Modelling the Spread of the Coronavirus: A View from Economics

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Abstract

This article reviews the modelling of the spread in Australia of COVID-19 from the point of view of the discipline of Economics. After a brief overview of the epidemiological approach, we show that other modelling is needed for policy purposes and especially to provide a full understanding of the economic and social costs of disease control. We look at microeconomic aspects of infection, focusing on individual behaviour, the choices facing the individual and implications for policy. The use of a cost–benefit approach and macroeconomic aspects of the pandemic are examined together with the economic consequences of policy response.

1. Introduction

Modelling has played a major part in the analysis of the spread of the virus, SARS-CoV-2, and in the development of policies that are designed to control the disease, COVID-19, in Australia. However, the models are new and have been modified from time to time as more information is revealed about the virus. This article reviews the modelling of the spread in Australia of COVID-19 from the point of view of the discipline of Economics. We provide a brief overview of the epidemiological approach. We then show that other modelling is needed for policy purposes and especially to provide a full understanding of the economic and social costs of disease control.

Economics has an important input into a review of this modelling for several reasons. First, the virus is spread by human agents who face economic and social choices and are assumed to make decisions often from a selfish point of view. Some models of economic behaviour are relevant to the analysis of the spread of the virus. Second, the costs of measures adopted to control this virus and its disease have large and widespread effects on the economy, which should be taken into account. Third, Economics as a discipline has developed a very large number of models for many different situations and consequently is a discipline well experienced in model building.

This article is structured as follows. In the next section we consider a simple heuristic model of the transmission process to gain an understanding of the basic dynamics of
transmission and growth in the numbers of persons infected. We summarise the behaviour of an epidemic in the heuristic model and in the epidemiological models that have been developed to inform policy concerning the impact of COVID-19 in Australia, drawing attention to economic issues neglected in these models. In Section 3 we examine the usefulness of these models for framing government policies. Microeconomic aspects of infection focusing on individual behaviour, the choices facing the individual and implications for policy are examined in Section 4. In Section 5 we consider macroeconomic aspects of the pandemic and the economic consequences of policy response. The final section concludes the article.

2. Epidemiological Models of the Evolution of the Number of New Infections Over Time

2.1 A Small Heuristic Model

The classic models in epidemiology are ‘compartmental models’. In these models everyone in the population is assigned to a compartment (typically two or more of susceptible, infectious, recovered and exposed) and attention is focused on the changes in the number in each compartment as people move from one compartment to another.

The key features of these models and their policy implications may be illustrated by looking at a very simple compartmental model in which there are only two states, susceptible and infectious. This is called in the epidemiological literature an SI model. In the SI model there is no immunity and once infected individuals stay infected (and thus infectious) and sooner or later everyone is infected. (Immunity levels are discussed in Appendix A1).

Assume there is a given homogeneous population \( N \) made up of two types of people: those who at any time have been infected \((I)\) and those who have not yet been infected \((S)\) with \( I_t + S_t = N \). Note that these measures are stocks, not flows. Assume also that all infections are a result of ‘community transmission’. The likelihood of transmission occurring will depend (amongst other things) upon the number who are infected and thus capable of infecting others \((I_t)\), the number who are not yet infected and are susceptible \((S_t)\) and the amount of contact between the two groups.

We are interested in modelling the evolution of the number of new infections \( (dI/dt) \) over time. Suppose that a virus has been introduced into the community and hence a number of people are already infected (so \( I_0 > 0 \)). Suppose that each infected person has contact with \( \alpha \) individuals on average in each period. Not all people they have contact with will be susceptible as some may already have been infected. In order for transmission of the virus to occur, someone who is infected must come into contact with someone who is not yet infected. If contacts occur at random the chance that a contact will be with a susceptible person is \( S_t/N \) and the number of contacts each infected person will have with someone who is susceptible will equal \( \alpha (S_t/N) \). This implies that in any period the total number of contacts in the population between the infected and the susceptible will equal \( \alpha (S_t/N) I_t \). ‘Contact’ between an infected person and a susceptible person may not result in transmission. For example, the contact may be of very limited duration, or the people involved are wearing masks or maintaining a ‘safe’ social (really, physical) distance. Let \( \beta \) measure the proportion of contacts that result in transmission. This means that on average each infected person generates \( \alpha \beta (S_t/N) \) newly infected individuals and, in the aggregate at any time, the total number of new infections will equal \( \alpha \beta (S_t/N) I_t \). Hence,

\[
\frac{dI_t}{dt} = \alpha \beta \left( \frac{S_t}{N} \right) I_t = \alpha \beta \left( (N - I_t) \right) I_t
\]

Equation (1) tells us that the number of new infections in each period will vary positively with both \( \alpha \) and \( \beta \). When considering the policy implications of the above, the aim of policy must be to lower \( \alpha \) and/or \( \beta \). We will return to this shortly.

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How does the number of new infections \((\frac{dI}{dt})\) evolve over time? During an epidemic and in the absence of any intervention, the value of \(I\) will continually rise over time and as \(I\) rises the value of \((N - I)\) will fall. To keep things simple the values of \(\beta\) and \(\alpha\) are assumed to be constant. It follows from equation (1) that the behaviour of \(\frac{dI}{dt}\) over time depends solely upon the behaviour of \((N - I)I/N\) over time. Since \((N - I)I\) may be written as \(IN - I^2\), and given that \(N\) is constant by assumption, \(\frac{dI}{dt}\) will behave as a bell-shaped curve—this is illustrated in Figure 1.

Notice that, for given values of \(\alpha\), \(\beta\) and \(N\), the behaviour of \(\frac{dI}{dt}\) after it reaches its maximum is a mirror image of the behaviour of \(\frac{dI}{dt}\) before it reaches the mid-point.

When \(\frac{dI}{dt}\) is a maximum \(\frac{d(dI/ dt)}{dt}\) will be zero. Differentiating (1) with respect to time we find that

\[
\frac{d(dI/dt)}{dt} = \{\beta \alpha - 2 \beta \alpha (I_i/N)\} \frac{dI}{dt}
\]

As the values of \(\beta\), \(\alpha\) and \(N\) are given, \(I\) is the only element on the RHS of (1) that is time-varying. Since \(\frac{dI}{dt} > 0\), the maximum requires \(\{\beta \alpha - 2 \beta \alpha (I_i/N)\} = 0\). Hence, we find that \(\frac{dI}{dt}\) will be a maximum when \(I_i = 1/2 N\). Substituting that result into equation (1) yields an expression for the highest value \(\frac{dI}{dt}\) will reach during the course of the epidemic. This is denoted by \(\frac{dI_{max}}{dt}\). It will be equal to

\[
\frac{dI_{max}}{dt} = \beta \alpha 1/4N
\] (2)

The model also shows the ways in which policy to ‘flatten the curve’ operates. To flatten the curve it is necessary to lower \(\beta\) (for example, by mandating the wearing of masks) and/or \(\alpha\) (for example, by mandating a ‘stay at home’ policy for all except essential workers in the community). If the policies succeed in doing this, then they will lower the maximum value that \(\frac{dI}{dt}\) will adopt—see equation (2). Figure 2 shows the time path of \(\frac{dI}{dt}\) for two values of \(\beta \alpha\), given \(N\).

