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Title: How Timing of Stay-at-Home Orders and Mobility Reductions Impacted First-Wave COVID-19 Deaths in US Counties

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Data Availability Statement: Processed data and model code are available with no restrictions at github.com/audiracmichelle/covid_timing

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Running Head: Timing of Stay-home Orders and Mobility Reductions.

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Abstract

As SARS-CoV-2 transmission continues to evolve, understanding how location-specific variations in non-pharmaceutical interventions and behaviors contributed to disease transmission during the initial epidemic wave will be key for future control strategies. We offer a rigorous statistical analysis of the relative effectiveness of the timing of both official stay-at-home orders and population mobility reductions during the initial stage of the US epidemic. We use a Bayesian hierarchical regression to fit county-level mortality data from the first case on Jan 21 2020 through Apr 20 2020 and quantify associations between the timing of stay-at-home orders and population mobility with epidemic control. We find that among 882 counties with an early local epidemic, a 10-day delay in the enactment of stay-at-home orders would have been associated with 14,700 additional deaths by Apr 20 (95%

credible interval, 9,100, 21,500), whereas shifting orders 10 days earlier would have been associated with nearly 15,700 fewer lives lost (95% credible interval, 11,350, 18,950). Analogous estimates are available for reductions in mobility—which typically occurred before stay-at-home orders—and are also stratified by county urbanicity, showing significant heterogeneity. Results underscore the importance of timely policy and behavioral action for early-stage epidemic control.

Keywords: Bayesian hierarchical model; counterfactuals; SARS-COV-2; intervention analysis; non- pharmaceutical interventions; stay-at-home orders; Covid-19

SARS-CoV-2, the causative virus of COVID-19, continues to threaten the world with nearly 9.2M re- ported cases and 348,000 deaths as of Jan 1st, 2021 in the US [1]. It is clear that both non-pharmaceutical interventions (NPIs) and behavioral changes have impacted transmission of the virus[2–6]. However, there are multiple population-specific factors that influence epidemic trajectories and how they change including demographic characteristics and, importantly, the timing of such NPIs and behavioral responses [7,8]. Decou- pling the impacts of these factors and the relative timing of actions or behavior changes presents important challenges [4,9]. A key problem particularly in the United States, is that policy changes and mobility shifts happened rapidly in late March and April 2020 in response to growing COVID-19 epidemic and happened simultaneously across the country, so it has thus far been difficult to disentangle the relative impact of earlier vs. later action and behavioral responses from NPIs.

In this work, we quantify the impact of the timing of stay-at-home orders and mobility reduction relative to local epidemic conditions. Specifically, we developed a spatial Bayesian statistical model of county-level COVID-19 mortality between January 21, 2020 and Apr 20, 2020 across 882 counties, most of which had either: a) an official stay-at-home order in place or b) a reduction in population mobility of at least 50% relative to their baseline. We model how county-specific trajectories of COVID-19 deaths changed as a function of timing of control efforts and county-level features and use the model to predict county-specific death trajectories under alternative timing of stay-at-home orders or mobility reductions.

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METHODS

County-level COVID death and demographic data

Our analysis relies on multiple county-level data sources. First is the dataset reported by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University [10], which counts COVID-19 related deaths as well as the dates in which different NPIs took place in each county. Web Appendix 1 provides details of such NPIs, namely: gathering bans; restaurants, business and school closures; and stay-at-home orders. For our statistical model, we focus specifically on stay-at-home orders for two reasons: first, they exhibit wide variation in timing among counties; second, counties typically had COVID-19 deaths prior to the stay-home-orders, a condition useful for the statistical estimation of pre- vs. post-intervention trajectories. For instance, 56% of the counties had at least 10 days with observations before the stay-at-home orders (considering the days between infection to death). In contrast, for the five policies not included in the study, less than 25% of the counties show observation periods of at least 10 days before the intervention.

A second source of data pertains to county-level covariates, which are included in the analysis with two objectives: 1) to reflect the differences in disease dynamics associated with different types of counties and 2) control for possible differences between counties with different timing of stay-at-home orders or mobility reductions. As a summary measure of county characteristics known to relate to residents' contact rates and the reproduction number (population density, modes of travel, distance to major airports) and other factors expected to vary across the spectrum of rural and urban areas, we use the National Center for Health Statistics (NCHS) Urban-Rural Classification Scheme for Counties [11], which classifies each US county to be in one of the following six categories: 1) large central metro; 2) large fringe metro; 3) medium metro; 4) small metro; 5) micropolitan; 6) non-core. In addition, we extract from the US Census American Community Survey other county-level covariates that have been reported to have a strong relationship with COVID-19 death rate and are not captured by the NCHS county classification. These covariates are further described in the Methods section.

