Combining behavioral economics and infectious disease epidemiology to mitigate the COVID-19 outbreak[*]

Johannes Haushofer[†]   C. Jessica E. Metcalf[‡]

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Abstract

Behavioral economics has made progress in recent years in identifying and testing interventions that can improve preventative health behaviors, such as handwashing. We review this evidence and suggest how it could be leveraged to mitigate the current outbreak of the novel coronavirus. We then describe how the impact of these interventions could be maximized using insights from infectious disease epidemiology. First, the nonlinear dynamics of disease transmission imply that saturation, i.e. the share of individuals in a community who adhere to protective behaviors, is an important determinant of impact. Saturation should therefore be systematically included in intervention design and evaluation. Moreover, contagion processes can themselves be used to maximize the spread of protective information and behaviors. Finally, infectious disease transmission is temporally complex, but interventions are often evaluated using snapshot measurements. This can lead to erroneous conclusions, and underscores the importance of careful measurement over time.

COVID-19 is a clear threat to global health. The only approaches currently available to reduce transmission are behavioral: handwashing, cough and sneeze etiquette, and social distancing. Behavioral economics has made significant strides in identifying inexpensive approaches to improving adherence to such behaviors, especially in resource-poor settings, which are expected to be particularly affected by the outbreak. The power of this body of work is that it is grounded in careful experimental design and empirical measurement, often using large-scale randomized controlled trials in field settings. However, this approach has not fully taken advantage of the essentially dynamic nature of epidemics. The novel coronavirus outbreak therefore challenges scientists and policy-makers to combine the advantages of this approach with the theory of infectious disease dynamics. This synthesis is of particular urgency for the development and deployment of interventions to combat COVID-19, but also for preparedness for future emergence events.

A variety of interventions is available to modify behaviors relevant to reducing pathogen transmission. Here we consider how their costs and benefits intersect with two features of infectious disease dynamics: the nonlinear dynamics of transmission, and the time-course of outbreaks.

Light-touch behavioral interventions are often surprisingly effective and low-cost, both in absolute terms, and relative to the outcomes they achieve. These approaches work particularly well for behaviors that people want to engage in, but find hard to follow through because of forgetfulness, inattention, or procrastination. For example, simple text message reminders increase adherence to antiretroviral drugs in Kenya from 40 to 53 percent (Pop-Eleches et al., 2011). A study in Sierra Leone showed that colored bracelets with which parents could signal that they completed the full course of vaccinations for their children increased completion rates from 54 to 62 percent (Karing, 2018). Small financial or in-kind incentives, such as a bag of lentils given for vaccinating children, or a small payment for collecting HIV test results, have been found to increase these behaviors, likely because the payments overcome procrastination rather than a large cost of the behavior itself (Banerjee, Duflo, Glennerster, & Kothari, 2010; Thornton, 2008). A psychological "imagin-

ing the future" intervention in Kenya increased rates of chlorine in household drinking water from 22 to 28 percent (Haushofer, John, & Orkin, 2019).

Such interventions are strikingly cost-effective, and are often easy to deploy. For example, even the comparatively involved psychology intervention to increase chlorination only cost $1.33 per child. Similar interventions could be used to increase desirable behaviors in the COVID-19 outbreak. For example, a recent study in India found that 23% of households in which low-cost soap dispensers were installed used these dispensers daily at dinnertime (Hussam, Rabbani, Reggiani, & Rigol, 2017), an encouraging estimate in light of the importance of handwashing in containing COVID-19. Another study in India found that a hygiene promotion campaign based on emotional messaging, rather than information provision, increased handwashing (Biran et al., 2014). A study in Iraq showed that embedding toys in children's hand soap also increased handwashing (Watson et al., 2019).

However, these behavioral interventions often do not bring adherence to very high levels: usage rates remain relatively low even among those treated. Economic incentives, such as payments conditional on engaging in desired behaviors, can be combined with nudges to make them more effective; for example, the study by Hussam et al. added a condition in which participants received vouchers for household goods if they used the dispenser. At the same time, this modification also increases the cost of the intervention.

