The spread of severe acute respiratory syndrome coronavirus has thrown the world into crisis. Public health responses have been prolific, but the success of these interventions is uneven. As ever, we need to know what works for whom in what circumstances and in what respects. Realist approaches have been devised to answer this question and this working paper series is designed to promote this cause.

The series offers immediate readership and has no formal refereeing process. They are working papers in the sense that they are intended to raise hypotheses leading to more productive evidence. They may be developed (or indeed withdrawn), they may go on to be published in journals and books. Above all, they are attempts to provoke dialogue in the realist community and beyond.
The Relevance of Realism in the Pandemic

Working Paper 2: ‘All models are wrong’

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George Box was a pioneer of statistical model building and so his tongue was partly in cheek when he first used this famous phrase: ‘All models are wrong, but some are useful’. Box’s essential idea was that the worth (or the inadequacy) of a model depended on the veracity (or the deficiency) of the many assumptions and estimates built into it. Epidemiological model builders have a central role in UK Scientific Advisory Group for Emergencies. The UK policy response to the crisis has been guided by their projections on the likely course of the disease. This paper examines in close detail the assumptions built into one particularly influential model.

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‘All models are wrong’

Abstract

The research community has acted with great urgency in providing evidence to inform the healthcare response to the coronavirus outbreak. As is often noted, the pandemic is entirely unprecedented and so the methodological challenges in producing timely, reliable, valid and effective evidence are considerable. This paper examines the fortunes of one such research method, infectious disease modelling, against these desiderata. Simulation models produced in prestigious centres for mathematical biology have played a significant role in informing UK policy. Such models, as often noted, are only as accurate as the assumptions that drive their predictions. The paper examines the authenticity of the basic parameters of a particularly influential model.

Key words

Coronavirus, infectious disease modelling, non-pharmaceutical interventions, complex systems, organised scepticism.

Introduction

‘All models are wrong’. This striking aphorism, usually attributed to the British statistician George Box, takes on renewed significance as science struggles to predict the trajectory of the coronavirus outbreak. In the face of the pitiless challenge of the covid-19 pandemic, political leaders throughout the world have been quick to vouchsafe that they will ‘follow the science’. The science in question, mathematical biology, was perhaps not so well known to the public but in the space of a few weeks the basic concepts and imagery associated with the modelling of infectious disease have become remarkably familiar. Not a day goes by without an announcement from the Assemblée nationale or from the Bundestag or from Westminster about renewed efforts to ‘flatten the curve’. The ‘curve’ has taken on emblematic significance - but what is it?

Epidemic modelling

The basic transmission curve in a major epidemic takes shape as a disease moves through four groups – the susceptible, the infected, the recovered and the deceased. There is a generic pattern, the bell shape, whereby the number of cases increases exponentially until the proportion of the of the susceptible has been sufficiently depleted (through recovery or death) so that the growth rate then slows and the number of cases drops eventually so that the epidemic is no longer sustained [1]. This curve, of course, varies from disease to disease and the modelling for the spread of a particular infection begins with knowledge of its ‘basic reproduction number’, denoted $R_0$. This provides a measure of its transmission potential, the average number of secondary cases generated by a single infected individual. In popular parlance it is often understood as an indicator of the basic ‘aggression’ of the infection. It is regarded as the basic ingredient of any model of disease progression – the higher the $R_0$ the faster the disease will progress [2].

Quite remarkably, there is no agreed figure for the covid-19 $R_0$. Many studies have attempted to estimate the reproduction number and two overviews of those investigations have collated the various estimates. Its range is reported to vary from 1.5 to 6.49, with a mean of 4.2 in a study by Liu et al [3] and from 1.9 to 6.49, with a mean of 3.38 in a review by Alimohamadi et al [4]. These estimates differ from the estimates (mean 1.4-2.5) widely used by the World Health Organisation [5].
and the $R_0$ (2.4) used in an influential report by the Imperial College Covid-19 response team, to which we will return [6].

