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How bad data quality can turn a simulation into a dissimulation that shapes the future

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ABSTRACT

During the spread of SARS-Cov-2, Germany imposed various restrictions, including the closure of schools on March 16 2020, and an extensive lockdown on March 23 2020. In this paper, we show how the influential simulation of the purported beneficial effects of this lockdown in Germany was based on wrong data, but nevertheless played a decisive role in shaping the future by allegedly producing evidence for the effectiveness of these measures, lending scientific credibility to policies. We point out that the evaluation of the success of such policies depends critically on data quality. Using publicly reported confirmed cases for the calculation of time series statistics is apt to produce misleading results because these data come with unknown variable time lags. Using data on incident cases, i.e., dates of the onset of symptoms, produces results that are much more reliable. Using this method demonstrates that previous analyses stating that the mitigation strategies of the German government were necessary and effective are indeed flawed. This in turn shows that model simulations and dissimulations are very close neighbors.

1. Introduction

Simulations have become omnipresent during the recent SARS-Cov-2 pandemic. These simulations tried to forecast the development of the infections (an der Heiden & Buchholz, 2020, 2020b; Ferguson et al., 2020), or to model how various nonpharmaceutical interventions (NPIs) might contribute to a reduction in the spread of the virus (Dehning, Zierenberg et al., 2020). While simulations are known to be heavily dependent on the starting parameters, they nevertheless determine reality, if their predictions are taken at face value and their potential limitations are not kept in mind (Fuller & Loogma, 2009). In this short communication, we point to the shortcomings of one such simulation. We show that if a simulation is not taken as a simulation but as a model describing reality, the reality that is assumed becomes real, and by the same token, the simulation morphs into a dissimulation. This has to do with the fact that humans, like all biological systems, are anticipatory systems (Rosen, 1985), and that the actual state of the system is intimately entangled with its anticipated trajectory (Fuller, 2017).

During the SARS-Cov-2 pandemic many countries adopted various nonpharmaceutical interventions (NPIs) following simulation exercises that factored in the potential effect of such NPIs (Ferguson et al., 2020). These NPIs harmed economies tremendously and had strong negative impacts on physical, mental, and social health conditions, such as increases in mental health disruption or domestic

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violence (Christakis, Van Cleve, & Zimmerman, 2020; Evans, Lindauer, & Farrell, 2020; Ioannidis, 2020; Kampf & Kulldorff, 2021; Racine et al., 2021). Given such adverse effects, it is important to determine whether the measures were actually successful in curbing the spread of the coronavirus SARS-CoV2. Such an evaluation is also important for gauging the effectiveness of NPIs for future mitigation strategies and for the status of simulations in general. The question we wish to answer is: Were these measures indeed effective and were the simulation models correct (Dehning, Zierenberg et al., 2020), or were they rather dissimulations?

Germany prohibited large public gatherings on March 9 2020, closed its schools and other educational institutions on March 16 2020, and imposed an extensive lockdown and contact bans on March 23 2020. Were these interventions necessary to avoid a medical disaster? Some studies, such as Dehning, Zierenberg et al. (2020), use data on reported confirmed cases to evaluate the impacts of the various NPIs. Section 2 reviews their principal finding and points out serious problems with the data used. In Section 3, we present an alternative approach that relies on official data provided by Germany's federal health agency, Robert Koch Institute (RKI). Section 4 concludes the paper.

2. Method

We analyze the publication of Dehning, Zierenberg et al. (2020), pointing to the inadequacy of their data-base. We then use the data published by the German Robert-Koch-Institut (RKI), Germany's official public health authority, to derive a more realistic estimate of whether NPIs were effective or not. This analysis was conducted shortly after Dehning, Zierenberg et al.'s (2020) analysis was made available. We communicated this finding to Dehning et al. who then changed their own model. Unfortunately, they did not communicate this fact widely, such that the findings of the flawed model became part of the construction of reality and thus a dissimulation in the sense of deception of oneself and others. This procedure can be used to demonstrate how delicately prediction models depend on the assumptions and underlying data, and thus, how close simulation and dissimulation, support and refutation are.

