Challenges of integrating economics into epidemiological analysis of emerging infectious diseases

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Abstract

COVID-19 has shown that the consequences of a pandemic are more wide- reaching than cases and deaths. Morbidity and mortality are important direct costs, but infectious diseases both generate other direct and indirect benefits and costs and produce changes in behaviour that modify and relocate these benefits and costs. These additional effects can, in turn, feedback on health outcomes to create a complicated interdependent system of health and non-health outcomes. As a result, interventions primarily intended to reduce burden of disease can have wider societal and economic effects and more complicated, and possibly unexpected system level influences on the epidemiological dynamics themselves. To capture these effects requires a systems approach that encompasses more the direct health outcomes. Towards this end, we discuss in this article the importance of integrating epidemiology and economic models and we set out the key challenges which merging epidemiology and economics presents. We conclude that understanding behaviour is key to developing a more complete and integrated economic-epidemiological approach to help society understand how best to respond to future pandemics.

Introduction

Pandemics do more than make people sick. Pandemics lead to changes in peoples' behaviour, changes in income, and changes in demand for 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 both 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. By doing so, now it will be more like that models used by health officials will be more consistent with models used by central banks, labour and education ministers, and housing authorities.

How the scope of an epidemic is defined 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 both 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 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-care worker may need to reduce the time spent on patient care to meet increased demands of childcare, and this affects health outcomes. These indirect effects can only be captured by integrating epidemiological with economic models, as illustrated in Figure 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.

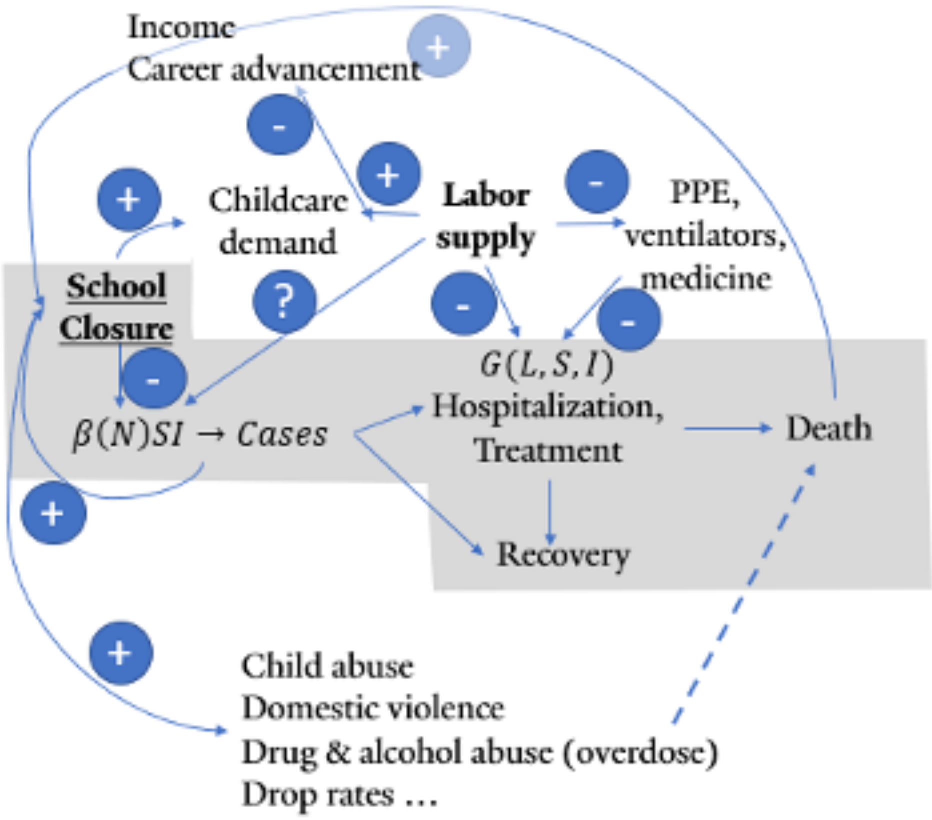

Figure 1. Illustration of how economic processes are affected by and effect epidemiological outcomes for the example of school closure measures. The grey region is the domain of traditional epidemiological models and how these might analyse a school closure intervention.

