The unintended consequences of inconsistent pandemic control policies

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ABSTRACT

Controlling the spread of COVID-19 – even after a licensed vaccine is available – requires the effective use of non-pharmaceutical interventions, e.g., physical distancing, limits on group sizes, mask wearing, etc.. To date, such interventions have neither been uniformly nor systematically implemented in most countries. For example, even when under strict stay-at-home orders, numerous jurisdictions granted exceptions and/or were in close proximity to locations with entirely different regulations in place. Here, we investigate the impact of such geographic inconsistencies in epidemic control policies by coupling search and mobility data to a simple mathematical model of SARS-COV2 transmission. Our results show that while stay-at-home orders decrease contacts in most areas of the United States of America (US), some specific activities and venues often see an increase in attendance. Indeed, over the month of March 2020, between 10 and 30% of churches in the US saw increases in attendance; even as the total number of visits to churches declined nationally. This heterogeneity, where certain venues see substantial increases in attendance while others close, suggests that closure can cause individuals to find an open venue, even if that requires longer-distance travel. And, indeed, the average distance travelled to churches in the US rose by 13% over the same period. Strikingly, our mathematical model reveals that, across a broad range of model parameters, partial measures can often be worse than no measures at all. In the most severe cases, individuals not complying with policies by traveling to neighboring jurisdictions can create epidemics when the outbreak would otherwise have been controlled. Taken together, our data analysis and modelling results highlight the potential unintended consequences of inconsistent epidemic control policies and stress the importance of balancing the societal needs of a population with the risk of an outbreak growing into a large epidemic.

Keywords: COVID-19, SARS-COV2, social distancing, non-pharmaceutical interventions, human behavior

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**Introduction**

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2, the virus that causes COVID-19) has swept the globe, revealing the strengths and weaknesses of our international, national, state, and local public health systems. Emerging evidence from countries such as Vietnam\(^1\), Thailand\(^2\), Singapore\(^3\), South Korea\(^4\), New Zealand\(^5\), China\(^6\), and others\(^7\) suggests that coordinated, national-level policies can control SARS-CoV-2 transmission. However, in many locations – in particular the United States of America – efforts to stem the spread of SARS-CoV-2 were instead implemented as a patchwork of self-isolation, school closures, and business restrictions\(^8\). For example, throughout the months of March and April 2020, US states, counties, and cities often independently implemented stay-at-home orders, mask mandates, limits on gathering sizes, etc.\(^9\). A potentially dire epidemiological consequence of this lack of coordination is that individuals can easily travel to areas with different control measures and avoid locally disrupted services and gatherings.

Even in countries with more uniform policies, religious activities have been the subject of much debate as the local risks associated with the the activity\(^10\)–\(^12\) clashed with protections of the activity as an essential service to individuals and the community\(^13\). Choirs and large services in particular have led to many superspreading events\(^14\), with attack rates well-above 50% in some cases\(^15\). Unfortunately, there have been little efforts devoted to replacing religious services with safe alternatives, leading individuals to defy public health recommendations. As an example, individuals have defied church closures and attended mass gatherings, at times leading to legal prosecution\(^16\),\(^17\).

Other essential services have seen similar patterns, with public spaces such as urban and suburban parks and trails also being the subject of inconsistent visitation patterns and closures. As other businesses close, there has been increased foot traffic in parks with many reporting overcrowding. When some, but not all, parks and trails close, individuals may travel further to areas remaining open potentially seeding virus to previously uninfected areas\(^18\).