2.1. Data on reported cases

Dehning, Zierenberg et al. (2020) model the growth rate of SARS-CoV-2 infections in Germany using a Susceptible-Infected-Recovered (SIR) model combined with Bayesian parameter inference. The authors report change points in the growth rate that correspond closely to three NPIs that became effective on 9 March 2020 (prohibition of large public gatherings), 16 March 2020 (closing of schools and other educational institutions along with the closing of nonessential stores), and 23 March 2020 (extensive lockdown, including a contact ban). Their main conclusion is" that the full extent of interventions was necessary to stop exponential growth" (p. 4). Fig. 1A (upper panel) illustrates this central finding. It shows that the coronavirus SARS-CoV2 grew with a positive effective growth rate until the first NPI, which slowed down the spread. The second NPI reduced the effective rate further, and the third one, the extensive lockdown, drove it into negative territory.

There are several fundamental methodological issues that cast serious doubt on the conclusions drawn by Dehning, Zierenberg et al. Accounting for these issues suggests that the opposite of their principal inference is actually correct: none of the governmental interventions could have had any effect on the spread of the virus because the number of new infections declined much earlier than estimated in their study. Furthermore, the authors ignore direct empirical evidence showing that such countermeasures had very low

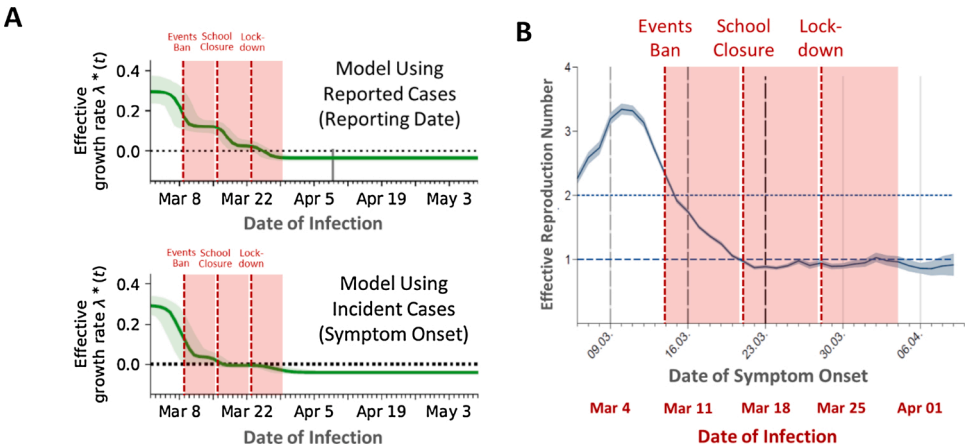

Fig. 1. Illustration of flawed (data on reported cases) and valid (data on incident cases) estimation of the spread of new infections. (**A**) Estimation of the spread of new infections (effective growth rate) in Germany using data on reported cases (upper panel; Source: Fig. 3A in Dehning, Zierenberg et al. (2020)) versus incident cases (lower panel; Source: Fig. 17A in (Dehning, Spitzner et al., 2020). (**B**) Estimation of the spread of new infections (effective reproduction number) in Germany using incident cases (Source: Fig. 4 in an der Heiden and Buchholz (2020); an der Heiden & Hamouda, 2020). The dates on the x-axis show the date of symptom onset (without brackets) and dates of infections (with brackets). Red vertical lines indicate the dates of the three main non-pharmaceutical interventions in Germany. The lambda parameter in panels A are growth parameters which are comparable but not identical to the reproduction number in panel B.

or even no effects. We consider their study to be seriously flawed. Many authors have pointed out some of the flaws in so-called e-letters which are brief online comments posted in "Science" without external review together with the article (https://www.science.org/doi/10.1126/science.abb9789; accessed 22nd Sept. 2021), but the publication remained unchallenged in the literature.

To assess the potential effects of NPIs on the spread of a virus, it is crucial to determine the date of infection as exactly as possible. With imprecise infection dates, any conclusions about the effect of NPIs are meaningless. The authors estimated the date of infection based on the date when a confirmed case was reported, according to the Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE) dashboard. To infer the infection date from the reporting date, they included a parameter in their SIR model that aims at determining the so-called 'reporting delay', i.e., the delay between infection date and reporting date. Critically, their parameter estimate is constrained by an informative prior that, in turn, is based on the assumption of an incubation period of 5–6 days and a test delay. Using their priors, the authors estimated a total delay of 8.6 days during the initial phase and 11.4 days during the later phase.

