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A missing behavioural feedback in COVID-19 models is the key to several puzzles

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Human actions are at the heart of epidemics. From government lock-down decisions to individual mask wearing, social distancing and vaccination choices, evolving actions of individuals and policy makers have conditioned observed patterns of COVID-19 pandemic.[1] In fact, scholars have increasingly called for integrating the interplay between human actions and dynamics of infectious diseases and offered theoretical models in support of those calls.[2 3] A common approach has been to use data (eg, on enacted policies or mobility) to quantify the impact of individual and policy choices on disease transmission, which enhances models' fit to historical data.[4] Less explored is closing the feedback loops connecting human behaviour and outbreaks. Such feedback loops follow the recognition that changes in human behaviour (individual and policy) are driven by (among others) the ongoing cases and deaths and the perceived risks.[3] Consider one such behavioural feedback loop (which we call 'risk-driven response'): During a pandemic, as infections and deaths rise, people and governments perceive a higher level of risk, which enhances the adoption of transmission-reducing Non-pharmaceutical interventions (NPIs). Then, as the cases and, consequently, the perceived risks decline, people relax the adherence to NPIs, leading to higher interactions and more cases, and the cycles continue.

While intuitive and theoretically recognised such behavioural feedback mechanisms, with some exceptions[3 5–7], have not permeated the relevant research and the resulting policy insights. For example, examining over 60 models providing predictions to the Center for Disease Control's (CDC) COVID-19 forecast hub, we found only one model accounted for the risk-driven response endogenously.[8] Here, we draw on recent studies to argue that this missing feedback is central to resolving some important empirical puzzles, providing novel policy insights and offering better forecasts.

SUMMARY BOX

- ⇒ Human actions have played a key role in shaping the COVID-19 pandemic patterns. While theoretically recognised, existing models of epidemics often do not endogenously capture many of the feedback loops connecting people's choices and epidemic dynamics, for example, adoption of non-pharmaceutical interventions (NPIs) by individuals and governments shapes disease transmission, which in turn alters perceived risks and future NPI adoption.
- ⇒ Such 'risk-driven response' feedback is central to explaining important empirical puzzles of the COVID-19 pandemic, including the convergence of reproduction number to 1 across nations, multiple waves of pandemic, mortality variance and limited trade-off between economic and health outcomes in adoption of NPIs. Capturing that feedback also enhances pandemic forecasting and offers distinct and more effective vaccination strategies.
- ⇒ Much remains to be explored in modelling diverse behavioural feedbacks, from endogenous testing and vaccination choices to the building of infrastructure for various responses. Integrating those with epidemiological models offers promising new discoveries and enhanced policy design.

RISK-DRIVEN RESPONSE AND CONVERGENCE TO R_E~1

Global monitoring of COVID-19 pandemic across diverse communities has revealed an important regularity: that the effective reproduction number, R_e, has hovered around one in every community. For example, average estimated R_e values across all countries up to May 2022 (over 140 000 daily data points) is 0.97 with averages for 140 countries remaining between 0.9 and 1.1.[9] R_e reflects the average number of new cases started by an index case, a measure of risk-normalised interaction levels. With so much variability in demographics, culture, economic activities, social distancing, vaccination and other determinants of risky interactions, it should be surprising that R_e remains close to one in every community. The risk-driven response offers an explanation: when R_e is above one, the epidemic grows exponentially, increasing cases and deaths. The growth continues until elevated risk levels compel individuals and policy makers to respond, adopting NPIs that bring down risky interactions and thus R_e below 1. The resulting reduction in cases and deaths will then weaken risk perception and promote the relaxation of NPIs consequently causing a gradual rise in R_e. Risk-driven response creates an attractor for the system's dynamics at R_e~1.

WAVES OF THE PANDEMIC

COVID-19 pandemic has unfolded in waves, with 3–7 peaks to-date across different nations. These peaks have been a few months apart, some synced across nations while many occurring independently. Existing explanations for cycles in pandemic range from seasonality, to loss of immunity, and emergence of new variants. Yet the cycles are not fully seasonal, nor are they of similar periodicity across nations implied by loss of immunity; and many peaks do not coincide with any new dominant variant. Risk-driven response feedback offers a complementary explanation due to delays associated with risk perception and changes in interaction routines. Such delayed negative feedback loops are known as drivers of oscillations from engineering systems to supply chains,[10] and predict COVID-19 waves.[11] The strength and periodicity of cycles vary across communities depending on the delays involved in risk perception, response adoption, and forgetting of risks, and can be empirically estimated.