Why the discrepancies? Although the basic definition, ‘the average number of secondary cases generated by an infected individual’ seems impeccably clear, its operationalisation is beset with difficulties. It turns out that there are several different methods for calculating $R_0$ – starting with the distinction between ‘individual-level’ and ‘population-level’ approaches [7]. The former use real-time contact-tracing to follow infection from a diagnosed individual but the considerable resources required to do this are rarely in place at the outbreak of an infection. The latter, of which there are many variants, estimate the $R_0$ based on different subsets of biological, socio-behavioural and environmental parameters.

There are other more mundane but more significant reasons for the liquidity of the reproduction numbers. They are time-specific (social contact responds very quickly to the outbreak of disease) and context-specific (contact networks vary significantly from location to location, community to community). Disputes continue and remain unresolved on the optimal $R_0$ estimation methods [7, 8]. They need not detain us here, however, for there is a simpler methodological message to deliver – the reproduction number is the first and key ingredient of mathematical models of disease transmission. Its value is itself an estimate, a model within a model. Its contested nature warns us that it is also a seed of the eventual indeterminacy of simulation exercises.

Moving further into the modeling exercises, the task is to ascertain whether transmission potential turns into transmission actuality and onto pandemic status. Movement along this pathway depends on dozens of other processes [9]. Some of the issues concern the inherent variability of the pathogen and its infectious dose and viral load. Some refer to the individual hosts and the significant variation in their levels of immunity, by age, by co-morbidity, etc. Thereafter and at the point an epidemic becomes a public health issue there is the vital issue of the contact network of the infected. These interconnections carry the disease but vary immensely according to the everyday interactions of different social groups, which are conditioned in turn by environmental, cultural, demographic, economic and even seasonal differences. Neither are these transmission networks static for they depend on the popular and institutional understanding of an unfolding epidemic. News of an impending virus changes public behaviour which changes its transmission trajectory.

Finally, of course, there is the issue of the national response to an epidemic and the array of interventions aimed at preventing or mitigating or treating or testing for the virus – hand hygiene advice, provision of protective equipment, installation of ventilators, recruitment and training of extra critical care staff, the closure of shops, stadiums and schools, social distancing and lockdowns, etc. etc. We cannot know in advance how these programmes will work for their outcomes depend on human action and reaction. They are realised through implementation chains, information campaigns, production and distribution networks, funding streams, logistic assessments, and multi-agency collaboration. All such processes are potentially fragile, all of them are under constant adaptation, all bear social and economic costs, and all of them are introduced and withdrawn as matters of political judgement.

In short, we can say that understanding the progression of the covid-19 epidemic depends on having an adequate understanding of disease dynamics at every level from its microbiology to its macroeconomics. We are now in a better place to understand the challenge facing the mathematical modelers. In order to predict the trajectory of a new variant of an infectious disease, they need to make estimates of rates and changes of rates in the multitudinous process described above. In the jargon, they need to ‘parameterize’ the model. Sometimes these parameters, such as infection
characteristics and population densities are borrowed from empirical estimates from previous pandemics and from census data. But in considerable part they are assumptions, they are estimates, they are best guesses.

And this brings us back to George Box. Box was a pioneer of statistical model building and so his tongue was partly in cheek when he first used the phrase in this form: ‘All models are wrong, but some are useful’ [10]. Box’s essential idea, developed across a range of further publications, was that the worth (or the inadequacy) of a model depended on the veracity (or the deficiency) of the many assumptions and estimates built into it. His thesis more fully formed goes like this: ‘All models are approximations. Assumptions, whether implied or clearly stated, are never exactly true. All models are wrong, but some models are useful. So the question you need to ask is not “Is the model true?” (it never is) but “Is the model good enough for this particular application?”’ [11]

A UK case study

Let us follow this advice and put the requisite question to a particularly influential model that informed the early UK response to the epidemic, the Imperial College report on the likely impact of non-pharmaceutical interventions (NPIs) to reduce Covid-19 mortality and healthcare demand [6]. Figure 1, reproduced from the report figure 2, examines a particular outcome, critical care bed provision required over time, mapped according to which prevention strategy is put into place. The results are dramatic, different interventions are predicted to produce significant shifts in both peak capacity requirements and a delay in timing of necessary provision.