It is possible to depict what happened recently in Victoria—where failures in managing and operating hotel quarantine resulted in a second wave of infections and deaths—with reference to Figure 2. These failures would be captured in our model by a rise in the value of \(\alpha\), that is, a rise in the average number of contacts made by infected people. The result is a rise in the value of \(dI\), \(I\) and also a rise in the value of \(\frac{dI_{max}}{dt}\)—see equation (2). The consequence of a rise in the value of \(\alpha\) (assuming \(\beta\) is given) would be depicted by a movement from the red line in Figure 2 which shows the evolution over time of \(\frac{dI}{dt}\) for a given ‘low’ value of \(\alpha \beta\) to the blue
line which shows the evolution over time of $\frac{dI}{dt}$ for a higher value of $\alpha\beta$.

The model set out above can also be used to derive the reproduction rate ($R_0$) and the immunisation rate necessary to achieve ‘herd immunity’ (see Appendix A1).

The SI model constructed above is very simple but also very useful to identify the key determinants of the spread of the virus and also the policies and measures that have been adopted to counter it. The model shows the basic forces that drive the rate of new infections and it produces a bell-shaped curve that closely resembles the actual path of the virus in Australia and also the second wave in Victoria. It serves too as an introduction to more complex models which allow for two additional compartments: the Recovered ($R$) — and thus the SIR models — and the Exposed ($E$) and thus the SEIR models. However, the essential insights of our SI model will also be applicable to the SIR and SEIR models.

### 2.2 A Brief Outline of Epidemiological Modelling in Australia

A large number of papers putting forward epidemiological models and simulation exercises using the models have been published in Australia since the outbreak of the coronavirus SARS-Cov-2 in January 2020. Some of these present models of the epidemic as a whole. Sometimes the epidemiological models have been used to investigate a specific policy issue such as the effectiveness of travel bans for travellers from China (Costantino, Heslop and MacIntyre 2020), the effect of the introduction of the mobile smartphone tracking app (Currie et al. 2020), the effectiveness of social distancing (Golding et al. 2020; Milne and Xie 2020), the impact of COVID-19 upon the demand for intensive care services (Moss et al. 2020; Price et al. 2020; Fox, Trauer and McBryde 2020) and the effect of the six-week lock-down in Victoria (Blakely et al. 2020).

We are primarily interested in those that present a comprehensive model of the whole epidemic. These are as follows:

1. The Doherty Institute model (Moss et al. 2020).
2. The model created by authors at the University of Melbourne and other universities and centres (Price et al. 2020).
3. The University of Sydney Centre for Complex Systems model (Chang et al. 2020b).
| Model | Type of model | Purpose/objective | Measures modelled | Recommendations/findings |
|-------|---------------|------------------|------------------|--------------------------|
| 1     | Non-stochastic disease transmission, stratified by age & risk | To inform transmission-reducing measures & health-system preparedness | Case isolation, quarantining, social distancing | Unmitigated COVID-19 would dramatically exceed capacity of health system |
| 2     | Stochastic    | To examine hospital ward & intensive care capacity | None | Hospital ward & intensive care below capacity |
| 3     | Stochastic agent-based model | Evaluation of intervention strategies | School closures, social distancing | School closures of limited effectiveness; social distancing of limited effectiveness if compliance <70% |
| 4     | Stochastic agent-based model | Estimating probability that a six-week lockdown in Victoria will achieve elimination | Stage 3 Victorian lockdown measures | A 10-point plan to maximise chance of successful elimination |
| 5     | Stochastic    | To consider the impact of several policy scenarios | Several policy scenarios | None |
| 6     | Mixed deterministic/Stochastic model | To examine the effect of state measures coming out of first wave lockdown | Policy settings for schools, shops, workplaces & supermarkets; contact tracing; travel restrictions | An 11-point list of recommendations for Commonwealth & state governments |
4. The University of Melbourne School of Population and Global Health model (Blakely et al. 2020).
5. The University of Newcastle model (Eshragh et al. 2020).
6. The Grattan Institute model (Duckett, Mackey and Chen 2020; Parsonage and Mackey 2020).

As the models have been built by teams of researchers at medical centres of research into epidemiology, population health and related medical areas, in the list above they have been named after the research centre in which all or most of the authors are located.

The National Cabinet commissioned the Doherty Institute model and has used it and Model 2 for its own modelling exercises. The Doherty Institute has created a separate model to assess the spread of COVID-19 in the Asia-Pacific region (Shearer et al. 2020). The models presented in Eshragh et al. (2020) and in the Doherty Institute model have been used by the Australian and Victorian Governments (see Department of Health 2020; Department of Health and Human Services 2020).

These models are found on earlier epidemiological models of infectious diseases which have been widely used around the world, including models of other airborne coronaviruses and earlier models of measles, with appropriate modifications for the particular characteristics of the current coronavirus (see, for example, Moss et al. 2020). The research centres building these models have also used other techniques to increase knowledge of the features of the virus; for example, genomic sequencing used by Doherty Institute to identify the origin of breakouts.

As the models are all different in many respects, there is no one dominant model.

Table 1 lists the key features of each of the six models. The features listed are those that relate to the role of models in understanding the course of the virus and in advising governments on virus control. The models differ considerably in relation to all of the features listed here.

In relation to the type of model listed in Table 1, some of the models are a mix of deterministic and stochastic components. The deterministic components of models are typically presented in terms of a system of first-order differential equations. Thus, the equations represent changes, at a point of time, in the values of variables of the model— the number susceptible, the number of infected, the number of deaths, etc. In these models, rates of change are expressed as a function of explanatory variables, usually at least one other endogenous variable, with constant parameters. The models reported in Chang et al. (2020a) and Blakely et al. (2020) are ‘agent-based’, that is, the agents transition from one infection status to another and interact according to stochastic processes and parameters expressed in terms of probability distributions. Similarly, the ‘partially observable’ model in Eshragh et al. (2020) is based on stochastic processes.

These models contain detailed modelling of the infection process. They divide the total Australian population into a number of groups according to their infection status: infected, infectious, susceptible (or exposed), recovered and deceased, or variations thereof. Then, there is a further breakdown for each group. For example, the infected are described in terms of the incubation, latent and infectious periods. In the latent phase an individual is infected but not yet infectious. This is incorporated in the models by explicitly including an additional component to separate out from the number infected those who have been ‘exposed’ (denoted by E) but who are not yet infectious. Various parameters or probability distributions determine the rates at which people transition from one status to another. In relation to the purposes listed there is also considerable variation. Some are concerned with examining the adequacy of the capacity of our hospital wards and the preparedness of the healthcare system more generally. Others examine specific government measures. The measures examined differ from one study to another. One examines the measures and policies that might have been
adopted as the country emerged from strict lockdown in the first wave. The recommendations or findings also vary depending on the purpose of the study.

The extent of the breakdown of the Australian population of infectious and infectible persons varies greatly in the six models. Some treat the whole population as homogeneous and some break it down into groups. We comment on this feature in Section 4.1.

The parameters and equations of the models have been subject to periodic revisions as the knowledge of the virus has improved and the modes of transmission from person to person have changed during the course of the present virus. Modelling a novel and evolving epidemic requires an adaptive modelling process.

However, it is difficult for us to observe these changes as the full details for some of the models and simulations have not been published or are not easily accessible. Of additional concern is the lack of detailed information about advice to governments. All details of models, simulations and advice to governments should be fully transparent.

There has been a second wave of modelling and modelling exercises since the second wave of the virus broke out in Victoria. Grafton et al. (2020) model the payoffs of hard versus soft lockdowns using a measure of social distancing.

2.3 A Fundamental Equation

At the heart of every model of infection involving contact between an infectious person and a susceptible person, there is one fundamental equation. This equation expresses the probability of an infectible person becoming infected as the product of the probability that the infectible will come into contact with a person who is infected, and the probability that the infectible will become infected upon contact.