We propose that the contagion process of infectious disease transmission can improve the effectiveness of psychological and economic interventions. In the context of disease transmission, individuals who do not directly receive the treatment may still benefit from indirect protection from their neighbors: each protected person also reduces the risk of exposure for those they encounter. Importantly, these indirect effects may differ by saturation level, i.e. the share of a community that receives the intervention. Standard models from infectious disease epidemiology suggest strongly increasing returns to coverage in terms of protection (Keeling & Rohani, 2011). In Fig. 1, we use a standard SIR model to plot the number of infected individuals in an outbreak as a function of time. The red-shaded curve, and the red bar in the inset bar chart,

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describes the time-course of the outbreak for untreated communities. Delivering an intervention to 20% of a community leads to a moderate reduction in the size of the outbreak, shown in blue. In contrast, increasing the coverage to 60%, shown in purple, generates a more-than-proportional reduction in outbreak size, due to the nonlinear dynamics of infection arising from depletion of susceptibles. These nonlinear returns to saturation are typically neglected in tests of behavioral (and other) interventions, because studying them requires variation in spatial saturation of intervention delivery. For example, groups of 15 villages might be randomized to a "low-saturation" condition in which a third of villages and households are treated, or to a "high-saturation" condition, in which two thirds of villages and households are treated. This approach has been demonstrated by recent large-scale studies on the general equilibrium effects of economic interventions (Egger, Haushofer, Miguel, Niehaus, & Walker, 2019; Muralidharan, Niehaus, & Sukhtankar, 2020). Thus, tests of behavioral interventions to combat COVID-19 should take advantage of, and measure, these nonlinear effects of saturation.

The contagious dynamics of transmission can also be leveraged in another sense: Behavioral interventions will be even more effective if they themselves "go viral". Higher levels of saturation can be achieved not only through increased treatment effort, but also when good behaviors are transmitted from treated individuals to others. Note that this spillover effect in terms of adoption is separate from spillovers in terms of disease transmission: For example, distributing information about good hygiene practices both decreases transmission from targeted individuals, and may increase adoption of good hygiene practices by others. Existing evidence suggests several ways in which such information and adoption spillovers can be maximized. For example, targeting individuals who are central in a network (Kim et al., 2015), or good at spreading information according to their peers (Banerjee, Chandrasekhar, Duflo, & Jackson, 2019), can increase the "virality" of the information. In addition, cleverly incentivizing individual people to spread information through a social network can be highly effective in facilitating transmission (Pickard et al., 2011). The power of these approaches lies in the fact that they can create a

"dueling contagion" that can beat a virus at its own game (Fu, Christakis, & Fowler, 2017).

A final insight from epidemiology which can inform interventions and studies to combat COVID-19 is by taking into account the time-course of the outbreak. Field experiments often measure the effect of interventions on current or recent adherence to desirable behaviors, or current or recent infection. However, standard epidemiological models suggest that interventions that reduce transmission will have different treatment effects at different points in time. In Fig. 2, we show the time-course of infections in a hypothetical control group (red), and a hypothetical treatment group (blue). The treatment is highly effective, as can be seen in the lower total size of the outbreak (bar graph inset). However, the intervention also has the effect of spreading the infections over time. As a result, snapshot measurements at single or multiple timepoints, say, 6 months after the intervention, may lead to treatment effect estimates that differ markedly from the total size. Indeed, the observed effect can even go in the opposite direction of the true total effect. Thus, careful measurement at multiple timepoints, or use of biomarkers (serology) that provide a measure of ever having been exposed (Metcalf et al., 2016), can capture the full effect of interventions on outbreaks.

The fact that a "successful" intervention has the effect of spreading the infections over time also suggests an important caveat: the desirable behaviors induced by any intervention may have to be maintained for longer to outlast the duration of the outbreak. This fact may impose psychological and economic costs on the population that are larger than those which would be incurred in a more temporally condensed outbreak. At the same time, a temporally extended outbreak may provide more opportunity for habit formation around the desirable behaviors, potentially strengthened by behavioral interventions to promote habit formation (Hussam et al., 2017). Such effects would partially offset the costs of an extended outbreak, and also have positive broader health effects. In addition, a suppressed but extended outbreak has a lower risk of overburdening the health system—a scenario of particular concern in the case of COVID-19.