In what follows, we discuss challenges in applying both positive and normative approaches to understand the implications of alternative policy choices during a pandemic. For example, in the positive analysis of policy, there is what economists refer to as the Lucas Critique: it is naïve to presume you 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 they 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: i.e., how the intervention affects expectations. Likewise, in normative analysis, there is the challenge of how to compare what many will regard as incommensurable impacts. For example, how can we compare a life lost, with an increase in domestic violence, with a loss of earnings? A second comparison challenge is that it is difficult to measure avoided bad outcomes.

In the our section, we reflect on a different policy problem—the challenge associated with preventative policy formation. For example, how might society overcome a natural bias towards focusing resources on dealing with current problems, rather than those that might arise in the future? What would an economically sensible programme of investment in prevention look like, given the likelihood of new diseases arriving in the future?

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 focus on "trying to achieve the most good for the most people" given constraints including infectious disease burdens, money and time (Roughgarden 2001). In contrast, epidemiologists are typically more narrowly focused on minimizing adverse health outcomes. Both are challenging at the start of a novel pandemic as decisions need to be made quickly under great uncertainty about the short (and longer) term impacts of the pathogen and potential control measures. In the early phases of a pandemic, the spillover effects are assumed to be small, so focus is 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 focus more broadly on how we might better evaluate policy decisions in the broader context, whilst noting that this may be difficult to achieve in the early phases due to the inherent constraints of real-time decision making under uncertainty.

Traditionally, health economists have used cost-effectiveness analysis to evaluate health care interventions such as vaccination programmes. Cost effectiveness typically focusses on how to achieve a pre-defined target at least cost. This pre-specified target does not account for the full range of benefits or costs of interventions and is unconcerned with the path to achieving the target. As a result, it can miss out many impacts which are relevant for well-being. 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 for this purpose that takes into consideration both the direct and indirect impacts of an intervention, and which asks: thinking about all of the quantifiable impacts of an intervention, do the benefits outweigh the costs? For cost-benefit analysis, we do not take as given the target that should be achieved, since we need to evaluate how social benefits and costs change as both the target and the means to achieve it are altered.

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 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 the status quo (no lockdown). What counts as a benefit or cost within CBA is any positive or negative change in well-being for an individual, or performance of an institution (firm, government), whether these are typically thought of as "economic" (valued by markets) or not. 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 <u>potential</u> 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 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. Second, governments may have no intention of actually compensating those who lose out, undermining the ethical basis of the Kaldor-Hicks test (Sen, 2000). 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 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

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

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., Jones, 2016; Addicott et al., 2020), and in knowing how best to aggregate gains and losses to different parties over time. Yet CBA remains, in most economists' eyes, the most useful framework to help guide complex public policy appraisal.

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 instance, for something beneficial like a vaccine, 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.

Challenge 1a: Measuring Long Term 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 lockdown have readily identifiable prices. However, a significant challenge arises because CBA requires all costs, present and <u>future</u>, 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, and 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; Smith et al., 2009; Bayham et al., 2020). A further complication is 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 (i.e., childcare), carbon emissions that might be avoided, or innovations that are spurred by the change in people's circumstances. Answering questions like this related to the long-term economic costs of interventions is difficult with a new virus. This is in part because of the huge uncertainty, particularly at the start of the 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.

[2] GDP is good a measuring production of relatively homogeneous physical goods that do not experience rapid innovation. This was useful in the middle part of the 20th century.

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 was deemed impractical because epidemiology models predicted health systems quickly would become overwhelmed. The only option considered was suppression until pharmaceutical interventions became 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 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 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 in the UK was treated more as a flu-like pandemic and the evidence suggests elimination in such cases is both difficult and expensive (Ferguson et al. 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). 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. In the case of the COVID-19 pandemic, some countries applied a lockdown until there were no recorded cases, and then relied on test, track and trace and local lockdowns to eliminate any future outbreaks. These economies have typically avoided the 2nd and 3rd waves that came with the intermittent version of the suppression strategy, and so these countries may have suffered lower losses in GDP than would otherwise have been the case (Fernandez-Villaverde and Jones, 2020). The point, however, is that, with a new virus, it is difficult to know what longer term health-wealth trade-offs 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.

[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/

Challenge 1b: Quantifying the Wider Social and Health Costs of Interventions

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.