Figure 1 about here

At face value these results have clear action implications and immense policy significance (not to mention great visual elegance). One can see at a glance how the curve may be flattened. But are its underlying assumptions warranted? Are the predictions spurious? Is the model ‘good enough for this particular application’? As Box advises the underlying assumptions in a model are sometimes implied and sometimes clearly stated but we can make some headway with a close reading of this particular simulation. The Imperial College report begins with a detailed catalogue of estimates built into the covid-19 transmission model and then moves on to provide rather more scanty descriptions on its assumptions about how various NPIs would be implemented [6].

Let us begin with the former. Estimates are noted of parameters for population density, household distributions, workplace sizes, commuting distances, school class sizes and so on that are used to model person-to-person contact rates. Estimates of infection ratios ($R_0$), incubation periods, numbers of symptomatic and asymptomatic individuals, and so on are ascertained from the initial Wuhan outbreak and from other epidemics. Estimates of disease progression in terms of treatment and bed requirements, the number of cases requiring hospitalisation, the number of patients and time needed in Intensive Care Units (ICUs), the number of eventuating deaths are provided. Some of these metrics are attributed to ‘expert opinion’ and some to ‘personal communication’, for example: ‘We assume that 30% of cases requiring hospitalisation will require critical care (invasive mechanical ventilation or ECMO) based on early Covid-19 cases in the UK, and Italy (Professor Nicholas Hart, personal communication)’ [6, p5]. As can be seen from this brief summary, an immense research effort goes into parameterizing the key drivers of the infection. We return to its reliability and validity in due course.
The next batch of estimators is applied to what the authors refer to as ‘non-pharmaceutical intervention scenarios’. A number of such action plans are modelled: case isolation, voluntary home quarantine, social distancing as applied to different groups, stopping mass gatherings, and the closure of schools and universities. Recall that the models were published in advance of significant government action (and indeed were influential in national decision making). This is territory much less travelled in previous empirical research and accordingly the estimates are much simpler and fewer than their clinical equivalents and are clearly rooted in the authors’ own assumptions. For instance, the model for an intervention involving the closure of schools and universities assumes: ‘The closure of all schools, 25% of universities remain open. Household contact rates for student families increase by 50% during closure. Contacts in the community increase by 25% during closure’. The model for social distancing those over 70 assumes: ‘Reduce contacts by 50% in the workplace, increase household contacts by 25% and reduce other contacts by 75%. Assume 75% compliance with the policy.’

Both sets of assumptions are then loaded into a model and outcomes for a range of different interventions may be simulated. Figure 1 depicts some key outcome predictions as they pertain to critical care capacity. Do the inputs warrant the outputs? Are the assumptions sufficiently robust to guide future policy? We arrive at the critical question and it is not the first time it has been put, as acknowledged in this famous 1864 quotation from Charles Babbage, the father of computing:

‘On two occasions I have been asked, "Pray, Mr. Babbage, if you put into the machine wrong figures, will the right answers come out?" … I am not able rightly to apprehend the kind of confusion of ideas that could provoke such a question’ [12].

Given that the Imperial simulation centres on critical care provision, it is appropriate to return to a key driver of the model, namely the assumption, care of Prof Hart, that ‘30% of cases requiring hospitalisation will require critical care’. To what extent do other inquiries agree with this estimate? There is a considerable discrepancy with the largest UK tracking exercises. Of 16,749 patients with confirmed covid-19 admitted to 166 UK hospitals ‘17% required admission to High Dependency Intensive care units’ [13]. Curiously, the authors refer to this figure as a ‘high proportion of patients’. A recent study from Italy reports ‘the percentage of patients in intensive care reported daily between March 1 and March 11, 2020 has constantly been between 9% and 11% who are actively infected’ [14]. Another influential survey from the World Health Organisation estimates the surge in ICU requirements as follows: ‘The data from China suggest that 15–20% of COVID-19 cases require hospitalization, with around 15% of cases presenting with severe symptoms and 5% requiring intensive care. In Italy and Spain, 40–55% of COVID-19 positive cases have been hospitalized, with 7–12% requiring admission to intensive care units’. [15]