Behavioral economics and infectious disease epidemiology have made tremendous strides in recent years in understanding and creating behavior change, and in understanding the dynamics of outbreaks. If policy-makers and scientists can combine the strengths of both approaches, they will have a powerful tool for reducing transmission in outbreaks. The speed required to inform interventions on time-scales relevant to the current COVID-19 pandemic is challenging, but powerful behavioral interventions are often strikingly simple to deploy, the research tools required to appropriately interpret their effects are available, and the rewards of will be considerable.

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Figure 1: Accounting for spillovers
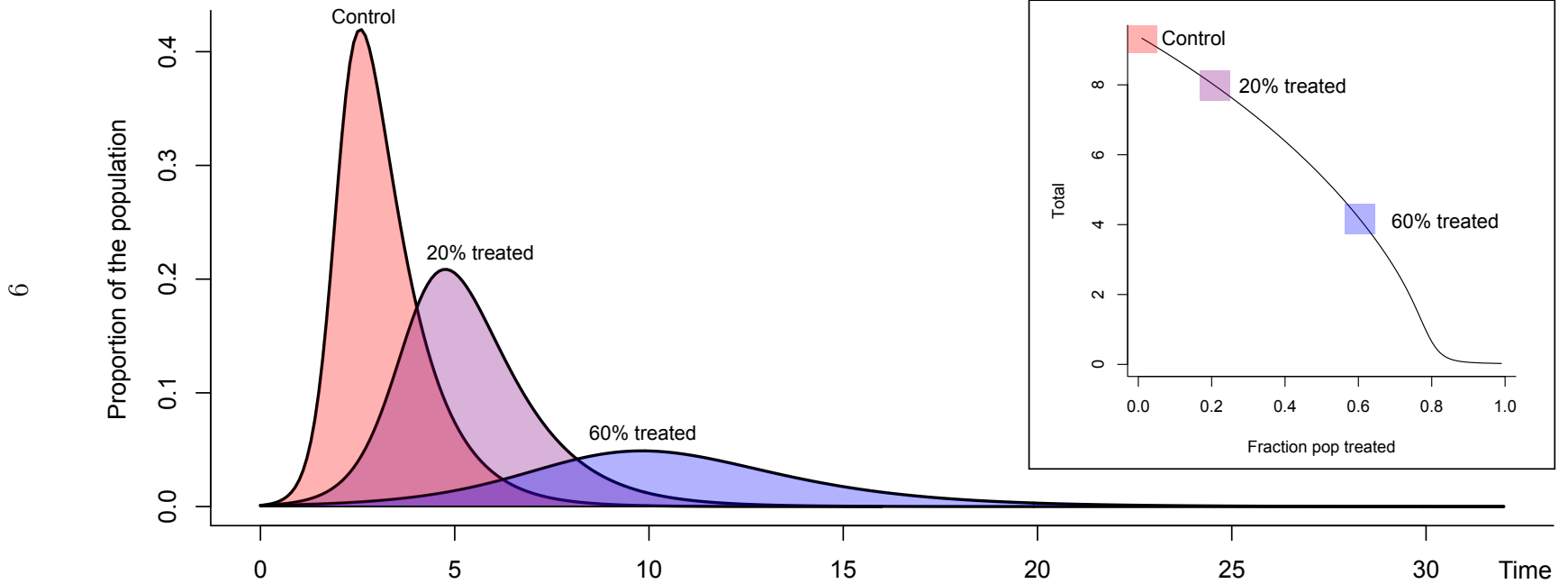
Notes: Time course of infection where different fractions of the population are treated. As the proportion of the population treated increases, total incidence declines nonlinearly (right panel) as a result of the effects of indirect protection.