Let $i$ be any person who is infectible at time $t$ and $P_{it}$ be the probability of this infectible person becoming infected at this time. $I_{it}$ is the probability that the infectible will come into contact with a person who is infected, and $I_{it}$ is the probability that the infectible will become infected after contact at this time conditional on contact with an infected person having been made. Then, for any individual $i$ at time $t$,

$$P_{it} = C_{it}I_{it}$$

Both $C_{it}$ and $I_{it}$ vary across individual persons and over time. In general, $C_{it}$ and $I_{it}$ are not independently distributed as the probability of infection after contact may be correlated with the probability of contact. However, unless there is a reason to believe they are correlated, they may be treated as independent. The equation then reduces to the simple product of two probabilities. These are usually regarded as constants for the population or for groups within the population. (This form of the equation has been used often in Economics, where it is called the Hazard Rate. See Appendix A.2).

While our fundamental expression is quite general it is easy to show that it captures the essence of the heuristic model set out in Section 2.1 as a special case. Imagine a single susceptible individual who has $\alpha$ contacts in any period. If contacts occur at random the chance that a contact will be with an infected person is $I/N$ and so the number of contacts each susceptible person will have with someone who is infected will equal $\alpha(I/N)$. Clearly this is the equivalent in our heuristic model of $C_{it}$ in the fundamental equation (equation (3)). The equivalent in our heuristic model of $I_{it}$ is $\beta$, as this is a measure of the proportion of contacts that result in transmission. In terms of the special case of the little heuristic model set out above we find for a ‘representative individual’ that

$$P_{it} = \alpha(I/N)\beta$$

The fundamental equation also provides a two-fold classification of measures that may be adopted to slow the spread of the virus. There are measures that reduce the probability of contact and other measures that reduce the probability of infection once contact has been
made. The former includes border controls, quarantining, curfews, rules limiting the number of persons visiting each other and rules restricting the number of attendees at various events. The latter includes the wearing of masks, hand hygiene and physical distancing.

3. The Usefulness of Models for Framing Government Policies

3.1 Understanding the Dynamics of the Virus

The primary use of an epidemiological model is to help epidemiologists to understand how the virus spreads among the population and to convey this information to governments. This is the classic role of epidemiological modelling. It has become more important in the second wave in the state of Victoria.

Epidemiological models have undoubtedly been very useful in understanding the spread of the virus and the disease and related questions such as the demand for hospital beds and the usefulness of particular restrictions. This has been a vital input into the development of policies in the Commonwealth and the states.

3.2 Developing Public Policy and Measures to Control the Spread

It is essential to distinguish between public policy towards the control of the virus and its disease on the one hand and policy measures on the other. Public policy, or strategy as it is sometimes called, covers the general approach of governments to the spread of the virus. Three strategies have been put forward around the world; these are, in order of decreasing severity or stringency—elimination, suppression and herd immunity. Measures cover the restrictions or rules that governments have mandated in order to try to suppress or eliminate the spread: quarantining, social distancing, restrictions on the numbers of persons at any gathering, curfews, wearing of masks, etc.

In relation to public policy or strategy, throughout the course of the spread of the virus to date, both the Commonwealth and state governments have not been explicit about the approaches they have adopted. This history is complicated by the federal structure of our government. Both the Commonwealth and the governments of all states have introduced their own sets of measures, with a wide variation among them. Duckett, Mackey and Chen (2020) provide a detailed account of the different stages of government policies and measures up to June 2020.

No Australian government has adopted herd immunity as a goal. All Australian governments have adopted a policy of suppression but with varying degrees of severity among the jurisdictions and over time. Initially none was fully committed to a policy of elimination, however, on 2 July the Commonwealth Government unambiguously stated a national GOAL of elimination. The Victorian Government also adopted a policy of elimination as the second wave neared its end.

Because of the novelty of the virus and its disease and the time it took to develop new models of this coronavirus, the Commonwealth and state governments were forced to initiate strategies without models that were specifically tailored to the new virus. In the early stages of the spread general policy was described in terms of ‘slowing the spread’ or ‘flattening the curve’. As the second wave developed, particularly in the state of Victoria and also to a much lesser extent in New South Wales, the Commonwealth has talked of ‘aggressive suppression’.

In relation to the use of measures, the measures they have adopted from the outset are suppression measures. In this regard, epidemiological modellers have given much valuable advice to governments. In particular, during the second wave in Victoria, the Victorian Government has relied heavily on the advice of its modellers at the University of Melbourne and Newcastle University to assist it in devising the restrictions, that is, the measures, that were introduced in Stage 4 on 2 August and again in the extension of the Stage 4 restrictions on 13 September.

3.3 Opinions of Epidemiologists and Economists

Epidemiologists who have modelled the spread of the virus and its disease in
Australia have a variety of opinions regarding the policies and measures they have recommended. However, the range of opinions among epidemiologists in Australia seems less than in some other countries, notably the United Kingdom and Sweden. In both of these countries at an early stage of the epidemic their chief medical officers recommended the ‘herd immunity’ approach. In general, Australian epidemiologists have supported stringent measures of suppression with small differences over individual measures. It appears that they made recommendations regarding measures such as distancing and quarantining to the government based solely on the medical features of the epidemic.

However, the use of epidemiological models is not sufficient to design policies and measures to reduce the spread of the virus and disease. This is because the models discussed above omit the costs of government measures which are vital to inform policy decision making.

In contrast to epidemiologists, opinions with respect to the choice of policies and measures among economists in Australia seem to have covered a wider spectrum. A few have advocated elimination; see, for example, the recent paper by Duckett, Mackey and Chen (2020). At the other end of the spectrum, some, and notably Foster (2020), have advocated the Swedish model. Her views, which aired on Q&A, the ABC television program, on 28 July caused an uproar. Her opinions have been slated by a number of economists. In an article published after this event by the journalist Jessica Irvine (2020) it is reported that, because of these views, Foster has been called some colourful names such as ‘an embarrassment to the profession’ and ‘a neoliberal Trumpkinaut’.8 The common view of economists is represented in The Open Letter to the Government (Hamilton et al. 2020), which was co-signed by 265 Australian economists. This is a majority view and it is close to a consensus. These economists declared: ‘We recognise the measures taken to date have come at a cost to economic activity but believe these are far outweighed by the lives saved and the avoided economic damage due to an unmitigated contagion’.

To conclude this section, we note that two additional areas of modelling need to be undertaken. One is the modelling of the choices individuals make in responding to government measures. The second is the neglect of the cost of measures to the macroeconomy that result in lost jobs, income and production, costs that should inform not only the policy decision itself (for example, ‘stay at home’) but also the length of time the policy (for example, a Stage 4 lockdown) is to be in place. In Sections 4 and 5 we set out some ideas on how economic analysis may be used to provide an expanded policy framework in these two areas.

4. Individual Behaviour

The coronavirus is spread by two modes—by droplets in the air expelled by infectious persons in proximity to infectious persons, and by infectious persons contacting surfaces that have been previously touched by infectious persons. In both modes, infectious and infectible persons make decisions that increase or decrease the probability of transmission. This makes transmission a more complex process than that for diseases like measles and it requires that we examine the behaviour of persons who may transmit or receive the virus.

Economic models emphasise that individual economic agents respond in different ways, that is, they are heterogeneous.