To compound the risk posed by unintended increased travel to obtain certain essential services, the rush to reopen US states with stay-at-home orders has been similarly haphazard, leading to massive upticks in cases in previously well-controlled states\(^19\). Taken together, the non-uniform implementation and relaxation of US state-level interventions has left the country with high numbers of cases and potential distrust of public health interventions\(^20\). Quantification of how movement patterns have changed from one’s local closed business to a neighboring open business has been under-explored. Also needed are more general investigations into the impacts of non-uniform implementation of interventions on the transmission dynamics of SARS-CoV-2 and other pathogens. Here, we first examine online information seeking and physical foot traffic data to see how gathering-specific behavior has varied across the US during the COVID-19 pandemic, and then study a model of epidemics with partial gathering restrictions and partial adoption of said restrictions. Finally, we discuss the implications of these results especially as they relate to current discussions on relaxing or re-implementing stay-at-home orders and allowing gatherings.

**Changing mobility and information-seeking**

We use data from SafeGraph to quantify human mobility after the adoption of physical distancing measures. SafeGraph is a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places. To enhance privacy, SafeGraph excludes census block group information if fewer than five devices visited an establishment in a month (two devices in a week) from a given census block group. Using these data we use counts of visits and unique visitors to businesses across the US as well as the distance traveled from ‘home’ (defined as the common nighttime location for the device over a 6 week period where nighttime is 6 pm to 7 am).

What is clear from the data is that many individuals are willing to travel further to attend certain gatherings, in particular church services. We find that despite seeing an overall 56% (95% CI: 40–76) decrease in visits to churches comparing the first to last week of March, individuals that do visit a church travel on average 13% (95% CI: 4–26) further to churches across most states in the country (Fig. 1).

That individuals are looking and traveling further for churches is also seen in Google search trends (as downloaded from the Google API for Trends), where queries for ‘churches’ have increased since the beginning of March while searches for “parks” have decreased. We compared search volumes for church on Sundays between March 13 and April 13, 2020 to Sundays earlier in the year. Comparison to previous years should alleviate potential biases as the previous years act as counterfactuals to 2020. Overall, we see 49.6% (95% CI: 46.4–52.9) higher search volumes for churches in 2020 as compared to 2010–2019, with similarly higher volumes across states. Indeed, only two states (D.C. and NV) did not show statistically significantly higher search volumes in 2020, with the others ranging from 10% (95% CI: 7.0–11.8) in MA to 106% (95% CI: 100.5–111.3) in WY (Fig. 2). Conversely, we fit a series of sinusoidal regressions to estimate the expected number of searches for “parks” and find a 22% (95% CI, -10 to -31) decrease after the declaration of national emergency. These patterns of searches indicate increased information-seeking for churches, potentially because an individual’s normal church is closed. From a social network perspective, traveling to a more distant church is an unintended
We find a correlation between increases to visits to churches with increases in visits to grocery stores (Pearson’s r = 0.44) with increases to grocery stores being higher than to churches (slope = 0.9, 95% CI: 0.37–1.44; Fig. 3). Additionally we find increases to churches and grocery stores to be largely independent of whether the state had a stay-at-home order in place, suggesting that the phenomenon is closely related to the local distribution of services and behavior of the local population rather than top-down interventions.

Even ignoring the fact that these additional visitors travel further and are therefore likely to increase the coupling between distinct communities, they also simply increase the number of contacts in their new church. Given that the expected number of contacts is expected to increase non-linearly with the number n of participants in a gathering (i.e. potential contacts are proportional to n(n−1)/2 ∼ n²), it is unclear whether or not closing some churches might be worth the increased risk in the remaining open churches. To investigate this trade-off, we now design a simple model.

**Mathematical model**

To more broadly explore the potential unintended consequences of inconsistent epidemic control policies, we formulated a simple, mathematical model which we call cloSIR to couple disease dynamics with closure policies. Specifically, we model an epidemic in a population of size N uniformly distributed across M gatherings of size \( n = N/M \). We assume that a fraction \( X \) of gatherings are closed at time \( t_c \) to help contain an outbreak and that a fraction \( Y \) of members in closed gatherings then decide to defy the closure by travelling to one of the remaining open gatherings. These open gatherings could be under a different set of rules in a different location or the venue/location itself may be defying government restrictions. Closures therefore protect the local community, which does comply with the closures, but can potentially increase attendance in any open venues.