MORTALITY VARIANCE, AND THE LIMITED TRADE-OFF BETWEEN ECONOMIC AND HEALTH OUTCOMES

Cumulative per capita COVID-19's deaths across nations span more than two orders of magnitude, are only weakly correlated with population age, and have little correlation with mobility, healthcare capacity, government responses or changes in Gross Domestic Product among others.[12] Risk-driven response offers a novel explanation for this puzzle. The convergence of R_e to one means over the longer term the ongoing interactions in the community (and resulting economic outcomes) settle at levels corresponding to R_e~1. All nations pay the economic costs of NPIs associated with keeping R_e~1. Those costs only vary modestly across communities because the required NPIs depend on the basic reproduction number and susceptible fraction, but not deaths. This explains the (lack of a) correlation between death rates and economic outcomes, mobility or even government policy stringency measures.[13] But lack of a correlation does not mean NPIs are unimportant. Perceived risks settle at the level of deaths that compels a community to adopt the NPIs required to bring R_e to around one. Thus, the long-term death rates are determined by responsiveness to risk: the social/psychological/policy function connecting societal death rates to the strength of risk-driven responses. Responsiveness is estimated to vary by two orders of magnitude across communities, driving large variations in mortality not explained by usual suspects.[11,12] Thus, more responsive communities have avoided a large number of excess deaths with no major additional economic costs. Without appreciating this implication of risk-driven response feedback, much debate in the COVID-19 era has assumed a false and misleading trade-off between saving lives and livelihoods.

ENHANCING FORECASTS

To assess the value of risk-driven response loop for forecast accuracy we extended the classic Susceptible-Exposed-Infected-Recovered (SEIR) model to include a behavioural version of the feedback ('SEIR*b*').[8] This model is otherwise simplistic: it only has four state variables and ignores loss of immunity, vaccination, variants, medications, differences in acuity, symptoms, hospitalisation, age, travel and any data other than cases and deaths. Yet, it ranks among the top in forecasting performance against all COVID-19 models contributing death predictions to the CDC's forecast hub for all USA states until April 2021 and outperforms the ensemble forecast[14] in death projections. Even a simple version of risk-driven response raises the forecasting performance of a simplistic epidemic model to the level otherwise reached only by the state-of-the-art models.

VACCINE PRIORITISATION POLICY

Behavioural feedbacks may change policy recommendations. Consider vaccination prioritisation among population groups to minimise deaths when new vaccines are introduced. Several modelling studies on COVID-19, ignoring risk-driven response, have concluded that prioritising elderly first for vaccination will minimise deaths.[15,16] Noting that long-term death rates are determined by responsiveness to risk, consider a community consisting of two interacting population groups: the cautious (more responsive) and the unresponsive. Resulting death rate will be between those tolerable by the two groups. In this setting, vaccinating the unresponsive first would reduce their weight in the resulting balance, bringing down death rates experienced in the community. This model relies on responsiveness (more than age), prioritising occupations unable to be responsive (eg, first responders or low-income service workers) or sub-communities who have historically suffered most deaths (a signal of low responsiveness). It also alters the received wisdom about age: the elderly may be more responsive due to high IFR. So, counterintuitively, vaccinating the youth first, by bringing down the tolerated death rates among the remaining unvaccinated, may save more lives than vaccinating the elderly first.[17] In fact a recent study[18] after replicating a well-known prior model[16] shows that just adding the risk-driven response to the original analysis (and even without prioritising on responsiveness) reverses the optimal allocation from elderly-first to high-contact-first in early vaccine administration in the USA.

DEFINING AND ANTICIPATING THE ENDEMIC STATE

The risk-driven response loop is key to demarcating epidemic and endemic states. Endemic state emerges when a continuous stream of infection becomes part of the normal life when the ongoing risk of the disease does not elicit changes in individuals' or government's responses. Such waning of risk-driven response may come from reduced cases (eg, due to acquired immunity), low fatality rates (eg, due to vaccines or treatments) or increased tolerance for risk. Only by estimating those factors for each community one can assess whether and when the new normal could arrive.[19] Given the large variations in risk-driven responses across different demographics and regions, we should expect that different communities will arrive at the endemic state at different points in time.

IMPLICATIONS

Even though the relevance of the interplay between human behaviour and epidemics has been repeatedly noted in the past,[2 3] the explicit treatment of the implied feedback loops has been surprisingly uncommon. Models of epidemics rooted in economics have come closest to taking this perspective.[20] Yet adopting a rational agent view, those models often focus on normative implications with insights qualitatively distinct from empirically grounded behavioural models. Evidence suggests the promise is great: If more policy makers had realised that the tradeoff in adopting NPIs vs sustaining economic activity is illusory, they could have saved many lives with little additional costs; predictive models could have been significantly more accurate; vaccination policies could have saved more lives; and by empirically tracking risk-driven responses locally, communities can account for local heterogeneities, assess when a new normal is reached or what its implied costs would be. The marginal gain from incorporating this feedback mechanism is large compared with many nuances currently prioritised.

Much more remains to be explored, from accounting for the multidimensional nature of risk-driven response and enhancing its empirical estimates to assessing its impact on other policy questions. Nuanced policy analysis requires accounting for, among others, heterogeneities in Risk-driven Response feedback, demographics and access as well as attending to equity outcomes. Moreover, other behavioural feedbacks are missing but potentially relevant: adherence fatigue dynamically changes future compliance with NPIs; learning from experience reduces infection fatality rates; willingness to test and vaccinate changes over time as a result of both risk perception and adherence fatigue; and vaccination and test capacities change dynamically in response to cases, deaths, and risk perceptions. This is an exciting grand challenge for the research community, and the COVID-19 pandemic has provided the motivation, and the data, to tackle this challenge effectively.

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