4.1 Individuals are Heterogenous

Person-to-person contacts have different probabilities of infection depending on the behaviour of individuals and circumstances; for example, in the open air versus a crowded indoor environment and for a long duration versus a fleeting contact. Consequently, the set of all infectibles and/or the set of all infectious in the population at time \( t \) can be broken down into subsets, each of which has distinct features from the point of view of person-to-person transmission. For example, they could be the set of all those in quarantine,
or those in aged care facilities, or those in hospital wards, meatworks or capital cities.

Epidemiological models in Australia were slow to distinguish these groups. Some of the epidemiological modelling assumes that the whole population, or at least large sections of it, respond in the same way in a given circumstance. Others break the population into age groups. The Doherty Institute model distinguishes between Indigenous and non-Indigenous peoples. As the modelling has progressed in the course of the epidemic more groups have been distinguished. Chang et al. (2020a) distinguish between groups of households, schools, workplaces and neighbourhoods. The Grattan Institute model (Duckett, Mackey and Chen 2020) distinguishes between supermarkets, workplaces, schools, major events and households. In the same way, in Victoria, one should separate the regions and Metropolitan Melbourne because the two regions exhibit quite different behaviour.

In principle, any subset of the total population that has distinct features from the point of view of transmission should be separated and modelled separately.

4.2 Modelling Human Responses

None of the epidemiological models contain any modelling of human responses to policy measures used to control the disease or use any such modelling. Some epidemiological modellers have modified parameters to reflect variations in individual behaviour over the course of the pandemic but this has been done in an ad hoc way. There is no use of modelling the time variation in individual behaviour. Behavioural economists and psychologists have developed models of relevant behaviour such as non-compliance and also where individuals make choices that take into account a benefit to the community rather than solely maximising their own utility (see Bavel et al. 2020 and the references cited therein for examples of work along these lines).

As an example where the economic analysis of individual behaviour may complement an epidemiological model, consider the decision on the part of someone not yet infected to move out of self-isolation and have contact with other people, that is to become infectible. This is treated as a binary variable with \( B = 0 \) if the person decides to stay in strict isolation, and one if the person decides to move out of isolation. Conditional upon that decision, the likelihood that someone who is not yet infected will be infected in any period \( (P_i) \) depends on the likelihood of there being contact with an infected person once the decision has been made to move out of self-isolation \( (C_{it}) \) and the probability that the infectible will become infected after contact, conditional on the contact having been made \( (I_{it}) \). Hence, we may rewrite equation (3) as

\[
P_i = B_i C_{it} I_{it}
\]

All three of the variables in equation (4) reflect decisions freely made by the individual or imposed by regulation and adhered to by the individual or imposed by regulation and not adhered to by the individual.

The decision to move out of self-isolation and have contact with other people\(^9\) (that is, a decision to become infectible) can be seen as reflecting a choice based on the expected payoff relative to private costs.\(^{10}\) An example of a payoff would be income earned by going to work, the psychic benefits of seeing friends, etc. The costs will reflect a view of the chance of being infected, the severity of the infection—this is likely to be age-related—and the size of any penalty that may be imposed if the decision involves breaking the law/directions together with the expected probability that that person is found by the police to be breaking the law/directions. The size of any penalties and the chance of being detected are both subject to policy decisions as to the penalties involved and the amount of resources to be devoted to detection. Policy is likely to prioritise detection and penalising people who have been tested and found to be infected and are violating a stay-at-home order and also those who have been tested but are awaiting results and who are violating a stay-at-home order.

The likelihood of there being contact with an infected person once the decision has been
made to move out of self-isolation \((C_0)\) can itself be cast in probabilistic terms with the aid of the binomial distribution.\(^{11}\) The simplest way to do this is to pose the following question: What is the probability of a person who moves out of self-isolation making contact with at least one infected person if they have random contacts with \(n\) people when the proportion of people infected is \(i\)?\(^{12}\)

Now the probability of a person who moves out of self-isolation making contact with at least one infected person (we will write this as \(\Pr(X \geq 1)\)) will be unity minus the probability that a person who moves out of self-isolation will not make contact with any infected person (that is, \(\Pr(X = 0)\)), that is

\[
\Pr(X \geq 1) = 1 - \Pr(X = 0).
\]

Using the binomial distribution the probability that a person who moves out of self-isolation will not make contact with any infected person will be:

\[
\Pr(X = 0) = (1 - i)^n.
\]

This implies that the probability of a person who moves out of self-isolation making contact with at least one infected person will be

\[
\Pr(X \geq 1) = 1 - (1 - i)^n. \tag{5}
\]

The value of \(i\) we will take as given for any individual while \(n\) is both a decision variable for the individual and subject to regulation from the point of view of policy (examples would be limiting the number of people attending a sporting event, a wedding, the amount of time that may be spent on exercise, etc.).

The probability that the infectible will become infected after contact, conditional on a contact having been made \((I_a)\), will reflect a number of things, some of which are again possibly influenced by policy. It will likely depend upon age, the duration of the contact, whether social distancing is followed and whether a mask is worn or not. With this knowledge of the risk, an individual person can decide whether to move out of self-isolation.

This requires a rule for the individual making the choice. This rule involves weighing up the gains to the individual from removing themself from isolation and enjoying more activities against the costs incurred in the event that the individual does actually become infected. A rule commonly adopted in economics is that the individual chooses to maximise an expected utility function. In this instance we may write this function as \(U = f(\bar{U}, dU_1, dU_2)\) where \(\bar{U}\), \(dU_1\) and \(dU_2\) are respectively the utility enjoyed before a decision to remove oneself from isolation, the utility derived from the gains of more activity after removing oneself from isolation and the utility lost after removing oneself from isolation in the event of actually becoming infected. Because of the probabilistic nature of this decision, it also involves the individual's attitude to risk-taking. An individual who is more risk-averse will not remove themself from isolation in order to avoid the risks and costs of doing so.

As a second example of the use of economic modelling to shed light on the best measures to control the spread of the disease, we consider non-compliance with a mandatory government order to quarantine. We know that many individuals have breached these orders. In a survey conducted in Victoria over a period of a week in late July, a survey found that roughly 25 per cent of those in quarantine went outside the isolation location. The common reason given for this behaviour is that many of these individuals were in casual employment and their work contracts did not have provision for paid sick leave. These workers are generally poorly paid. Hence, they had a strong incentive to go to work to provide for themselves and their families.

In this situation, economic models of individuals who break laws show that they will make the decision to break the law by weighing up the risk of being detected and fined against the benefits of breaking the law. In the example, we again need a rule for the
individual making the choice. If the expected utility criterion is used, the individual can make a decision to break the law or rule. This decision will depend on the level of the fine and the probability of detection. For each individual, there will be a level of the fine that deters them from breaking the law or rule. When the extent of this problem became apparent in the quarantine rule, the Victorian Government more than trebled the level of fines for breaching the rule. Soon after the level of non-compliance was measured at roughly 5 per cent.

There are some individuals who are risk-prefering, that is, they wish to behave in such a way that they are exposed to more risk. For those individuals a policy that reduces the risk to them of venturing out (for example, a policy that masks must be worn when people are outside their home) will likely result in them venturing outside more than would otherwise be the case and perhaps having less respect for social distancing than would otherwise be the case.

5. The Economist’s Approach to Controlling the Spread

In their published work, epidemiological model builders have assumed that the objective of government policy is to reduce the spread of the virus but they have paid little attention to costs other than the medical costs of the virus.

5.1 The Objective of Government Policy

Every government intervention in the working of the economy and society requires a justification. When asked for the justification of government policies and measures to control the spread of the virus, most people, both epidemiologists and the general public, would reply immediately that the objective is to save lives. This seems obvious but it needs a little investigation.