As a first approximation, we ignore any spatial features and contacts occurring outside of average gatherings. We track Susceptible-Infectious-Recovered (SIR) dynamics within gatherings by assuming that the natural normalized transmission rate of the disease is \( \lambda \) (with a recovery rate equal to 1 for time units set to the recovery period). We use \( S_o/c \), \( I_o/c \) and \( R_o/c \) to denote the number of susceptible, infectious and recovered individual in a typical open/closed gathering, respectively. Applying standard SIR dynamics in open gatherings but removing transmission events in closed gatherings, we write

\[
\begin{align*}
\frac{dS_o}{dt} &= -\lambda S_o I_o \\
\frac{dS_c}{dt} &= 0 \\
\frac{dI_o}{dt} &= \lambda S_o I_o - I_o \\
\frac{dI_c}{dt} &= -I_c \\
\frac{dR_o}{dt} &= I_o \\
\frac{dR_c}{dt} &= I_c.
\end{align*}
\]

(1)

(2)
Figure 2. Changes in information-seeking for churches and parks. Sparklines show Google searches for “church + churches” (obtained using the Google Trends API for search) for all states in the US. Dark line indicates searches in 2020 and lighter lines 2010–2019. Percent increases are comparing Sunday search volume in 2020 to Sunday volumes in 2010-2019. Map on bottom left shows the percent increases as displayed in the sparklines. Bottom right plot shows searches for “park + parks” from January 1 through April 14th, 2020. Light line shows a sinusoidal regression fit to January 1 to March 13 and projected forward to show expected searches over March 13 to April 13. Dashed line indicates Trump’s declaration of a national emergency.
Figure 3. Prevalence of churches and grocery stores with increased numbers of visitors. Scatter plot of different states based on their increase in visits to essential services as well as whether the state had a stay-at-home order in place before March 29th. These are grocery stores or churches who had an increase in visits comparing the first and last week of March. The horizontal axis shows the fraction of churches with an increase in number of visits, and the vertical axis shows the fraction of grocery stores with an increase in number of visits. There is a positive correlation between both but not clear distinction with local policy, suggesting that the phenomenon is related to the local distribution of services and behavior of the local population.
The critical part of the cloSIR model is the implementation of closure policies at time $t_c$. At time $t < t_c$, all gatherings are open and we have $S_o + I_o + R_o = N/M$ and $S_c = I_c = R_c = 0$ such that all derivatives are equal to zero in closed gatherings for $t < t_c$. Once the intervention is implemented at time $t = t_c$, we redistribute non-compliant individuals from closed to open gatherings. Since $XM$ gatherings are closed, we have $XM \times (YN/M) = XYN$ non-compliant individuals to redistribute across $(1-X)M$ open gatherings. This connection between increases in intervention and displacement is based on the correlations observed in Fig. 1(c). This mechanism increases the population of open gatherings to $N/M \times [1 + XYN/(1-X)]$, and similarly decreases the population assigned to closed gatherings to $N/M(1-Y)$.

After closures are implemented, the dynamics of the cloSIR model are still governed by the same set of ordinary differential equations. As the outbreak progresses, we are interested in two key observables: first, the total number of infectious individuals

$$I(t) = \begin{cases} M I_o(t), & \text{for } t < t_c \\ (1-X)M I_o(t) + X M I_c(t), & \text{for } t \geq t_c \end{cases} \quad (3)$$

and, second, the total fraction of recovered individuals

$$R(t) = \begin{cases} M R_o(t), & \text{for } t < t_c \\ (1-X)M R_o(t) + X M R_c(t), & \text{for } t \geq t_c. \end{cases} \quad (4)$$

Finally, note that $N$ and $M$ are used to help us write the equations but only act as scale factors in our results and can therefore be set to $N = M = 1$ for simplicity and without loss of generality.