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) wellbeing (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). However, this has not been attempted for COVID-19.
- Mental health effects of isolation (Rossi et al. 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 (Zacher and Rudolph, 2020).
- Disruption of education (school closures) also leads to lower mental well-being amongst schoolkids, 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, if these are part of lockdown, can also 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 workers are able to supply: Bayham and Fenichel (2020) found a 15% decline in labour supply due to school closures in the US, which reduces the quality of treatment outcomes for COVID-19 patients. Another impact of school closures is rising inequality amongst parents and children. Women have seen greater wage losses than men (Alon et al., 2020). Even before the long-term school closures of the pandemic, children from lower income families show declines in math test scores over summer holidays (Cooper et al., 2000).
- 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.

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, Sullivan and Shogren, 2020, Evans and Taylor 2020 and Hall, Jones, and Klenow, 2020). There a variety of ways in which economists impute a £ or $ 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 people questions like 'how much would you pay for an environmental intervention that reduce your chances of dying from air pollution by 3 in 100000 to 2 in 100000?'. Suppose the average answer were $30, then in a population of 100,000 where 1 life is saved through then 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., 100000x$30). This is the baseline figure recommended by the OECD in more usual policy evaluations where 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. This is unlike an air pollution intervention, because pollution-based respiratory diseases are not infectious in the way that COVID-19 is. 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 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 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.

Challenge 1d: Valuing the Indirect Benefits from Interventions

Focus health 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).

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., 2021). This has led to numerous calls and some efforts to create behavioural epidemic models (Funk et al., 2015; Funk et al., 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 maximization based on adaptive expectations, in which a representative individual maximizes the private net present value of utility flows from contacting others to provide a description of behavioural adaption. The key parameter is the elasticity of behavioural response to prevalence (Philipson 2000; Fenichel 2013).

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 susceptible individuals contact infectious individuals, and

$\beta(\cdot)$ represents the likelihood that contact with an infectious individual results in transmission. Traditional, analysts have treated β as fixed and driven by host-pathogen biology. However, it is increasingly clear that β must also capture "the quality" 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.[4] These choices are modelled based on behavioural 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 maximization 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 minimizes 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 lose from expected infection (e.g., Acemoglu et al., 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. 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 the probability of disease transmission for each unprotected contact between infected and at-risk individuals, may increase overall contacts in the population and thereby increasing aggregate disease transmission and make everyone worse off.

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[4] If $C = 1$, we have shown frequency dependent transmission; if $C = N$, we have shown 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 generalized 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 parameterized behavioral responses.

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

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 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 or over the health of others (Fehr and Schmidt, 1999).

Challenge 2b: Constraints

Second, constraints that influence behaviour also need to be a function of future health outcomes, economic states, and constraints 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).

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 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).

Challenge 2d: Behavioural departures from rationality

COVID-19 poses risks to private health. These risks are defined by the combination of (a) the probability a person becomes infected/ill, and (b) the severity of the illness if realized. 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 big problem (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 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—either ignore these risks completely or overestimate the chance they might suffer from such a risk. Both reactions could render policy ineffective if it was designed presuming that citizens would respond rationally to health risks. Policymakers must presume 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.

Challenge 2e: Time-Invariant Parameters

Estimating the time-invariant parameters associated with utility functions, expectation functions, 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.

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 parameterizing such models, there is the challenge of determining the aggregation rules with which to undertake policy evaluation.

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 realized 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 realized 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.

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 epidemic or pandemic have not been as successful. Pike et al. (2014), Berry et al. (2015), and Berry et al. (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 development of a standing stock of appropriate assets and a flow of investment to keep these 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.

Recently, Dobson et al. (2020) demonstrate the significant cost savings that can be achieved from improved efforts to prevent zoonotic disease spillovers with primary prevention. 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.

Conclusions

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 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 childrens' 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 both 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, and lead to the need for and effects of policy interventions being overstated. But by the same token, by not adequately taking into account 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 having caused 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 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[5]. 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, e.g. numbers of cases, hospital admissions and deaths. However, as we have argued throughout this paper, pandemics don’t just make people sick, and in order to identify strategies to manage future pandemics, it is vital that evidence presented to policy makers takes into account these complex interactions between different systems. Therefore, a key challenge is building strong relationships between the economics, behavioural science and epidemiology modelling communities to ensure better representation on government advisory panels for future pandemics.

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