The standard economic analysis of problems involving the interaction between two or more economic agents is to treat these interactions as an externality problem. Externalities result from the actions of a producer or consumer which affect other producers or consumers in ways that are not captured by market prices. Coronavirus cases are the consequences of social actions by infectious persons in the main—decisions to go out from lockdown to see someone or to exercise etc.—and thereby to risk transmitting the virus to others. We could, perhaps, call these spillover effects a social externality. Such spillovers cause a divergence between the interest of an individual and the interests of the community. Individuals acting to maximise their own welfare may ignore the costs they impose on other individuals. Economists call these social costs. For example, an individual breaking quarantine to work imposes costs on others if they are infectious and make contact with infectibles, resulting in transmission.

These contact spillovers are a very complex case. Transmission is by droplets expelled by the infectious or by contact with surfaces touched by the infectious. Such transmission is a probabilistic process and the transmitter and transmitee are not aware of the transmission. This calls for government measures to reduce the circumstances in which transmission occurs. Governments also play an important role in providing information to both infectious and infectible individuals which will lead them to take precautions that reduce the probability of infection. Government may introduce measures that compel either infectious or infectible persons to take actions that reduce the probability of infection—to wear masks or go into lockdown, etc. But how far should they go?

5.2 Cost–Benefit Analysis of the Benefits and Costs of Government Interventions

In relation to the benefits, we have noted that the epidemiological models only assess the benefits in terms of reductions in new infections and deaths. To compare benefits with costs requires a monetary value for lives saved or other health gains. Health economists commonly do this for other reforms that improve health.
In relation to the costs imposed on individuals as a result of government actions, epidemiologists are of course aware of considerations other than the health of individuals. For example, Blakely (2020) lists two considerations other than the health costs of the epidemic. These are hospital management and what he calls ‘the societal and economic functioning’ which includes the economic costs of disease control measures. Nevertheless, epidemiologists appear to have based their recommendations solely or at least principally on the simulations and other results of their epidemiological models alone. Epidemiological models deal only with the results of their epidemiological models alone.

Nevertheless, epidemiologists appear to have downplayed the social costs of mortality and morbidity on the economy when disease control measures are adopted on the other. This is a vital aspect of the assessment of what measures should be adopted. An obvious example of such a trade-off is where requiring people to remain at home reduces the spread of the virus but also lowers educational and training attainment, lowers employment and thus state and national gross product. The goal is to maximise the net benefit (Total benefits–Total Costs) for the country.

We can pose the problem of evaluating costs and benefits by supposing there is a stringency index, S, which measures the degree or level of stringency of the measures adopted by the government at any time. The level of stringency can be conceived as the reduction in the number of deaths (or the reduction in new cases). The more stringent the policy the more lives saved. Levels of stringency could be arrayed on an interval of the line ranging from zero to unity where zero indicates that no measures were adopted with no reduction and unity indicates a total close down of the economy which would eliminate the virus. Now, each level of stringency will yield a benefit, B, and it will be achieved at a cost to the economy, C.

Any change in the level of stringency will have complex lagged effects on the benefits and costs. Also, since both benefits and costs are distributed over the life of the epidemic, a discount rate will have to be decided upon and used to make all costs and benefits comparable in terms of their present values. An additional feature is that both benefits and costs are distributed unevenly across members of the population. The virus is likely to have disproportionate effects on those with low incomes and those seeking work. This may require some differential weighting across individuals. Costs may be reduced by government support measures, such as support for mental health. The costs included in the cost–benefit analysis should be net costs.

However, a cost–benefit analysis of this type is impossible during the early phases of an epidemic because this is a very complex and lengthy exercise that would require a team of economists. Kompas et al. (2020) compare the health and economic costs of early suppression versus late suppression. ‘Our findings provide robust evidence that “go hard, go early” suppression, at least in a high-income country like Australia, is the preferred approach from both a public health and economic perspective’ (p. 17). That is, there is no negative trade-off between health benefits and economic costs as early action speeds the subsequent economic recovery. This is an important result. However, their exercise illustrates another problem with cost–benefit analysis as the article was written before the second wave in Victoria which...
dramatically changed the costs and benefits of government intervention.

Even without an empirical cost–benefit study to guide government policy, the framework of cost–benefit analysis provides two rules that should guide all choices of measures.

First, for any level of stringency, the choice of individual measures to achieve this level should be achieved at least cost. Individual measures vary in terms of the costs per new case saved and deaths saved. In addition to epidemiological examination of the effectiveness of different measures in reducing the spread, this choice involves estimation of the cost of measures to the economy. This is a task that necessarily involves economics.

Second, for any given schedule of benefits and costs, the level of stringency should be increased to the point where the marginal benefit of stringency is equal to its marginal cost. The benefit in terms of cases reduced and lives saved increases with the level of stringency. We can plot this as a function, \( B = f(S) \), on the closed interval \([0,1]\). At any level of \( S \), there is a marginal benefit, MB. Graphically this is the slope of the function \( f(S) \). MB can be expected to be positive for the whole range of the function. It is likely to decrease as \( S \) increases due to the law of diminishing returns but it could be constant or even increase at some levels. The function \( f(S) \) is taken to be concave. Similarly, at any level of \( S \), there is a cost function, \( C = g(S) \), on the closed interval \([0,1]\). This cost function indicates the total costs of the (least-cost) measures necessary to achieve each level of stringency. At any level of \( C \), there is a marginal cost, MC. Again this is given graphically by the slope of the function \( g(S) \). Costs increase with \( S \) and the marginal cost increases with \( S \) as coverage of the population expands from areas of high population density into areas of low population density. That is, the function \( g(S) \) is convex. The rule now states that we should increase the level of stringency to the point where \( MC = MB \). Figure 3 depicts the MC and MB curves. Given the shape of the curves, there is a unique solution at some strictly positive level of \( S \) as we can rule out zero intervention at one extreme and complete closedown at the other.

If the two rules set out in the previous paragraphs are not followed, two types of mistakes may be made by those in government setting the policies and measures. First, for any chosen level of stringency, the measures adopted may not be least-cost and as a consequence unnecessary costs are imposed on the community. Some measures may yield lower benefits for a given cost or even no benefits. In the second wave in Victoria, for example, some considered that the five-kilometre limit on travel was unnecessarily restrictive and others judged that there was no benefit from the night curfew in terms of reduced transmission of the virus. An extreme error occurs when a measure has negative rather than positive effects. This occurred with the breakdown in quarantine arrangements in Victoria.

Second, the level of stringency may be too low or too high in which cases the community is missing out on the benefits from a higher level of stringency or facing the excess costs of a level that is too high.

5.3 Extended Cost–Benefit Analysis

A full cost–benefit analysis of alternative measures should include the costs of the loss of freedom to residents of the country when measures are adopted. At times all states have adopted measures that severely restrict the freedom of individuals to move intra- and interstate, the freedom to make purchases of

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goods and services, and the freedom to socialise. The last includes restrictions on attendance at important family events such as deaths, births and marriages. As the spread of the virus has progressed there has been increasing concern in the community over the costs of these restrictions. Most concern has been expressed over the restrictions on travel and family gatherings. From late September in Victoria, after the Stage 4 restrictions had been in effect for some weeks, there was a sudden increase in protests about the loss of liberties.