Human mobility data

Focusing on a single well-defined intervention, here, the stay-home orders, is not

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able to parse the possible contributing effects of other concurrent or overlapping early-epidemic control efforts. For this reason, we also investigate the timing of a mobility-related behavior change to capture policy-induced or voluntary behavioral responses to the epidemic. Thus, for our third data source we use human mobility data from SafeGraph, a company that provides anonymized population mobility information representing 45 million smartphone devices (http: //SafeGraph.com). SafeGraph data aggregates visit counts to numerous points of interest (POIs) classified into categories. As a proxy measure for overall mobility behavior in each county, we extract data (accessed from Safegraph in May, 2020) on the number of visits per day to POIs; in particular to schools, colleges, restaurants, bars, parks and museums, and obtained time series of daily total visits for each county. The average total visits per day between Jan 15, 2020 and Feb 15, 2020 is used to establish county-baseline levels of mobility. We define the date of the mobility-based intervention to be the date on which the right-aligned ten-day moving average of total visits to POIs decreased 50% relative to baseline. All counties in the data set reached at least a 40% mobility reduction, with a few counties reducing by more than 75%. After mobility was substantially decreased, it held fairly constant during the analysis time frame as detailed in Web Appendix 2. Therefore, the date at which the 50% cut-off was reached is chosen as a practical balance to represent the start of a period of low levels of visits to POIs.

Analysis data set

County-specific daily counts of COVID-19 deaths were extracted from Jan 21, 2020 through April 20, 2020 which we take to be a loose definition of the end of the first US epidemic wave, as mobility started to rise again after this date. During that period, 1243 counties (out of a total of 3221 US counties) had reached a threshold of 3 deaths per 10 million residents, signaling arrival of a local epidemic. We restrict attention to those counties that have at least seven days recorded after reaching their threshold and excluded 222 counties due to lack of sufficient Safegraph mobility data to characterize baseline mobility. A map in Web Figure 1 depicts the 882 counties of interest that comprise the analysis dataset in which 93.4% instituted stay-at-home orders, and 99% exhibited at least 50% mobility reductions. Web Table 1 summarizes the number of counties and population covered in each NCHS classification category, indicating that this fraction of US counties

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in the dataset covers approximately 234 million, roughly 71.5% of the total US population.

Statistical methods

We propose a spatial Bayesian hierarchical model to capture the impact of the timing of an intervention (stayhome or mobility decrease) as measured by a change in trend in death trajectories. The analysis consists of two distinct variations: 1) *Stay-at-home model*: Here, the intervention and relative timing are defined according to the date at which a county instituted a stay-at-home order, 2) *Mobility model*: Here the "intervention" is not actually a discrete policy intervention, but the date at which a county reached a 50% reduction from baseline mobility patterns. Throughout, we continue to refer to the mobility reduction as an "intervention" for simplicity.

To model death trajectories, we use the time series of each county's 7-day centered rolling average of daily deaths, and specify a log-linear model for the expected number of deaths in each county using a negative binomial distribution and a two-stage quadratic function of the "epidemic time", defined as the number of days elapsed since reaching a deaths threshold of 3 per 10 million residents. The two-stage time function is modeled to change after a pre-specified delay following introduction of an intervention, resulting in different pre- and post-intervention trajectories. A schematic representation of the components of the proposed model appears in Web Figure 2. Note that this work focuses on estimating the difference between post-intervention trends under different intervention timing, and not on a comparison with the implied extension of the pre- intervention trend through the post-intervention period (which would correspond to no intervention at all). Refer to Web Appendix 3 for a detailed mathematical formulation of the model and specification of the parameters' priors; inferences are based on posterior simulations from the models. We fit all models using the R language (4.1) with the package Rstan (the R interface to Stan. Package version 2.21.2. Stan Development Team. 2020. mc-stan.org/rstan/articles/rstan.html). Processed data and model code are available with no restrictions at https://github.com/audiracmichelle/covid_timing.