These figures are derived in (slightly) different time periods, for different countries, using different baselines but none of the information suggests there is a definitive, 30% metric for UK hospitalised cases requiring critical care provision. All that can be said with any authority turns out to be a mere truism – the higher the assumed throughput, the higher will be the predictions about pressures on critical care capacity, on its ability to cope, on staffing pressures and thus on eventual ICU death rates. The Imperial estimate is at the higher end of the range, with obvious and dramatic consequences.
Before we leave the matter, however, there are perhaps more instructive lessons to be learned from current ICU research. Most mathematical models utilise fixed estimates, as illustrated above. But what is estimated, in many instances, is a responsive, self-transforming process. In model world, it is perceived that there is some enduring context called ICU provision, which will come under arithmetic pressure as the number of cases requiring critical care multiply. In the real world, ICU services are closely monitored, snags and bottlenecks are identified, patients are closely triaged, wards are adapted, and the whole process is continually remodelled. Change management is the norm. And crucially from this perspective ICU turns from a ‘recipient of’ to a ‘response to’ the virus. It becomes an intervention rather than an installation.

Phua et al’s paper [16] pulls together an extensive catalogue of how ICU practitioners, hospital administrators, governments and policy makers have adapted to the substantial increase in critical care needs. Recommendations are offered on how to improve: access and triage; infection protection in the unit; the donning and doffing of PPE; the ventilation of units; the spacing of beds; logistical planning for equipment; consumables and pharmaceuticals; workforce load and augmentation; workforce communication and support; patient medication; collecting respiratory tract samples; post-ICU care, etc, etc. The following quotation on ‘intubation’ from the paper provides an example of how one aspect of ICU clinical response can be modified and improved. Many details may be lost on the non-specialist reader (and this author), the point is to demonstrate the inevitable and perpetual adaptation of the service that is lost in the models.

‘Intubation of patients with COVID-19 also poses a risk of viral transmission to healthcare workers, and intubation drills are crucial. The most skilled operator available should perform the task with full personal protective equipment (PPE) and the necessary preparation for difficult airways. The number of assistants should be limited to reduce exposure. Bagmask ventilation, which generates aerosols, should be minimised by prolonged pre-oxygenation; a viral filter can be placed between the exhalation valve and the mask. Rapid sequence induction with muscle relaxants will reduce coughing. End-tidal carbon dioxide detection and observation of chest rise should be used to confirm endotracheal tube placement. The use of closed succioning systems post-intubation will reduce aerosolisation’ [16, p3]

If one adds these modifications to the dozens and dozens of other ICU adaptations reported in the Phua paper, one sees rather vividly the inevitable gap between model assumptions and everyday actuality.

The same goes for the Imperial modelling of the many NPIs that carried the first-wave response to the virus. Recall the scenarios for school shutdown - ‘The closure of all schools, 25% of universities remain open. Household contact rates for student families increase by 50% during closure.’ This sounds clear and simple, but what is really involved? To get a proper measure it is useful to consult government guidance in the document: ‘Actions for schools during the coronavirus outbreak: What schools need to do during the coronavirus (COVID-19) outbreak’. [17]. The first question is who will manage the closure and we see the first glimmer of complexity in the list compiled at the beginning of the report: ‘local authorities, local-authority-maintained schools, academies, free schools, alternative provision schools, pupil referral units, special schools, and independent schools.’ The governance of UK schooling is deliberately dispersed, and these diverse organisations have different authority, interconnections and responsibilities, hence the very first advice is to apply the guidance flexibly – ‘according to local need’. 
The report then moves on to pages and pages of advice of how to implement closure. These involve hundreds of separate recommendations on matters such as staffing levels, their pay and protection, attendance expectations and parental liaison, opening hours, curriculum, meals, exams, pooled provision and so on that defy detailed description here. Rather it is useful to highlight key items of guidance that impact on the intended reduction in social contact rates. The first of these, and contrary to a basic model parameter, is that most schools are in fact expected to remain open – to the ‘children of critical workers’ and to ‘vulnerable children’. Decisions on who precisely qualifies under these criteria and hence on the numbers of residual attendees involved proved difficult to pin down.

A list of eight categories of key workers was provided: i) Health and social care, ii) Education and childcare, iii) Key public services, iv) Local and national government, v) Food and other necessary goods, vi) Public safety and national security, vii) Transport, viii) Utilities, communication and financial services. Understandably these rather abstract categories were subject to continuous clarification – one of which, too ironic to ignore, was that ‘parliamentarians’ are indeed critical workers. But as with all social programmes, decision making is often delegated down the implementation chain and so individual schools were left to judge: whether a particular occupation was covered by a requisite category, whether one or both parents were key workers, and ultimately whether the child turning up at the school gate was genuinely in the ‘critical’ category.