This procedure is inadequate. First, Dehning, Zierenberg et al. (2020) use data from the JHU CSSE dashboard. As the Robert Koch Institute (RKI), Germany's federal health agency, points out in its profound FAQ section on the coronavirus SARS-CoV2 (Robert Koch-Institut, 2020), data from the JHU CSSE dashboard allow only limited conclusions because they stem from internet media reports and social media, and vary in reporting guidelines. Second, inferring infection dates from reporting dates would only make sense if reporting dates varied systematically with infection dates. However, the intervals between dates of actual infections, diagnostic testing, and reporting differ vastly across people and over time. Many suspected people were tested even before symptom onset, whereas true patients were at times tested more than 20 days after symptom onset (Buchholz, Buda, & Prahm, 2020). Therefore, it is hardly possible to conclude anything meaningful from modeling the spread of infections using reporting dates.

2.2. Data on "Incident Cases"

The nowcasting-procedure of Germany's RKI, (an der Heiden & Buchholz, 2020, 2020b), published 15 April 2020, employs a more sophisticated approach. This nowcasting model is not based on reporting dates but on identified dates of symptom onset, referred to as "incident cases". With an established incubation period of 5 days on average (e.g. (Lauer et al., 2020), 5.1 days, CI 95 % 4.5–5.8 days), incident cases reflect infection dates much more accurately. To describe the dynamics, RKI uses a growth factor R (reproduction number), which compares the 4-day mean of incident cases on one day with the corresponding mean 4 days before. By construction, R lags behind the actual dynamics by 4 days. To make our argument more succinct, we neglect this lag, consideration of which would strengthen our point. Had we taken this lag into account, the whole time series would have been shifted backwards by four days, which would make the difference even more obvious. Thus, we deliberately opt for a conservative analysis. Fig. 1B shows the actual growth factor of incident cases, R, determined by RKI.

Fig. 1B documents that the growth of incident cases reached its maximum already on 10 March 2020. With an incubation period of 5 days, the corresponding growth of infections reached its maximum on 5 March 2020, before the first NPI became effective. Therefore, it is obvious that the spread of the virus was already in decline before the first intervention. And it was even negative already at the time of school closure and long before the extensive lockdown.

In an addendum to their original article, Dehning, Spitzner et al. (2020) reconsider their model, using incident cases rather than reported cases. Their new principal result, shown in Fig. 1A (lower panel), corroborates our finding that Germany's lockdown was superfluous. As can be seen, the effective growth rate of SARS-Cov-2 started declining sharply on March 7 2020, i.e., before the first intervention. What is more, the effective growth rate reached a value of zero at the time of school closure, and became negative on March 17 2020, six days before the lockdown. This finding, derived from the same model but using more reliable data, puts the original inference of Dehning, Zierengerg et al. upside down: Neither school closure nor the extensive lockdown were necessary to stop the spread of the virus. Unfortunately, this subsequent correction of their original publication had practically no effect on the public. The simulation, although seriously flawed, had already been translated into scientific evidence for policies, and had thus become a dis-simulated reality.

3. Discussion

The simulation of a potential future or the simulation of an effect in the past can be disastrous, if based on flawed data. But, as we have witnessed, such simulations become and shape reality, and thereby become dissimulations, whether willfully or accidentally is irrelevant. Especially during the Corona-crisis scenarios of potential benefits in the future have been constructed (Schwab & Malleret, 2020). But such anticipated or predicted futures can also become recipes for dystopias (Roth, 2021). We have shown this for the simulation of the effect of NPIs to prevent the spread of SARS-CoV2 in Germany. In evaluating the necessity of NPIs during the SARS-CoV2 coronavirus crisis, data quality is crucially important. Employing reported cases yields meaningless results because these data come with uncertain and variable time lags that make it impossible to determine the path of the spread of the virus precisely. Using incident cases is preferable if such data are available. With known dates of the onset of symptoms, researchers must only subtract an incubation period of five days to determine the true dynamics of infections.