The ability of quadratic functions to naturally adapt to epidemic curves that start growing exponentially and eventually flatten was particularly useful to the Centers of Disease and Control Prevention during the first-wave of the Covid-19 pandemic when epidemiological parameters remained elusive [12]. The choice of a log-quadratic specification is further explored in Woody et al. [13]. Our approach is similar to theirs in that it modulates the coefficients of the log-quadratic

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trends, and in that it uses a negative binomial likelihood and county-level random effects. The model utilizes a lag of 14 days after introduction of an intervention before a change in death trajectories, a delay consistent with the first quartile of the distribution of time between infection and death [14–16], and informed by an analysis in Web Appendix 4 that estimates this lag from available data.

To parsimoniously capture variation across counties, a county's pre-invervention trajectory is modeled to interact with the county's NCHS county classification as well as county-specific demographics. These are meant solely to induce flexibility in modeling pre-intervention disease dynamics in different types of counties, and are all features with sufficient reason to suspect that they relate to disease transmission. The percent of black residents and percent of hispanic residents are included to account for the apparent disparities between infection and comorbidity and death rates among the population. To account for the age-related risk of death, we include the percentage of residents that are 65 years or older. Particular behaviors specific to students (whose main activity quickly became completely remote amid the early epidemic stages), are accounted with the percentage of residents attending college.

In addition to demographic covariates, three different types of random effects are included to model latent heterogeneity in the polynomial terms of the pre-intervention trajectories: two sets of county-level random effects model a) spatially-varying heterogeneity based on the Besag-York-Mollíe formulation [17] to capture correlation between neighboring counties and b) additional heterogeneity with unstructured random effects. A third set of state-level random effects model correlation among counties within the same state that adhere to state-level policies.

For the post-intervention trajectories, the same demographic factors are used as well as their interaction with time polynomials, augmented with an explicit term for the timing of the intervention. These covariates have the analogous role of allowing the change of the post-intervention death trajectory to vary or "bend" according to county features, modeling different deaths trajectories under different intervention timings.

RESULTS

Epidemic timing

Among the 882 counties in the present analysis, death thresholds of 3 per 10 million residents were reached at different calendar times with differences across levels of NCHS county

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classification shown in Web Figure 3. According to the average calendar date, the epidemic arrived earliest in large central metro areas. In terms of "epidemic timing," the median and IQR of the number of days between a county deaths threshold and the issuing of the stay-at-home order was -3 (-9, 2), and -9 (-15, -4) for 50% mobility reductions. As shown in Web Figure 4, the epidemic timing of stay-at-home orders exhibited the opposite temporal ordering of epidemic arrival with stay-at-home orders occurring earliest in epidemic time in non-core and micropolitan counties. The relative epidemic timing at which counties across different NCHS categories reached this mobility reduction showed the same ordering as the dates of stay-at-home orders. Note that mobility reductions occurred earlier, with mobility reductions tending to precede stay-at-home orders by a median of -5 (-10, -2) days across all NCHS categories.

Modeling results

County-specific death trajectories were fitted using the model described in the Methods section. Several diagnostics were performed to assess the adequacy and fit of the model, including MCMC convergence diagnostics, posterior-predictive checks, and prediction with a hold-out sample to verify that inferences were not dominated by a small number of large counties. Full details appear in Web Appendix 5, which yield confidence in the parsimonious yet flexible formulation of the proposed model. Web Appendix 6 displays the lack of significant residual spatial autocorrelation. Web Appendix 7 illustrates the posterior fit for six counties with heterogeneous interventions timing.

Impact of intervention timing

To evaluate the impact of intervention timing we offer posterior-predictive simulations for each county under hypothetical scenarios where the intervention occurred 10 days earlier or later than observed, tabulating estimated deaths through April 20. Figures 1 and 2 show the results of using the fitted statistical model to compute the *per capita* median trajectory of daily deaths for each NCHS category under the observed intervention scenario and hypothetical intervention timings. Figure 1 evidences that enacting stay-at-home orders 10 days earlier would have strongly mitigated the trajectory of daily deaths, particularly for the more urban counties, although the impact is noticeable in all NCHS categories. Figure 2 depicts analogous fitted and counterfactual trajectories for the Mobility decrease model. While the general shape of trajectories is similar to those of the stay-at-home interventions, some differences are apparent. For small metro and micropolitan counties, there is more pronounced evidence that earlier mobility intervention

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impacted the daily death trajectories. In contrast, the evidence of impact for non-core counties is less pronounced for mobility decrease.