The attendance of ‘vulnerable children’ is subject equally convoluted regulations. Existing statutory definitions apply in this instance but ensuring attendance requires much more direct and proactive communication between the school, social workers, and parents/guardians. The Department of Education guidance lists expectations on following up non-attendance, maintaining individual risk assessment, providing safeguarding and mental health oversight and even responsibilities for the continuing provision and home delivery of free school meals.

The point of this abbreviated example is to show that ‘school closure’ takes on many forms. It thus has variable impact on changing rates of social interaction and will have complex and unanticipated effects on disease circulation. If one adds in the fact that prior to the Government’s notice to close, schools suffered growing rates of absence from staff and pupils and that early indications from other countries show that attendance remains low on any subsequent reopening, it is clear that charting the causal outcomes of this particular policy remain immensely challenging. It is a classic example of the perils of trying to capture a self-transforming process as a model ‘parameter’.

Conclusion – all methods are fallible

Box suggested that the acid test of any model was whether it is good enough for its ‘particular application’. I have tried to show in the above examples that models of non-pharmaceutical interventions for disease control struggle under that test. When, as in the present instances, the intervention involves a maelstrom of complex decisions which mutate over time and under a variety of contextual forces simulation models can rarely cope. Their estimates cannot match the required levels of granularity and multiforment. Rather, the strength of simulation modelling lies in its ability to demonstrate outcomes at broader, strategic levels of public policy. The Imperial model is thus rightly celebrated for contributing to the shift in UK policy towards ‘suppression’ rather than ‘mitigation’. This part of the simulation meets Box’s test because the process modelled is extremely simple – lockdowns, distancing and isolation measures will clearly drive down social contact, with an obvious onward effect in reducing disease transmission rates. This is rather predictable – but even here complexity awaits. Note well Ferguson et al’s conclusion: ‘However, we emphasise that is not at
all certain that suppression will succeed long term; no public health intervention with such disruptive effects on society has been previously attempted for such a long duration of time. How populations and societies will respond remains unclear [6].

This brings us to the broader question about the coronavirus response and how it should be informed by science. A crucial methodical lesson follows directly from the analysis to this point. There are many different ways to evaluate the effectiveness of non-pharmaceutical interventions. All have their strengths and weakness but pooled together they will provide a sounder evidence base for assessing what works. To paraphrase Box ‘all methods are fallible, but some combinations are useful’. So how might a multimethod, transdisciplinary approach be pursued? I offer the briefest of sketches in this conclusion.

The first step is to buttress the simulations with some real-time analysis. There is an enormous, worldwide selection of dashboards and tracking systems that plot rates for covid-19 infection, hospital and ICU admission, and deaths [18]. They provide an overall measure of progress against the disease. They map directly the ongoing attempts to ‘flatten the curve’ and an immediate difference from the simulations is the absence of any bell-shaped progression. Real-time graphs illustrate the hard graft of the response. They invariably fluctuate, they often plateau, and they always differ from nation to nation, region to region. Their contribution is vital: they are a barometer of ongoing progress. Rolling records cannot, however, provide any understanding or weighting of the specific contributions that make up a national response. They do not help us with the attribution problem. Moreover, dashboard data are themselves fallible, disease surveillance is highly complex. Distinguishing a covid-19 death from one due to a patient’s underlying conditions is difficult enough in a hospital but nothing as compared to virus death toll measurement in care homes and in the community [19, 20].

Another important UK innovation is the large-scale (initially 20,000 representative individuals) ‘infection and antibody test study’, which takes us back to the tortuous issues of transmission numbers [21]. This study (still in roll-out at the time of writing) will combine self-administered swab testing and survey questions on symptoms and health behaviours administered in the home by ‘trained health workers’. Tracking will be initially repeated weekly and then monthly. Quite uniquely this research will offer real-time, rather than simulated, understanding of the spread of the disease. However, it too faces many challenges – some standard and some quite unique. Will response data overrepresent the inquisitive, altruistic, ‘worried-well’ – study volunteers are selected from groups that have already responded to ONS surveys and have consented to be contacted again. Conversely, will vulnerable and high-risk families engage with the study? Will all volunteers understand and execute the swab tests properly? What is the specificity, sensitivity and security of home testing? How and how readily will the peripatetic army of trained researchers be recruited. What are the logistical and social distancing challenges in home visits?

