilibrium effects.

3.6. Challenge 2f: heterogeneity

The epidemiology community has rightfully identified heterogeneity in personal traits, e.g., age and gender, as a key challenge in modelling behaviour (see Funk et al., 2015). In a simulation context it is relatively straightforward and common to extend the compartment structure to other classes, including age and gender. Bayham et al. (2021) argue that household size and income are also important classes. Household size is especially important when considering policies that encourage individuals to stay home (Bayham and Fenichel, 2016), but likely also matter for consideration of the role of economic and housing support during a pandemic. As compartments expand, the model starts to look more like an agent-based model or network model, and assigning parameter values associated with each compartment becomes more and more challenging. Some progress in integrating economics and epidemiology is being made on this front (Akbarpour et al., 2020). An alternative that balances the elegance of the compartmental model approach and agent-based modelling approach is the distributed or micro-parameters model (Hochman and Zilberman, 1978). Rather than using a mean-field approach, the micro-parameters approach integrates over a distribution continuously. Veliov (2005) applied this approach to infectious disease models. The challenge is that equations of motions are required for the sufficient moments of the distributions (e.g., mean and variance). Furthermore, if behaviour is assortative by type, then mixtures may become intractable. An insight from distributed parameters models is that the average behaviour, average wellbeing, and average physical impacts are unlikely to accrue to the same "average" individual (Fenichel and Abbott, 2014). Beyond the challenge of building and parameterising such models, there is the challenge of determining the aggregation rules with which to undertake policy evaluation.

4. Challenge 3: the prevention paradox – investment in pandemic prevention

The prevention paradox captures the idea that how people respond to health risks cuts in two ways. A person or policy maker confronting a health risk must address both (i) the risk posed by COVID-19 and (ii) the risk associated with the methods they use to reduce this risk. Intuitively, one might expect a risk averse person to choose *prevention* of the health impact rather than *control* of the realised health impact. But that is not always the case. Prevention is technologically a riskier input relative to control. To a more risk averse manager, a pound spent on control is worth more than a pound spent on prevention because the expected marginal effectiveness of control exceeds that of prevention. Uncertainty in the application of control is lower since it addresses existing health impacts. More uncertainty exists for prevention because it only reduces the chance of getting sick, if it is realised at all; prevention does not eliminate the risk. Since prevention and control act as substitute risk reduction technologies, a risk averse person has incentive to choose the safer bet—control. This is the paradox—one would think risk averse people would choose prevention, but they have more incentive to choose control since it is the less risky technology (Finnoff et al., 2007). This paradox suggests that to protect human health as reflected by the probability of illness and death from infection by COVID-19, people should not be overly cautious—they must be willing to take a risk with prevention.

Unfortunately, in many societies the problem is compounded by individuals placing a low priority on public spending to prepare for a pandemic disease (Pike et al., 2020). In a survey of U.S. citizens, Pike et al. (2020) asked respondents to value fatalities before and immediately after the highly visible 2014 West African Ebola Outbreak, relative to deaths from environmental disaster risks and/or a terrorist attack. In both cases, respondents undervalued the risk of pandemic death. This societal lack of a willingness to take a risk with prevention for crises such as COVID-19 has revealed a critical weakness in the global battle against the threat of pandemics – the lack of a well-funded, long-term strategy to pre-empt or quickly adapt to and control their emergence. Public management of the risk of a pandemic is hampered by insufficient capacity to deal with rare yet devastating events, and the global commons nature of the problem, requiring global, national and local coordination of strategies and responses.

While the importance of investments in vaccines and treatments (therapeutics) are well known, arguments for investments to increase the ability of public health managers to anticipate, detect, prevent, contain, mitigate and control a future disease outbreak so that it does not become an epidemic or pandemic have not been as successful. Pike et al. (2014), Berry et al. (2015, 2018) argue for the importance of investing in the near term to reduce the long-term risk of pandemics. Pike et al. (2014) noted the importance of investing in pandemic prevention sooner rather than later, and demonstrated the cost savings attainable by adopting a One Health policy focused on primary prevention of disease outbreaks in regions of the world in which they are more likely to emerge. Berry et al. (2015, 2018) consider the need to build capacity that can help contain, pre-emptively protect, mitigate, control and insure society against the risk of future pandemics. This reflects the two components of economic risk in this context: the probability of an outbreak and the economic consequences of an outbreak, including loss of life. The structure of the investment in this work is key, requiring both the rapid development of a large standing stock of appropriate assets and an increasing flow of investments to match expected increases in the background risk of a pandemic, and to keep these investments adaptable and operational. However, the specific investments required are left in general terms, and the approach is restricted to a national level, neglecting the global nature of the problem.