Table 1 provides estimates of cumulative deaths differences under earlier and later introduction of stay- at-home orders, the same are cast per 100,000 residents. Overall, the model predicts that implementing stay-at-home orders 10 days earlier would have led to 15,700 (95% credible interval: 11,350 18,950) fewer deaths through April 20. Effects are heterogeneous across county classifications with effects concentrated in the large central, large fringe, and medium metro counties. The evidence that delayed action would have led to extra deaths is slightly weaker; adopting stay-at-home orders 10 days later would have led to an additional 14,700 (95%CI: 9,100 21,500) deaths . Table 2 has analogous results for shifting mobility reductions 10 days earlier in these counties which would have averted an estimated 15,550 (95%CI: 10,450 19,400) deaths, while delayed mobility reductions by 10 days would have led to an additional 21,100 (95%CI: 14,500 29,200) deaths over what was observed. In total, the results from the *Mobility model* relative to the *Stay-at-home model* match expectations, since stay-at-home orders typically happened after a significant decrease in mobility had already taken place (*c.f.* Web Figure 4), with mobility drops persisting beyond the first date reaching a 50% reduction from baseline.

DISCUSSION

We have offered a rigorous evaluation of the association between the change in death trajectories and the timing of both stay-at-home orders and reduced population mobility, as measured by the number of visits to various POIs. The statistical approach presented here expresses county-specific curves of daily COVID-19 deaths in terms of pre- and a post intervention trajectories, dictated by both observed and latent county-level features and the epidemic timing of the interventions. An important feature of the analysis is that its focus on estimating the impact of early vs. late action, and not on the related impact of implementing vs. not implementing policies or behavior changes.

The descriptive analysis of the timing of interventions clarified both the heterogeneity in intervention timing relative to local epidemic conditions and that mobility reductions often occurred before stay-at-home orders, although not always. By-and-large, in more urban counties the epidemic arrived earlier in calendar time, with policy and mobility interventions in these areas tending to be later in epidemic time relative to less urban counties. Also, the total visits to

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POIs during the study's time period had often reached close to its minimum levels at the time an order was instituted. The suite of statistical models fit indicate that in large central metro counties the timing of mobility reductions had similar importance for dictating changes in the daily deaths trajectories than the timing of official stay-at-home orders, in medium metropolitan areas the mobility reductions were more important than stay-at-home orders, and the uncertainty of the results for rural counties are rendered inconclusive. This is not to say that the stay-at-home orders had no impact, and interpretation of the interplay between these two types of "interventions" is not within the scope or the present work.

The modeled associations and death projections under counterfactual intervention timing can be inter- preted as causal effects of the intervention timing under the assumption that the functional form of the model correctly characterizes death trajectories and that the model adjusts for relevant confounders that dictate intervention timing and deaths. Web Appendix 9 evidences the importance of the included confounders for their ability to explain variation in intervention timing, and also indicates no clear threat of unmeasured spatially-varying factors that dictated intervention timing. However, even with the apparent adequate fit of the model and the specific elements of the approach designed to address major threats to causal validity, the implications of the results should be viewed in light of the potential confounding due to unobserved factors might not be fully resolved.

Also worth noting is that the results herein pertain to the 882 counties included in the analysis which, despite containing 71.5% of the total US population, may not represent epidemic and intervention dynamics in other counties not included in the analysis. Included counties were selected primarily on the basis of having a pronounced epidemic during the first US wave, but 222 counties (114 of which reached the deaths threshold of 3 deaths per 10 million residents) were excluded due to lack of complete or inconsistent mobility data from Safegraph, which occurred due to low coverage of mobile phone data on visits to POIs, difficulty in our processing pipeline for linking POIs to county identifiers, or fewer than 100 days of observed mobility data during the study period. Reasons for counties exhibiting any of these difficulties are not clear, but counties omitted due to lack of mobility data spanned every category of NCHS county classification (with 5% of omitted counties in Large Central Metro areas, and 44% of omitted counties in Micropolitan or Non-core counties) and had no discernible geographic pattern. To the extent that disease dynamics might be different in counties with no pronounced epidemic during

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the first US wave or in counties with missing Safegraph mobility data, the results herein do not necessarily generalize to those counties.