Indeed, one can regard these restrictions in all states as draconian and many of them unprecedented in Australia. Over all jurisdictions in Australia and by comparison with other developed countries, they are not the most or least stringent. (See rankings compiled by Oxford University’s *Our World in Data* Index of Stringency (Oxford University 2020)). However, the restrictions on overseas travel are among the most strict in the world. In the crucial situation of the second wave in Victoria, the measures adopted by this state in moving to Stage 4 restrictions were among the most stringent adopted by governments anywhere in the world. Overall, they are roughly equal in stringency to those adopted by the New Zealand Government at the peak of intervention; for example, the lockdown rules in New Zealand were stricter than those in Victoria under Stage 4 but on the other hand New Zealand did not impose a night curfew. At their peak the New Zealand restrictions were rated the most stringent in the world by the Oxford University (2020) Index of Stringency.

Ideally, the choice of policies and measures to control the spread of the virus and its disease should be treated as the solution to an optimisation problem. As a first approximation to the representation of the choice problem, we can seek to maximise a linear function that attaches different weights to the arguments of the function:

$$\text{Max } \{ w_1 V_1 + w_2 V_2 + w_3 V_3 \} \quad w_1 + w_2 + w_3 = 1 \quad (6)$$

where $w_1$, $w_2$ and $w_3$ are the weights, and the arguments $V_1$, $V_2$ and $V_3$ are the health effects, the economic effects and the freedom effects of the epidemic respectively. Those who attach high weight to the first argument of the function will opt for a hard lockdown and other stringent policies while those who attach larger weights to the second and/or third argument will opt for less stringent policies and measures.

It must also be acknowledged that there will inevitably be some uncertainty about the degree to which policies will affect the arguments in the function. We are not dealing with a simple deterministic world but rather a complex system that must be approached in probabilistic terms. Amongst other things, that implies the need for: (1) a synthesis of models not a mere imposition of one on the other; (2) an explicit recognition of trade-offs between (say) health and the economy; and (3) recognition that in a probabilistic world the policymaker must be aware that there will be costs associated with making an error (for example, in deciding when to end a lockdown) and that these costs will likely not be symmetric—that is, there will not only be a health cost in opening up the economy ‘too early’ but also an economic cost in opening up ‘too late’.

### 5.4 Political Economy Modelling

Future work should also examine the factors that determined the decisions actually made by the Commonwealth and state governments. Increasingly, many different interest groups have been pressuring the governments to change individual disease control measures. The Business Council and other peak industry bodies have been arguing for a relaxation of controls because the controls hurt business. As an example, QANTAS has been urging a relaxation of border controls, both interstate and international. In these cases business representatives have been acting in their own self-interest rather than in the national interest.

Political economy models have been used to examine these determinants of government
decisions in many areas, for example, industry assistance and budgets. These models regard governments as decision makers who, like private households and businesses, go through a process of decision making. Governments are assumed to maximise their own interests, especially the chances of re-election. These models explore the role of interest groups and how they capture the attention of government decision makers.

The determinants in the virus situation may be rather different than those in normal government budgeting and industry assistance because of the speed at which the virus spreads and the need for governments to make sudden decisions. A feature of the choice of policies and measures in Australia (and other countries) is that choices had to be made very rapidly in the early stages when it became apparent there was a serious epidemic. There was little time to consult with interest groups. Moreover, in the early stages of disease control, households and businesses were not aware of the controls that were to be introduced or of their severity and effects.

Political economy models could also be applied to explain the different levels of stringency applied by different countries around the world. In this context, the possible explanatory variables include the nature of government (authoritarian versus democratic) and perhaps too the level of community awareness (some countries appearing to have a greater awareness of ‘community’ and a greater tolerance of government restrictions on economic and social activity) and prior exposure to viruses such as SARS and MERS.

In this context, the epidemiological modelling and the simulations produced from these models have been an essential component of policymaking. They have raised our understanding of the spread of the virus and assisted in the choice of measures adopted by both the Commonwealth and state governments. Yet, this is not enough. Epidemiological models deal only with the health benefits of measures used to counter an epidemic. They contain no information about the costs of government measures used. No government should make decisions regarding the measures it might adopt solely on the basis of the benefits.

We need a synthesis of epidemiological and economic/social models. Economists can play two main roles in future modelling. First, they (and other social scientists) can help in modelling the behaviour of human agents of transmission and the costs to individuals of alternative measures. Good choice of alternative measures must be in accord with the principle that any achievement in reducing the spread of the virus (as measured by new cases and perhaps the number of deaths) should be achieved at least cost and they should only be carried to the point where the marginal benefit and the marginal cost are equal. Second, they can develop and simulate models that show the costs to the economy of the measures adopted to control the virus and its disease. This should be an essential input into future government decisions to adopt policies and measures to control the present outbreak and future outbreaks of coronaviruses.

Endnotes

1. For surveys of the mathematical epidemiological models see Banks (1994), Hethcote (2000) and Keeling and Rohani (2011).

2. The exposed category is for individuals who have been infected but are not yet infectious themselves.

3. What follows is (loosely) based on Smith and Moore (2004).

4. Integration of equation (1) yields a logistic curve.

5. In practice the curve is unlikely to be symmetric either side of the peak as policy intervention after the epidemic has taken hold will aim to reduce the value of \( \beta \) and/or \( \alpha \).
6. We assume that the values of \( \beta, \alpha \) and \( N \) are given, so \( I \) is the only element on the RHS of (1), which is time-varying.

7. Barnet (2020) provides an excellent example of a probabilistic model based on equation (3). He considers passengers on US airlines who may pick up the virus from another already infected passenger. A variation of equation (3) models the choice US airlines have with respect to keeping the middle seat in a row empty in order to increase distance between passengers or not keeping it empty.

8. This outright rejection of her views is unfair. Given the absence of any conclusive research on these trade-offs in Australia, this is a tenable opinion, although clearly not one that is widely held.

9. In other words for \( B \) to switch from zero to one.

10. A referee has pointed out that the behavioral economics literature shows that individuals may not be good judges of relevant probabilities (see the survey by Camerer et al. 2004) but that government, through the severity of its regulations, may provide signals that alter the perceptions of individuals.

11. Provided \( n \) is large enough the binomial distribution approximates a normal distribution.

12. We assume that \( i \) does not vary with \( n \). It is possible that an individual decision maker may view \( i \) as depending on \( n \).

13. Loertscher and Muir (2020) investigate a model where policymakers choose the degree of a lockdown to meet a target value of \( \beta \) (the target is related to hospital capacity) while at the same time the degree of the lockdown determines the proportion of the population who are able to continue producing output. Since the policy does not aim to eliminate the virus but rather to have it at a ‘manageable level’ the economic costs are less than would be the case if a complete lockdown (as part of an elimination strategy) were imposed.

14. Duckett, Mackey and Chen (2020) provide a discussion of the economic effects of COVID-19 and (inter alia) draw attention to the disproportionate impact on the most vulnerable in our society.

15. Baker, Kvalsig and Wilson (2020) compare the regulations in New Zealand and Australia.

16. Blakely (2020) recognises explicitly that the choice of disease control measures is an optimisation problem. He lists three considerations: the health costs of the disease, hospital management and what he calls ‘societal and economic functioning’, which includes the economic costs of measures.

17. For more on complex versus simple systems see Snowden and Boone (2007) and Dettmer (2011).

18. Note that we continue to assume that in the absence of a vaccine the whole of the population is susceptible; we also assume that vaccination guarantees immunity.

19. The term \( R_0(1-u) \) is known as the effective reproduction number.

20. This result is well known in the epidemiological literature; see, for example Smith (1970), Dietz (1975) and the survey in Fine, Eames and Heymann (2011).

21. If the likely value of \( R_0 \) is in the range 2.5–4 we require the immunisation rate to be above 60–75 per cent. Of course, if there are costs for becoming vaccinated, there may be ‘free-riders’ and, depending on the scale, this may need to be addressed by policymakers.