Although there are significant challenges, in some instances public agencies have initiated prevention-based programmes. For example, in the US, the Centers for Disease Control (CDC) have promoted the One Health approach, in an attempt to prevent zoonotic transmission in regions of potential disease emergence (US Centers for Disease Control & Prevention, n.d.). Dobson et al. (2020) demonstrate the significant cost savings that can be achieved from improved efforts to prevent zoonotic disease spillovers with primary prevention targeted on regions of disease emergence. Strategies include restricting trade in wildlife species, reducing land use change, and promoting improved practices and protocols to prevent zoonotic disease spillovers to humans. However, this kind of primary prevention requires global cooperation and globally sourced funding, features subject to the global commons problem such as seen with the failure to agree adequate international policies in response to risks of climate change.

5Conclusions

This paper has set out three ways in which economics helps society think about how best to respond to pandemics, both in the present and potential future ones. The paper has also made clear the many challenges in applying these approaches.

The first is an evaluative or normative contribution and comes from the use of cost-benefit analysis (CBA). Interventions to manage pandemics create wide-ranging impacts on society, and cost-benefit analysis allows us to weigh up the benefits and costs to society of different actions, relative to some baseline. These benefits and costs stretch much wider than more obvious impacts on economic activity as measured by GDP to include, for example, impacts on environmental quality and crime; and mean that we consider what is best to do by thinking about more than just the impacts of interventions on prevalence. However, a big question is how to draw the boundaries around such a CBA. These boundaries extend across time (how far into the future are benefits and costs added up when we appraise different prevention strategies?), across people (how wide a set of impacts should be included?) and across space (if Germany imposes a lockdown, do we also count impacts in France within the analysis?). Stretching these boundaries allows us to recognise some of the less obvious impacts of interventions, such as the effects of school closures on children's well-being, and on labour supply to the health service by parents, but also poses greater challenges of understanding and quantification for the analyst.

The second is a positive contribution and comes from integrating the models of health and economic outcomes to understand better how interventions influence disease dynamics. The key to this is a model of individual behaviour within both an economic and health context. Pandemics impose economic and health consequences, and how people respond to these risks will affect transmission of the disease. A model of rational choice or utility maximisation is a natural choice for this purpose; but people do not always respond to risk in the way which is consistent with this standard model. Behavioural science shows that non-standard preferences, beliefs and behaviours all matter when trying to understand the feedbacks between the systems characterised by uncertain benefits and costs.

Thirdly, we set out some of the important paradoxes that would seem to hamper the development of appropriate preventative strategies, given the likelihood of future pandemics occurring.

Last, while we have presented the issues of policy evaluation and the integration of behaviour into disease modelling as separate challenges, the two are closely related. A complete cost benefit analysis requires an understanding and incorporation of individual behaviour. To see this, recall that the cost-benefit analysis calls on the analyst to weigh up the benefits and costs to society of different actions, relative to some baseline. However, the relevant baseline to evaluate interventions to manage the disease is itself dependent on individuals' voluntary behaviour to self-protect; and this in turn may depend on people's evaluation of the intervention. In a fully-fledged behavioural epidemic analysis, the reasonable worst-case scenario against which different policy measures are measured cannot be a "non-behavioural" benchmark scenario in which people do not respond to increasing risks by changing their behaviour. For such a comparison will be unreasonably pessimistic about what can be expected, and could lead to fatalism in individual models of expectations. In turn, this could lead to the need for and effects of policy interventions being overstated. But by the same token, by not adequately considering the role of voluntary behaviour to self-protect, such as has been the case with social distancing during the COVID-19 pandemic, policy will wrongly be viewed as causing more economic damage than it does. A fully-fledged economic epidemiological cost benefit analysis will disentangle how much of the costs of policy interventions are due to voluntary behavioural changes, and how much to mandated restrictions.

We end by alluding to an implication of the argument of this paper that economics and biomedical science need to be brought together for an improved understanding of pandemics. For example, in the UK while science has played an integral part of the evidence considered when developing policy (Brooks-Pollock et al., 2021), there has been a distinct lack of representation from the economics research community in the various advisory bodies.[6] As a result, the evidence presented to government has focused solely on the likely impact of control policies, e.g., closure on schools, contact tracing, on limited health outcomes, numbers of cases, hospital admissions and deaths. However, as we have argued throughout this paper, pandemics do not just make people sick—they affect the entire economy as people adapt and adjust to these new risks. Identifying strategies to manage future pandemics cost-effectively, it is vital that evidence presented to policy makers takes into account these complex interactions between different systems. The key challenge is building strong relationships between the economics and epidemiology modelling communities to ensure better representation on government advisory panels for future pandemics.

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Declarations of interests

None.

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