Our work surmounts some of the challenges of disentangling the intertwined local characteristics and events that unfolded around the time of the first wave of COVID-19 interventions. The statistical evidence generated from a model such as this is designed to complement that obtained from more traditional mecha- nistic epidemic models. Reproducing the full epidemiological cycle is not the intention of the model; we only attempt to quantify intervention impacts in the time frame surrounding observed stay-at-home and mobility reduction dates and during the early epidemic stages. In fact model fit noticeably deteriorated when fit to longer time periods. The limitations of this analysis notwithstanding, we move a step closer into parsing these events by providing evidence for the timing of official policy interventions and mobility-related behavior changes as important determinants of local daily COVID-19 deaths. These results point towards the need to investigate how official reopening policies and other policies that varied across counties interplay with changes in mobility beyond the time frame considered here and into the later phases of the US COVID-19 epidemic.

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We thank the UT COVID-19 Modeling Consortium for its valuable work supporting research and current thinking related to the pandemic response and Dr. Paul Rathouz for his useful insights on intervention modeling.

No conflict of interest is declared by the authors.

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Table 1: Bayesian posterior estimates using the *Stay-at-home model* for medians and 95% credible intervals of cumulative differences in COVID-19 deaths by 10-day earlier/later action for the 882 counties in the data set from the first death through April 20, 2020. Full details on how the intervals were computed appear in Web Appendix 8.

Counterfactuals	Large central metro (n= 20,673)		Large fringe metro (n= 7,617)		Medium metro (n= 3,332)		Small metro (n= 1,032)		Micropolitan (n=696)		Non-core (n=264)		Total (n=33,614)	
	Median	95% CrI	Median	95% CrI	Median	95% CrI	Median	95% CrI	Median	95% CrI	Median	95% CrI	Median	95% CrI
Deaths Averted by Earlier Action	10,400	(6,850 12,800)	3,900	(2,750 4,750)	1,150	(520 1,600)	200	(-10 320)	110	(25 180)	30	(0 55)	15,700	(11,350 18,950)
Deaths Added by Later Action	9,750	(4,950 15,950)	3,900	(2,100 6,150)	830	(270 1,700)	120	(-15 320)	105	(-5 255)	30	(-10 80)	14,700	(9,100 21,500)
Deaths Averted per 100k capita	11.1	(7.3 13.7)	7.1	(5.1 8.7)	2.1	(0.9 2.9)	1.2	(-0.1 1.8)	1.1	(0.2 1.8)	1.1	(-0.1 1.9)	6.7	(4.9 8.0)
Deaths Added per 100k capita	10.4	(5.3 17.0)	7.2	(3.8 11.2)	1.5	(0.5 3.0)	0.7	(-0.1 1.8)	1.0	(-0.0 2.5)	0.9	(-0.3 2.9)	6.3	(3.8 9.2)

Table 2: Bayesian posterior estimates using the *Mobility model* for medians and 95% credible intervals of cumulative differences in COVID-19 deaths by 10-day earlier/later action for the 882 counties in the data set from the first death through April 20, 2020. Full details on how the intervals were computed appear in Web Appendix 8.

Counterfactuals	Large central metro (n= 20,673)		Large fringe metro (n= 7,617)		Medium metro (n= 3,332)		Small metro (n= 1,032)		Micropolitan (n=696)		Non-core (n=264)		Total (n=33,614)	
	Median	95% CrI	Median	95% CrI	Median	95% CrI	Median	95% CrI	Median	95% CrI	Median	95% CrI	Median	95% CrI
Deaths Averted by Earlier Action	9,000	(4,200 12,300)	4,800	(3,850 5,500)	1,600	(990 2,000)	235	(25 390)	80	(-45 160)	-40	(-230 20)	15,550	(10,450 19,400)
Deaths Added by Later Action	9,300	(4,700 15,100)	8,500	(5,200 12,350)	2,650	(1,450 4,050)	260	(45 605)	70	(-35 240)	-20	(-50 20)	21,100	(14,500 29,200)
Deaths Averted per 100k capita	9.6	(4.5 13.1)	8.7	(7.0 10.0)	2.9	(1.8 3.6)	1.3	(0.1 2.2)	0.8	(-0.4 1.6)	-1.5	(-8.1 0.7)	6.6	(4.5 8.3)
Deaths Added per 100k capita	9.9	(5.0 16.1)	15.5	(9.5 22.6)	4.7	(2.6 7.3)	1.5	(0.3 3.5)	0.7	(-0.3 2.4)	-0.7	(-1.7 0.7)	9.0	(6.2 12.4)