Figure 2: Accounting for time
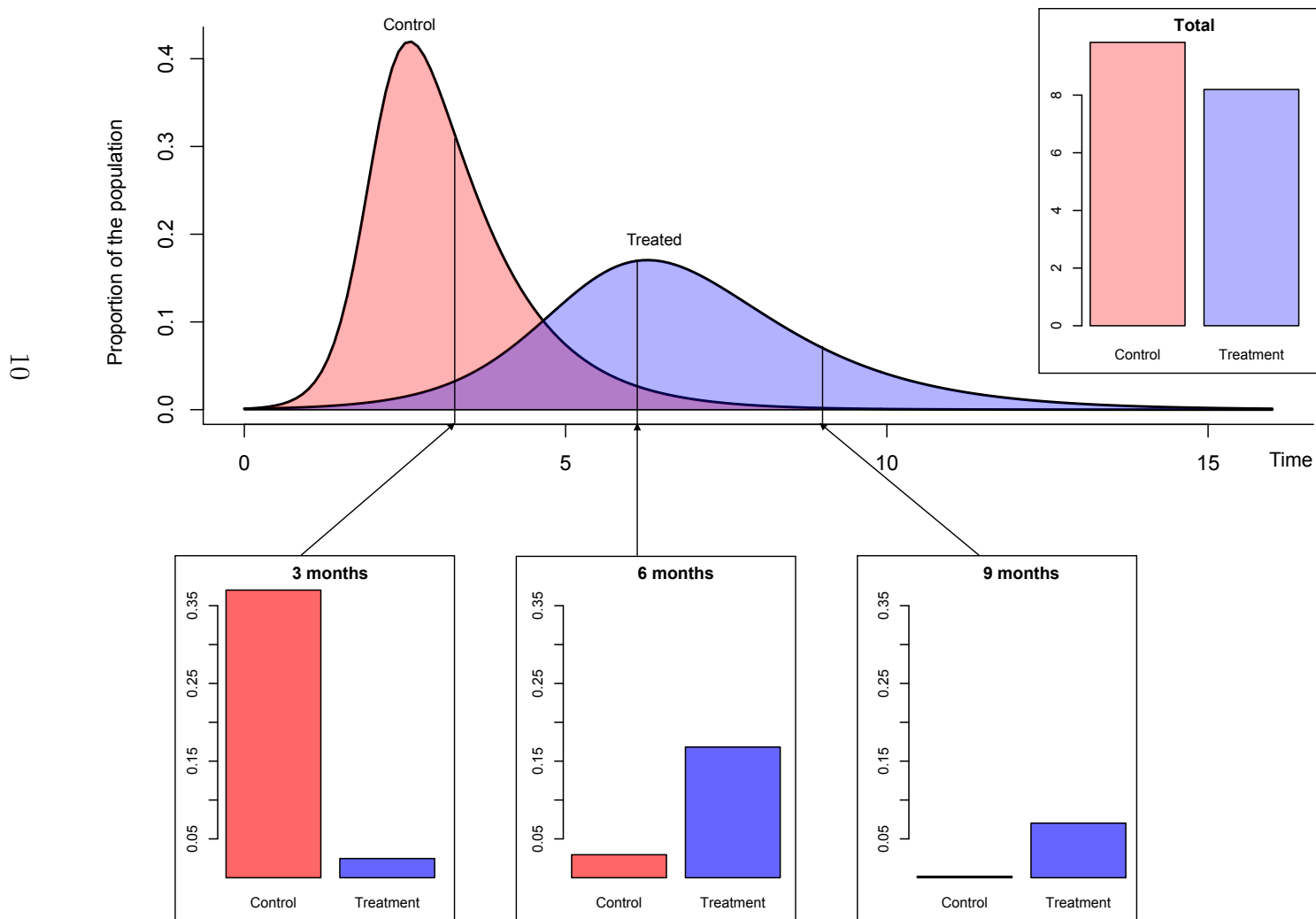
Notes: Time course of infection in the absence of an intervention (red) and with a behavioral treatment (blue). Measurement of the effect of the intervention occurring 3, 6, or 9 months after the start of the outbreak (lower panels) can be misleading, with the treatment appearing to inflate cases for later measurements simply as a result of the way it slows down the outbreak. The total number of cases (right panel) provides an appropriate measure of the impact of the treatment on incidence alone.