Ultimately, although the dynamics are governed by the classic SIR differential equations for all time, the cloSIR model offers an interesting tradeoff between controlling transmission by closing venues and intensifying transmission by aggregating contacts in a smaller number of still open venues. The question then becomes whether the redistribution of participants among gathering locations, e.g., churches or parks, will have a positive or negative impact on the epidemic. Assuming one cannot ensure the closure of all venues, is closing a certain percentage of venues worth the increase in visitors to those that remain open?

Strikingly, we find that in many scenarios the optimal strategy to minimize the size of the outbreak is often no intervention at all. Figure 4 shows that depending on the proportion of the population that chooses to go to another open business ($Y$) the final outbreak size is often minimized when $X = 0$ (no closures). In fact, close or below the epidemic threshold $\lambda_c = 1$, interventions can spark an outbreak in communities otherwise not at risk by increasing the concentration of susceptible individuals. However, for stronger epidemics (larger $\lambda$), although a complete closure of gatherings $X = 1$ might be the optimal strategy, the expected outbreak size often follows a non-monotonous function of $X$ such that the optimal outcome at $X = 1$ is next to a worst-case scenario at large values of $X$ just below 1. What this implies is that the outcome is highly dependent on the amount of non-compliance that one can expect in a population (i.e., larger values of non-compliance $Y$).

Similarly, poorly-timed interventions can actually lead to additional waves of infection. Figure 5 shows that secondary peaks of infection occur if intervention is initiated too late. Interestingly, stronger interventions tend to dramatically heighten the epidemic peak under many closure scenarios (colored curves) compared to the no-closure baseline (black curve).

The cloSIR model therefore provides the simplest possible example of the potential impact of the collective behaviour observed in the empirical mobility and search data from the US around essential services. Although future research should layer in additional complexity into models of policy interventions, within the idealized scenario considered by the model, one can solve for specific features: E.g., the final outbreak size, the optimal closure percentage $X$, and the critical value of non-compliance $Y$ such that weak interventions increase outbreak size. Analyses of these different questions are presented in the Supplementary Information document.

**Discussion**

Balancing the mental, economic, and social health of populations with the serious risks of COVID-19 means that restricting movement (e.g., cordons sanitaires) should only be considered as a last resort. Indeed, evidence from China suggests that while the cordon sanitaire of Wuhan may have delayed the outbreak, it was local measures that slowed transmission and ultimately controlled the outbreak$^{6,21}$. As now seen in numerous countries, COVID-19 can be controlled in the absence of strict mobility restrictions and an effective vaccine with coordinated public health responses$^7$. Despite evidence of the efficacy of consistent non-pharmaceutical interventions, many countries (especially the United States of America) continue to implement control measures in a scattered, patchwork manner$^8$.

Using real-time mobility and search data in the US, we found that distance traveled and the number of visits to essential services did not correlate strongly with any demographic variables (e.g. population density, average age). However, both of these responses did correlate with community tightness, with tight communities being those “with strong norms and little
tolling for deviance" (Fig. S1). Gelfand et al. (2020) found that countries with both efficient governments and those with tight cultures were the most effective in limiting COVID-19 cases and deaths\textsuperscript{22}. However, White & Hébert-Dufresne (2020) found the opposite for the United States, with the tighter states having the faster COVID-19 growth rates early in the pandemic\textsuperscript{9}. In the context of our cloSIR model, tight communities are those with strong restrictions (i.e. a high $X$) and few non-compliant individuals (i.e. a low $Y$). Thus, if we know the level of tightness of a community, in this case a state, we can make more targeted policy recommendations. For example, if a government expects a large number of non-compliant individuals and complete lockdown is not possible, it might be best to have no lockdown at all (Figures 4 & 5).