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Figures List

- Figure 1: Estimated death trajectories for observed timing of stay-at-home orders, and 10-day earlier or delayed timing stratified by county urbanicity: A)large central metro; B) large fringe metro; C) medium metro; D) small metro; E) micropolitan; F) non-core. Solid lines are posterior median estimates of deaths per 1 million residents at t days after epidemic arrival. Shaded areas are 95% posterior credible intervals.
- Figure 2: Estimated death trajectories for observed timing of mobility reductions, and 10-day earlier timing or delayed timing stratified by county urbanicity: A)large central metro; B) large fringe metro; C) medium metro; D) small metro; E) micropolitan; F) non-core. Solid lines are posterior median estimates of deaths per 1 million residents at t days after epidemic arrival. Shaded areas are 95% posterior credible intervals.

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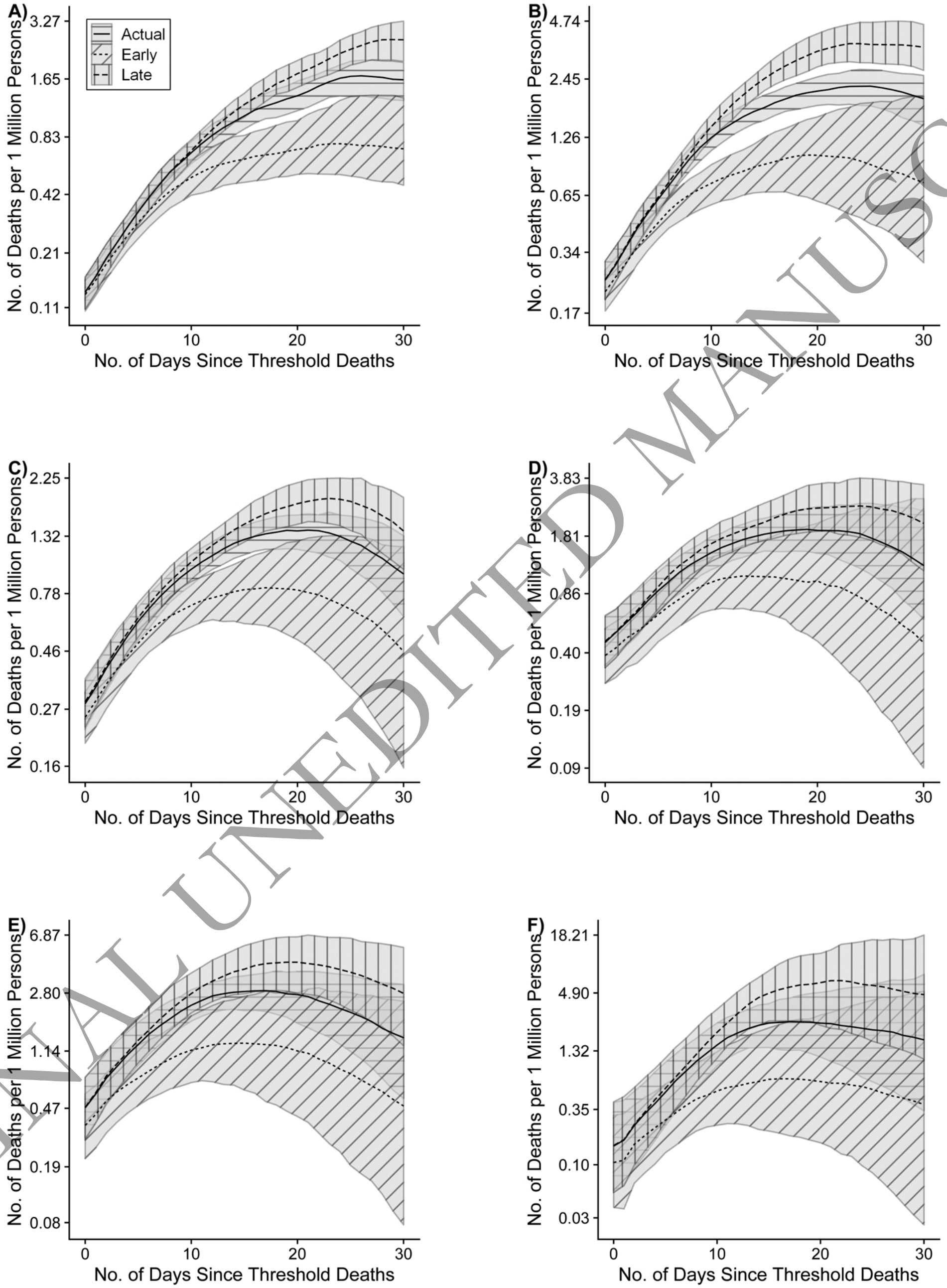