22. In addition to social distancing and hand hygiene.

23. Note that we are talking here about the economist’s Hazard Rate not the epidemiologist’s Hazard Ratio.

References

Banks, R. B. 1994, Growth and Diffusion Phenomena: Mathematical Frameworks and Applications, Springer-Verlag, Berlin.

Baker, M., Kvalsig, A. and Wilson, N. 2020, ‘100 days without COVID-19: How New Zealand got rid of a virus that keeps spreading around the world’, The Conversation, 7 August. Viewed January 2021, <https://theconversation.com/100-days-without-covid-19-how-new-zealand-got-rid-of-a-virus-that-keeps-spreading-across-the-world-143672>

Barnet, A. 2020, ‘COVID-19 risk among airline passengers: Should the middle seat stay empty’, medRxiv. Viewed January 2020, <https://doi.org/10.1101/2020.07.02.20143826>

Bavel, J. J. V., Baicker, K., Boggio, P. S., Capraro, V., Cichocka, A., Cikara, M., Crockett, M. J., Crum, A. J., Douglas, K. M., Druckman, J. N., Drury, J., Dube, O., Ellemers, N., Finkel, E. J., Fowler, J. H., Gelfand, M., Han, S., Haslam, S. A., Jetten, J., Kitayama, S., Mobbs, D., Napper, L. E., Packer, D. J., Pennycook, G., Peters, E., Petty, R. E., Rand, D. G., Reicher, S. D., Schnall, S., Shariff, A., Skitka, L. J., Smith, S. S., Sunstein, C. R., Tabri, N., Tucker, J. A., Linden, S., Lange, P., Weeden, K. A., Wohl, M. J. A., Zaki, J., Zion, S. R. and Willer, R. 2020, ‘Using social and behavioural science to support COVID-19 pandemic response’, Nature Human Behaviour, vol. 4, pp. 460–71.
Blakely, T. 2020, ‘The dynamics of the disease’, Podcast, Health and Wellbeing, Episode 76. Viewed January 2021, <https://pursuit.unimelb.edu.au/podcasts/the-dynamics-of-disease>

Blakely, T., Thompson, J., Carvalho, N., Bablani, L., Wilson, N. and Stevenson, M. 2020, ‘Maximizing the probability that the 6-week lockdown in Victoria delivers a COVID-19 free Australia’, The Medical Journal of Australia, forthcoming.

Borland, J. and Charlton, A. 2020, ‘The Australian labour market and the early impact of COVID-19: An assessment’, Australian Economic Review, vol. 53, no. 3, pp. 297–324.

Camerer, C., Loewenstein, G. and Rabin, M. eds, 2004, Advances in Behavioral Economics, Princeton University Press, Princeton.

Chang, S., Harding, N., Zachreson, C., Borland, J. and Charlton, A. 2020, ‘Maximizing the probability that the 6-week lockdown in Victoria delivers a COVID-19 free Australia’, The Medical Journal of Australia, forthcoming.

Dettmer, H. W. 2011, Systems Thinking and the Cynefin Framework: A Strategic Approach to Managing Complex Systems, Goal Systems International, Port Angeles, Washington.

Dietz, K. 1975, ‘Transmission and control of arbovirus diseases’, Epidemiology, vol. 104, pp. 104–21.

Dietz, K. 1993, ‘The estimation of the basic reproduction number for infectious diseases’, Statistical Methods in Medical Research, vol. 2, no. 1, pp. 23–41.

Duckett, S. 2020, ‘No, Australia should not follow Sweden’s approach to coronavirus’, The Conversation. 29 July.

Duckett, S., Mackey, W. and Chen, T. 2020, Go for Zero: How Australia Can Get to Zero COVID-19 Cases, Grattan Institute, Melbourne.

Eshragh, A., Alizamir, S., Howley, P. and Stojanovski, E. 2020, ‘Modelling the dynamics of the COVID-19 population in Australia: A probabilistic analysis’, arXiv preprint. Viewed January 2021, <https://arxiv.org/abs/2005.12455>

Fine, P., Eames, K. and Heymann, D. 2011, “Herd immunity”: A rough guide’, Clinical Infectious Diseases, vol. 52, no. 7, pp. 911–16.

Fontanet, A. and Cauchemez, S. 2020, ‘COVID-19 herd immunity: Where are we?’, Nature Reviews Immunology, vol. 20, 583–584.

Foster, G. ‘Opinion: Correctly counting the costs shows Australia’s lockdown was a mistake’, Australian Financial Review, pp. 35. 26 May.

Fox, G. J., Trauer, J. M. and McBryde, E. 2020, ‘Modelling the impact of COVID-19 upon intensive care services in New South Wales’, Medical Journal of Australia, vol. 212, no. 10, pp. 468-469.

Golding, N., Shearer, F., Moss, R., Dawson, P., Liu, D., Ross, J., Hyndman, R.,...
Zachreson, C., Geard, N., McVernon, J., Price, D., and McCaw, J. 2020, "Estimating Temporal Variation in Transmission of COVID-19 and Adherence to Social Distancing Measures in Australia", Doherty Institute Technical Report no. 15, Melbourne.

Grafton, Q., Kompas, T., Parslow, J., Glass, K., Banks, E. and Lokuge, K. 2020, ‘Health and economic effects of COVID-19 control in Australia: Modelling and quantifying the payoffs of hard versus soft lockdown’, medRxiv. Viewed January 2021, <https://www.medrxiv.org/content/10.1101/2020.03.31.20185587v1>

Hamilton, S., Peston, B., Edmond, C. and Holden, R. 2020, ‘Open letter to the government’, 20 April. Viewed January 2021, <https://newsroom.unsw.edu.au/news/business-law/open-letter-122-australian-economists-dont-sacrifice-health-economy>

Hethcote, H. W. 2000, ‘The mathematics of infectious diseases’, SIAM Review, vol. 42, no. 4, pp. 599–653.

Irvine, J. 2020, ‘Economists debate dollars and sense of lockdowns’, Sydney Morning Herald, p. 23. 8 August.

Kalb, G., Guillou, M. and Meekes, J. 2020, The Ups and Downs of the COVID-19 Crisis: A Gender Divide?, MIAESR Research Insight, University of Melbourne, Melbourne.

Keeling, M. J. and Rohani, P. 2011, Modeling Infectious Diseases in Humans and Animals. Princeton, Princeton University Press.

Kompas, T., Grafton, R. Q., Che, T. N., Chu, L. and Camac, J. 2020, ‘Health and economic costs of early, delayed and no suppression of COVID-19: The case of Australia’, medRxiv. Viewed January 2021, <https://www.medrxiv.org/content/10.1101/2020.06.21.20136549v1>

Loertscher, S. and Muir, E. 2020, Road to Recovery: Managing an Epidemic. Department of Economics, University of Melbourne, Melbourne.