Another much vaunted approach to containing the spread of the virus makes use of a ‘contact tracing app’ [22]. There are many variants of this action research strategy in use and in planning. The basic idea is to provide a system that will warn users of the app that they have recently been in close proximity to someone suspected to be infected with covid-19. The programme theory is as follows: i) individuals who have self-diagnosed as having coronavirus symptoms will declare this status on the
app, ii) the software will then flag a message to other users that they have come into sustained contact with the self-diagnosed carrier, iii) the contacted individual will then act accordingly and may be encouraged to self-isolate, iv) the warning and action advice to the new contact may come in different forms (yellow or red alert) according to whether the originator, on subsequent testing, is confirmed to have the virus. By any standards this is a complex implementation chain and there is considerable scepticism about whether sufficient members of the public will be willing to register and report symptoms and be able to obtain testing in order to for the scheme to have a meaningful effect. Add concerns about ‘trolling’, false flags and the NHS record in delivering centralised electronic systems and once again we face potentially copious but fragile evidence [23].

These three additional examples illustrate a methodological pattern. The coronavirus response consists of dozens of different measures evaluated by a portfolio of research strategies. All modes of inquiry can provide valuable data on potential and progress in coping with the virus. But all investigations are fallible, all the ensuing evidence needs to be scrutinised for erroneous assumptions and for overstretched and unsubstantiated claims. How does such critical appraisal work? The grand metaphysical solution for grappling with uncertain evidence can be uttered in a sentence - what is needed is a system for filtering out the weaknesses and synthesising the best in each research contribution. And, moreover, there is a social system for doing precisely this, whose name is ‘science’. The great philosophical and sociological accounts of the privileged status of scientific knowledge recognise that it owes that status through ‘organised scepticism’ [24]. Good science relies on careful scrutiny and close mutual monitoring from the ‘disputations community of truth seekers’ [25].

The norm is for findings to be validated, replicated, independently refereed and peer reviewed. As a result, scientific progress is often painfully slow, and this presents a problem for the rapid-fire science that is covid-19 inquiry. As noted earlier, most governments insist that their decision-making is ‘led by the science’. Under crisis management conditions there is a clear and present danger that too few voices representing elite modes of inquiry will provide that leadership. Scepticism is unlikely to be in high demand. Process data describing crucial local adaptations to action plans may well be overlooked. Currently in England there is some controversy about the ‘Sage committee’, the group of experts convened by Downing Street to advise on the coronavirus response. Its membership, as described in the press, is ‘top secret’. That decision may be welcome to its incumbents, but it is not good for the science.

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<td>The paper throws fresh light on an old problem. Science has a mixed record when it comes to predicting the future. Engineers build bridges based on foreknowledge of all the forces that they are likely to encounter – and their constructions tend to withstand the test of time. Predicting the future course of epidemics and building intervention to contain them is much more precarious. The uncertainties include the inherent variability of the pathogen, the considerable variation in immunity of the host population and, above all, the capricious human judgements of those designing, implementing and experiencing the national response to the outbreak. These factors are analysed in in detail in relation to UK simulation model of the course of the covid-19 epidemic. There is a considerable gap between the assumptions built into the model and the changing predilections of the people. On this basis it is possible to recast an old adage – ‘all models of complex, adaptive, self-transforming systems are wrong’.</td>
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Figure 1: Modelling Scenarios

Figure 2: Mitigation strategy scenarios for GB showing critical care (ICU) bed requirements. The black line shows the unmitigated epidemic. The green line shows a mitigation strategy incorporating closure of schools and universities; orange line shows case isolation; yellow line shows case isolation and household quarantine; and the blue line shows case isolation, home quarantine and social distancing of those aged over 70. The blue shading shows the 3-month period in which these interventions are assumed to remain in place.