Official data from Germany's RKI agency suggest strongly that the spread of the coronavirus SARS-CoV2 in Germany receded autonomously, before any interventions became effective. The main reason for such an autonomous decline may be the seasonality of SARS-CoV-2. As is known for common coronaviruses, coronavirus infections show a strong seasonal pattern in Western Europe, with the number of infections rapidly decreasing at the end of winter time (Evangelista, 2020; Merow & Urban, 2020; Visseaux et al., 2017). Regarding SARS-CoV-2, recent studies have shown that while lockdowns and other confining measures are not systematically

correlated with infection rates (Bendavid, Oh, Bhattacharya, & Ioannidis, 2021), the latter strongly correlate with latitude (Sagripanti, 2021; Walrand, 2021), suggesting that SARS-CoV-2 may show a strong seasonal pattern as well. Fig. 2 illustrates the development of the RKI reproduction number in 2021 for comparison. Taking into account that spring 2021 was exceptionally cold, it is altogether plausible that the virus receded about 4 weeks later, notwithstanding a 7-months lockdown period that started in November 2021. And again, stricter NPIs effective from 23 April, including a night-time curfew, do not appear to have influenced the recession of the virus. A further qualification of our argument concerns the possibility that media reports about Germany's first Covid19 deaths on 9 March 2020 may have had an influence on individual behavior that contributed to virus containment, because people behaved differently without being told so by executive order.

Finally, the ineffectiveness of NPIs is also supported by several other empirical studies where the effects of NPIs on infection and death rates have been examined across regions or countries (e.g. Chaudhry, Dranitsaris, Mubashir, Bartoszko, & Riazi, 2020; De Larochelambert, Marc, Antero, Le Bourg, & Toussaint, 2020; Wieland, 2020). By contrast, other studies seem to show some effects of NPIs (e.g. Brauner et al., 2021; Flaxman et al., 2020). Such an inconsistent pattern suggests that similar problems as those identified in this article regarding the study by Dehning, Zierenberg et al. (2020) may also exist in other studies in the field. Indeed, for instance, a closer look reveals that in studies where the course of infections has been estimated from the number of observed deaths (e.g. Brauner et al., 2021; Flaxman et al., 2020), estimations have been based on the date of reporting, despite the fact that there are reporting lags of up to several weeks (e.g. Jones, 2021). Such methods are flawed because if the true date of infection is estimated without taking into account reporting delays, the course of infections is estimated in a misleading way so that effects of NPIs cannot reliably be determined.

Furthermore, we once again emphasize that our analysis is conservative. Had we included the four-day delay that is inherent in the construction of the R-value and shifted our time series backwards, we would have seen a disjunction between NPIs and infection dynamic that is even more striking.

Our analysis uses one concrete but politically very influential example, the modeling study by Dehning, Zierenberg et al. (2020). It shows that its data base was flawed, its conclusions incorrect and the seemingly scientific support for NPIs non-existent. Despite the fact that we had pointed this fact out to the authors in personal communications quickly after their publication had appeared online, and others had published independent evidence for the missing effect of NPIs (Chaudhry et al., 2020; De Larochelambert et al., 2020; Wieland, 2020), NPIs remained politicians' and the public's favorite instrument of "infection control". Dehning, Zierenberg et al. (2020) did not retract their flawed analysis. The journal "Science" did not flag the article. Public media reports did not propagate the information.

This points to an interesting conundrum: Once fear has been installed into a community, as was the case with the media reporting on the pandemic (Bendau et al., 2021), rational argument seems to lose effectiveness due to an anxiety-induced hypersensitivity in recognizing, processing, and responding to threat-related information, even in the absence of actual threat and the presence of contradicting information (Bar-Haim, Lamy, Pergamin, Bakermans-Kranenburg, & van IJzendoorn, 2007). Anything that helps contain this fear is welcome, even if it is inflicting harm, and even if it is shown to be ineffective. Not only were these flawed analyses more prominent, having been published in high-impact journals with wide visibility, they also fulfilled a need in public perception: the illusion of control (Yarritu, Matute, & Vadillo, 2014). This human need to control contingencies leads to a perceptual bias favoring data and information supportive of the impression, and often illusion, that we can control our environment. This desire to control our environment became operative in this pandemic on a grand scale. Our analysis reveals how this not only befalls the public but also highly skilled scientists. The idea that we can plan and control our future is conceptually flawed, as any attempt to plan or control it will inevitably influence its outcome, often in unforeseen ways (Fuller, 2017).