Milne, G. J. and Xie, S. 2020, ‘The effectiveness of social distancing in mitigating COVID-19 spread: A modelling analysis’, medRxiv. Viewed January 2021, <https://www.medrxiv.org/content/10.1101/2020.03.20.20040055v1>

Moss, R., Wood, J., Brown, D., Shearer, F., Black, A., Cheng, C., McCaw, J. and McVernon, J. 2020, ‘Modelling the impact of COVID-19 in Australia to inform transmission reducing measures and health system preparedness’, medRxiv. Viewed January 2020, https://www.medrxiv.org/content/10.1101/2020.04.07.20056184v1

Oxford University. 2020, Our world in data: Coronavirus pandemic (COVID-19). Viewed January 2021, <https://ourworldindata.org/coronavirus>

Parsonage, H. and Mackey, W. 2020, COVID-19. Model Sa2. Model Policy and Epidemiological Assumptions of the COVID Package. R Package Version 028.0. Grattan Institute, Melbourne. Viewed January 2021, <http://github.com/grattan/covid19.model.sa2>

Price, D., Shearer, F., Meehan, M., McBryde, E., Moss, R., Golding, N., Conway, E., Dawson, P., Cromer, D., Wood, J., Abbott, S., McVernon, J., and McCaw, J. 2020, ‘Early analysis of the Australian COVID-19 epidemic’, medRxiv. Viewed January 2021, <https://www.medrxiv.org/content/10.1101/2020.04.25.20080127v1>

Shearer, F., Walker, J., Telliglug, N., McCaw, J., McVernon, J., Black, A., and Geard, N. 2020, Assessing the Risk of Spread of COVID-19 to the Asia Pacific Region. The Doherty Institute, University of Melbourne, Melbourne.

Smith, D. and Moore, L. 2004, ‘The SIR model for spread of disease: The differential equation model’, Convergence, viewed January 2021, <http://www.maa.org/press/periodicals/loci/joma/the-sir-model-for-spread-of-disease-the-differential-equation-model>

Smith, C. E. G. 1970, ‘Prospects of the control of disease’, Proceedings of the Royal Society of Medicine, vol. 63, pp. 1,181–90.

Snowden, D. J. and Boone, M. E. 2007, ‘A leader's framework for decision making’, Harvard Business Review, vol. 85, no. 11, pp. 69–76.
Appendix 1: Further Applications of the Heuristic Model

A1 The Reproduction Rate

An important concept in epidemiology is the reproduction number ($R$). It is an indicator of how infectious a disease is and is also used to forecast the future number of infections and thus the extent of immunisation required to lead to a decline in the incidence of infection.

The basic reproduction number ($R_0$) is defined as ‘the number of secondary cases one case would produce in a completely susceptible population’ (Dietz 1993, p. 23). If $R_0$ is greater than one, then one person with the virus infects more than one person and each of those in turn infect more than one person and so on across successive rounds or ‘generations’. Let $n$ be the $n$th round of infections generated by one infected person. The number of new infections in the $n$th round of infections will be $(R_0)^n$. If $R_0$ equals one, the number of new infections in each round will be constant (and equal to one for each infected person). If $R_0$ is greater than one, the number of new infections in each round will rise exponentially. If $R_0$ is less than one, the number of new infections will decline and eventually reach zero.

What determines the value of $R_0$ in the model set out in Section 2.1? We know that each infected person infects $\alpha \beta (S/N)$ people—see the text immediately before equation (1) in the main text. Since $R_0$ is the number of secondary cases one case would produce in a completely susceptible population, $R_0$ will be the value of $\alpha \beta (S/N)$ when $(S/N)$ is equal to one. This implies that in this model

$$R_0 = \alpha \beta \quad (A1.1)$$

It would seem that the likely value of $R_0$ is in the range 2.5–4 (Fontanet and Cauchemez 2020, p. 1). Since this range lies above one, it is clear that, in the absence of intervention, the infection rate will rise exponentially and sooner or later the whole population will become infected.

We mentioned above that the reproduction number can be used to make projections about the extent of immunisation required to lead to a decline in the incidence of infection. This can be shown as follows.

In the absence of any immunity each infected person infects $\alpha \beta (S/N)$ people, which is equal to $R_0 (S/N)$. Let the proportion of the population vaccinated be $\upsilon$. It follows that the proportion of the population that is not protected and thus susceptible will be $(1 - \upsilon)$. For the number of infections to sooner or later reach zero we require $R_0 \ (1 - \upsilon) < 1$. This will occur when the proportion of the population immunised ($\upsilon$) is

$$\upsilon > 1 - 1/R_0 \quad (A1.2)$$

This is also the condition required for ‘herd immunity’ since ‘[h]erd immunity is achieved when one infected person in a population generates less than one secondary case…..’ (Fontanet and Cauchemez 2020, p. 1).

The reproduction number can also provide policy guidance in the absence of a vaccine. A common policy aim in such a circumstance and an aim often made explicit is for policy actions to be directed towards a reduction in the value of the reproduction number $R_0$ (and ideally to drive it down to a value of zero). The policy or policies that achieve this aim will be policies that lower $\alpha$ and/or $\beta$ (see equation (A1.1)). Given that there will be an economic cost of actions taken to lower both $\alpha$ and $\beta$, policy should aim to select the instrument(s) that will achieve the target (lowering $R_0$) at the lowest economic cost.

The effect on $R_0$ of an increase in economic cost (EC) by one unit will depend upon:

$$(dR_0/d\alpha)(d\alpha/dEC) \text{ in the case of } \alpha,$$

and $$(dR_0/d\beta)(d\beta/dEC) \text{ in the case of } \beta.$$

Which policy (lower $\alpha$ or lower $\beta$) has the largest effect on $R_0$ for an increase in economic cost by one unit depends upon which of the two expressions given above is the largest. We know from equation (A1.1) that $(dR_0/d\alpha) = \beta$ while $(dR_0/d\beta) = \alpha$. So that the choice of policy depends on a judgement of the relative size of $\beta(d\alpha/dEC)$ and $\alpha(d\beta/dEC)$. Now we know that $\beta < 1$ and, given that we are taking policy action
because $R_0 > 1$, it must be the case that $\alpha > \beta$. So unless \((dz/dEC) < (dz/dEC)\)—which is most unlikely as to lower $\alpha$ we need lockdowns, curfews, working from home, etc.—we should focus on trying to lower $\beta$ and only move to adopt the more costly policies needed to lower $\alpha$ in the event that we believe the attempt to lower $\beta$ has not had the desired effect. All this implies that in the first batch of policies, mask-wearing (which will lower $\beta$) should be compulsory.\(^{22}\) In Victoria mask-wearing was not imposed until August 2020, six months after the pandemic had taken hold.

**A2 The Hazard Rate**

When asked to model transmission of people from one state (compartment) to another (for example movement of individuals from unemployment to employment), an economist would develop a model based on the relevant ‘Hazard Rate’.\(^{23}\) A Hazard Rate is defined as the probability of an event occurring in the current period, given that it has not yet occurred. In the context of modelling the transmission of a virus it is the probability that a person who is not yet infected will become infected in the current period.

We begin with a specific example of the determination of the Hazard Rate taken from the heuristic model of Section 2.1. Given the SI model as set out in Section 2.1, the Hazard Rate will be the number of people newly infected in any period. This is \((dI/dt)\) divided by the number who are not yet infected, that is \((N-I_t)\). Given equation (1), the Hazard Rate in the SI model will be

$$\frac{dI}{dt}/(N-I_t) = \alpha \beta (I_t/N)$$

(A2.1)

Notice that the number infected \((I_t)\) will rise over time. This means that, for given values of $\alpha$ and $\beta$, the probability that a person who is not yet infected will become infected in the current period (the Hazard Rate) will also rise over time. If policy lowers $\alpha$ and/or $\beta$ the Hazard Rate will fall.

However, this Hazard Rate, important as it is, has some shortcomings from the point of view of understanding the transmission of an infection. The specifics of the Hazard Rate will vary from model to model and the Hazard Rate does not capture the behaviour of individuals; nor does it recognise the heterogeneity in the population. To do this we need the more general approach put forward in Section 2.3.