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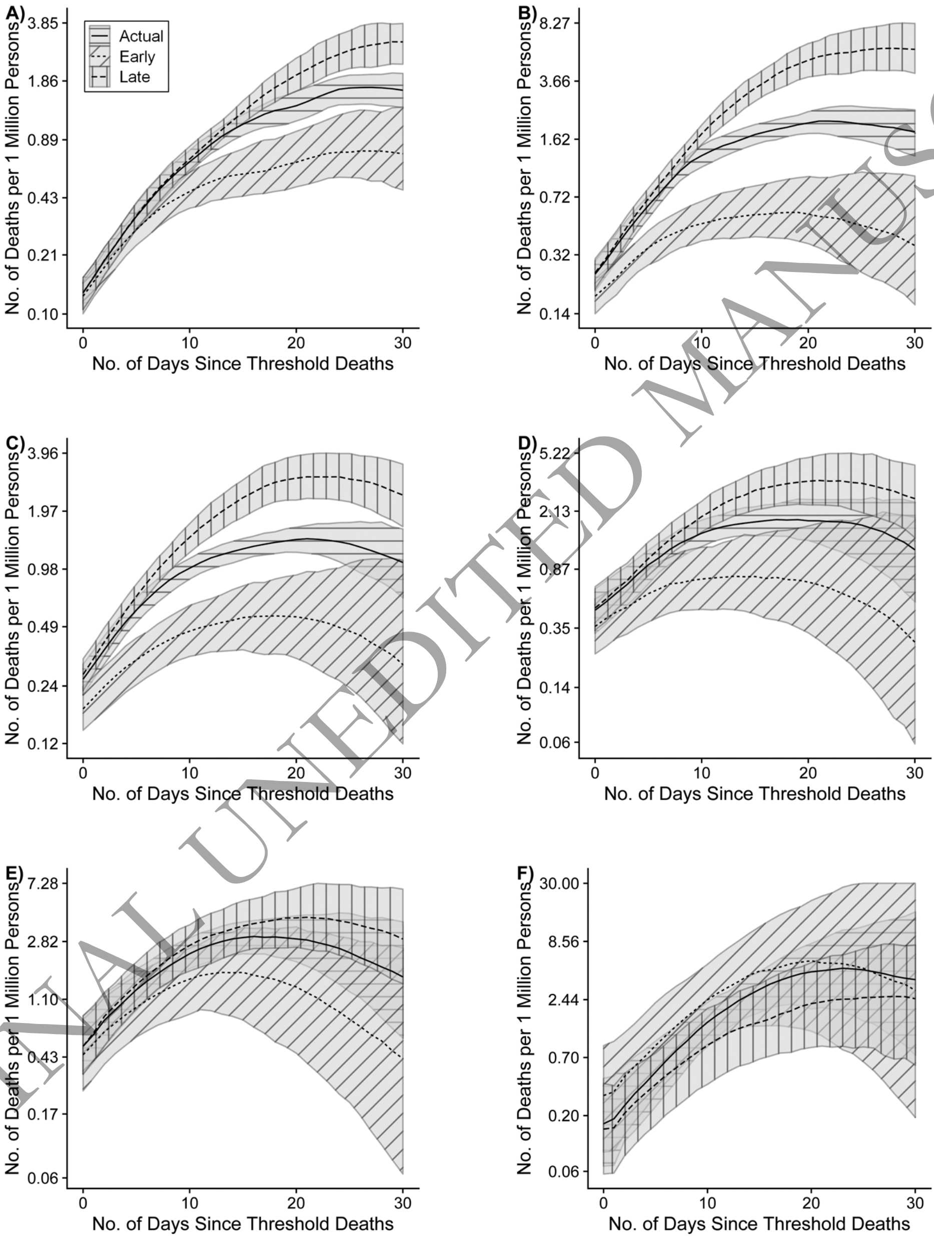

ORIGINAL UNEDITED MANUSCRIPT