Given these unintended consequences, instead of blanket closures of churches, parks, and other essential services, leaders can enact measures that provide for the benefits of physical distancing, while balancing the mental health costs of social isolation. For example, more frequent services with fewer members could increase compliance with physical distancing. Without balancing the requirements of the intervention with the needs of the people, partial measures can be worse than no measures at all. In the context of vaccination, such effects have been previously identified. Past work has shown that implementing stricter vaccination rules tends to cluster children that are under-vaccinated\textsuperscript{23,24}. These findings of a policy backfiring effect leading to disease spread are in line with our empirical and modeling results.

Our results are particularly relevant as the loosening of restrictions on businesses and other institutions is also occurring in a disorganized and spatially heterogeneous way across the US\textsuperscript{25}. As we say during the inconsistent shutdown, this lack of coordination at the policy-level creates incentives for individuals to travel to those areas which are open to purchase products.
and services, to access public areas, like beaches and parks, and/or attend religious services. For instance, the partial reopening of businesses in Georgia on Apr 24th, led to a 13% increase in visitors from nearby states\textsuperscript{26}. This surge in inter-state mobility both increases distance traveled and the amount of clustering in a limited number of areas. The same result occurs if individual businesses or institutions decide on different reopening strategies. For instance, in Burlington, Vermont retail stores were allowed to open with limited capacity on May 18th. While many stores opened on this date, many store owners decided to postpone openings out of safety concerns\textsuperscript{27}. Thus, if a state relaxes restrictions on businesses, but some businesses owners choose to remain closed, this has the same effect demonstrated in our analyses. Conversely, if stores are not allowed to open, but some businesses, or individuals defy these orders, it again has the same effect. Therefore, scattered or disorganized reopening after lock-down could spark second waves of infection. Critically, reopening more slowly is not necessarily better if done non-uniformly.

There are several caveats to our study. First, we developed a simple model that was able illustrate the potential unintended consequences of individuals adapting their behavior to seek essential services under inconsistent physical distancing policies. While the simplicity of this model is a strength when trying to isolate the effects of inconsistent control policies on COVID-19

**Figure 5. Importance of timing of the intervention and onset of second waves.** Panels show the effects of changing intervention time across ranges of X and Y. The black curve depicts the course of the outbreak without any intervention. The various colored curves peeling off from the black curve show the course of the outbreak given differently timed interventions. Colored dots indicate epidemic peaks larger than the no intervention baseline scenario. Intuitively, we find that earlier interventions are always better. We see that delayed and imperfect interventions can cause second epidemic waves.

While the simplicity of this model is a strength when trying to isolate the effects of inconsistent control policies on COVID-19...
transmission, future work will be needed before such models could be used to actively inform specific policy decisions. Second, because the SafeGraph data do not track individual users over long periods of time, those observed in late March are not necessarily the same individuals observed earlier in the month. Moreover, we may expect biases in the diversity and behaviors of individuals tracked by the system. Different types of gatherings attract different types of individuals which will not be sampled homogeneously by any one data source. Altogether, these limitations mean that small geographic regions should not be directly compared to one another, or even to themselves at a different time, and different locations should not be directly compared. This is why we coarse-grained our results over states, why we only compare relative changes and not absolute differences, and why we attempted to correlate our findings with a secondary data source like online searches. Future work is therefore warranted, on both data collection and analysis (comparing changing movement patterns for various other business types) and mathematical modeling (expansion to include more metapopulation structure to explore the interplay of interventions across scales).

As we have shown, it is of key importance that non-pharmaceutical interventions for the fight against COVID-19 – specifically related to business and venue closure – must be implemented in a uniform way to avoid situations where enacting an intervention is worse than no intervention to begin with. Further, relaxation of such interventions must be done methodically and over time, with a strong emphasis on equity across incomes and geographies to avoid endangering individuals with lower socioeconomic status. Human behavior is a strong driver of the transmission dynamics of SARS-COV2 and care must be taken to reduce the heavy burden imposed by COVID-19 and avoid unintended, negative consequences from inconsistent policies around implementing and relaxing non-pharmaceutical interventions.

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