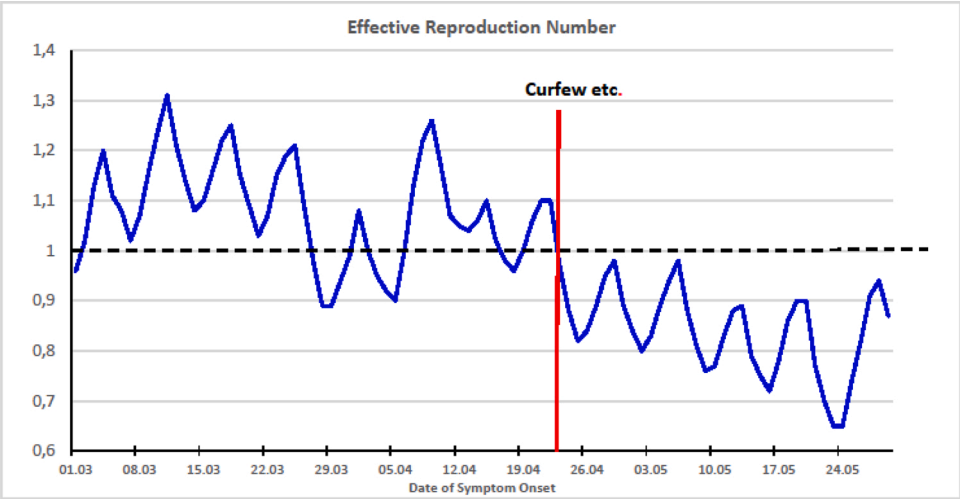

Fig. 2. Effective Reproduction Number, Germany 2021. An extensive lockdown was in effect already from 2 November, 2020. This was strengthened by a night-time curfew and other measures, effective from 23 April, 2021. Given the incubation period, infection dynamics slowed before that date, suggesting that the curfew was also ineffective. Data source: Robert Koch-Institut (2021).

By the same token this shows how closely linked simulations of a scientific nature and dissimulations are. Simulations help us, if skillfully performed and if based on correct data, to predict future events or retrodict the effect of interventions. But they can also become dissimulations if they are based on flawed data that have been used to support our illusion of control. The tragic situation in this case was: The simulation was not only a simulation, it also constructed reality and produced facticity (Fuller & Loogma, 2009), even though a factually wrong reality and a flawed facticity (Meyen, 2021). Thereby the simulation became a dis-simulation. If such dissimulations are based on supposedly scientific analyses, published in widely read scientific journals, then retractions or dementis become a barren road. The stone thrown into the water produces its waves and they cannot be recalled. This demonstrates how important it is to diligently choose the data base and the model. Else a simulation becomes a dissimulation, and by the same token science becomes quackery, and policy informed by such science produces more harm than the danger it is supposed to avert.

4. Conclusion

We conclude that the original simulation claiming that Germany's lockdown was necessary to contain the SARS-Cov-2 epidemic was flawed. Using the correct data-base, the infection date of cases instead of reporting dates, shows that the infectious dynamic declined autonomously, likely because of an intrinsic seasonality, even before any NPIs were put in place. This is a clear recent example how a bad simulation became a dangerous dissimulation.

Author contributions

Christof Kuhbandner, Stefan Homburg, Harald Walach, and Stefan Hockertz co-wrote the paper.

Data availability statement

No data was collected.

Contribution to the field statement

During the spread of SARS-Cov-2, many countries have imposed various non-pharmaceutical interventions (NPIs), and several studies have tried to determine the impact of these NPIs on the transmission of the virus. We point out that the reliability of such studies depends critically on data quality. To illustrate, we use the study by Dehning et al. on the effectiveness of NPIs in Germany, published in Science (Research Article, 15 May 2020: eabb9789). Specifically, we show that using reported confirmed cases to estimate the transmission of SARS-CoV-2 is apt to produce misleading results because these data come with unknown and variable lags. Using data on incident cases, i.e., dates of the onset of symptoms, produces results that are much more reliable.

Declaration of Competing Interest

The authors declare that they have no conflicts of interest. Author Stefan Hockertz was employed by the company tpi consult Gmbh. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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This is a considerably amended version of an earlier version of the manuscript which has appeared online as a preprint: https://advance.sagepub.com/articles/Comment_on_Dehning_et_al_Science_15_May_2020_eabb9789_Inferring_change_points_in_the_spread_of_COVID-19_reveals_the_effectiveness_of_interventions_/12362645.

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