Supplementary Material*

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* This supplementary material was provided by the authors to give readers further details on their article. The material was reviewed but not copyedited.

Section A. Details of COVAM

COVID-19 progression in an individual

Individuals in COVAM belong to one of eight possible COVID-19-related states at each simulated day (Figure 1 in the main text): Susceptible (S), Exposed-incubation (E), Infected with mild to moderate symptoms that is detected (IM+), Infected with mild to moderate symptoms that is undetected (IM-), Infected with severe symptoms (IS), Infected with symptoms requiring critical care (IC), Recovered (R), and Dead (D). We adopt our states using the clinical states as described by the CDC and also introduced by the SEIR model of Hill (3,13). A susceptible patient can be infected with COVID-19 only after exposure to SARS-CoV-2 from a contagious patient. If an individual is exposed to COVID-19, then s/he will move to the Exposed-incubation (E) state, and stay there during the incubation period of SARS-CoV-2. The individual may transmit the virus during the last several days of the incubation period, as evidenced by the literature (8-11). After the incubation period is over, the individual becomes symptomatic with mild to moderate symptoms. There is a possibility (also representing the limited availability of COVID-19 testing) that the symptoms will be very mild such that the individual will not be tested, and the case will thus not be confirmed by health authorities. This case is represented by the Infected with mild to moderate symptoms that is undetected (IM-) state. If the mild symptoms lead to testing that confirms the case, the patient moves to the Infected with mild symptoms that is detected (IM+) state. Following the CDC's guidance and definition, patients in both IM+ and IM- experience mild symptoms. IM+ may also include mild pneumonia. In most cases, individuals in the IM+ and IM- states do not need to be hospitalized.

Patients in the IM+ and IM- states remain in these states the same amount of time and then they either move to the Recovered (R) state or Infected with severe symptoms (IS) state. Following CDC's guidance, the IS state represents "dyspnea, hypoxia, or >50% lung involvement on imaging" (13). We assume that patients in the IS state require hospitalization. Patients in the IS state either recover and move to the Recovered (R) state or develop symptoms that require critical care, therefore moving to the Infected with symptoms requiring critical care (IC) state. Following CDC's guidance, we assume patients in this state experience respiratory failure, shock, or multiorgan system dysfunction, therefore they need to be treated in an intensive care unit (ICU) (13). Some portion of these patients require mechanical ventilation. Patients in the IC state either recover and move to the Recovered (R) state or die and transition to the Dead (D) state.

The primary mode of transmission for COVID-19 is human-to-human interaction, therefore we allow COVID-19 to be transmitted from individuals in the E, IM+, IM-, IS, IC states to individuals in the S state.

Details of Parameter Estimation

We made the following assumptions to represent the probability of transmitting SARS-CoV-2 to susceptible patients by different patient classes.

- If the patient is a contagious exposed patient, then the probability of transmitting SARS-CoV-2 to a susceptible patient is the same as that for when the patient is experiencing mild to moderate symptoms.
- If the patient is experiencing severe symptoms, then the probability of transmitting SARS-CoV-2 to a susceptible patient is a fraction of that for when the patient is experiencing mild to moderate symptoms. This is because we assume that patients with severe symptoms require hospitalization and will stay in the hospital throughout this episode of the illness. We assumed that the probability of transmitting SARS-CoV-2 to a health care worker is 0. Due to heightened awareness of COVID-19 in the hospitals, heightened infection control protocols, and PPE availability, patient to

health care worker transmission possibility is very low. Furthermore, there is little impact of this parameter on the overall epidemic, therefore we made this simplifying assumption.

- If the patient is experiencing critical symptoms, we assumed that the probability of transmitting SARS-CoV-2 to a health care worker is 0. These patients are assumed to be receiving care in the ICU setting. As above, due to heightened awareness of COVID-19, heightened infection control protocols, and PPE availability in the hospitals, patient to health care worker transmission possibility is very low. Furthermore, there is little impact of this parameter on the overall epidemic, therefore we made this simplifying assumption.

With these assumptions, the key input for transmissibility is the probability of transmitting SARS-CoV-2 from a patient experiencing mild to moderate symptoms to a susceptible individual when the patient is tested and confirmed positive with COVID-19. For this purpose, we followed a multi-step approach to adjust this parameter. We first started our parameter adjustment using the baseline estimate of R0 for COVID-19 as 2.6, which uses data from early days of the epidemic in China (27). We then used our model's base input parameter values to find the probability of transmitting SARS-CoV-2 from a patient experiencing mild to moderate symptoms to a susceptible individual such that the theoretical R0 value is 2.6. The parameters were as follows: there are 10 close contacts per person per day, duration for mild to moderate symptoms is 6 days, and the transmission rate for patients experiencing severe or critical symptoms is 0. We found that when the probability of transmitting SARS-CoV-2 from a patient experiencing mild to moderate symptoms to a susceptible individual is equal to 0.0418, the theoretical R0 value would be equal to 2.6 with these parameter settings.

Note that for this calculation, we did not account for the probability of transmitting disease from asymptomatic patients or from patients who experience mild to moderate symptoms and are not tested positive for COVID-19. This is because most models reporting R0 values for COVID-19 did not account for these transitions in their model development.

We set the values for the probability of transmitting disease from both 1) asymptomatic patients and 2) patients who experience mild to moderate symptoms and are not tested positive for COVID-19 to be equal to 0.0418; with this probability our model's theoretical R0 value increased to 3.34 (without any interventions). This R0 is still within the range of reported R0 values, that vary between 1.5 and 6.5 (26,27). In particular, a recent study based on the COVID-19 epidemic in Italy reported an R0 value of 3.47 (when a SIR model is used) for the early days of the epidemic (28). Similarly, a recent study estimated the median R0 value for the Wuhan region as 5.7 (52). Therefore, we concluded that our transmission parameters are within the acceptable range. The base-case parameters used for the Milwaukee metro area and NYC correspond to theoretical R0 values of 3.34 and 6.68, respectively.

Adherence to Social Distancing

An important input to COVAM is adherence to social distancing measures. As noted in the text, adherence to social distancing parameters represents several behaviors that reduce the transmissibility of SARS-CoV-2, including less frequent traveling, keeping at least 6-feet of distancing during person-to-person interactions, frequent hand washing, and wearing masks. COVAM does not have the ability to differentiate physical distancing, handwashing, and mask wearing behaviors from traveling frequency.

Our primary source for the social distancing parameter included in COVAM is distance traveled and maintenance of at least 6-foot distance during person-to-person interactions. There are three main data sources for this parameter:

- Google's COVID-19 Community Mobility Reports (33)
- Unacast's Social Distancing Scoreboard (31)

- University of Wisconsin-Madison's Geospatial Data Science Lab (32)

All three sources utilize cell phone data to estimate how the mobility of a community changed for each state and county in the US over time, however, they differ in the measurement of the mobility. For example, the Google Mobility Report provides the percentage change in the number of visits to different types of destinations including retail & recreation, grocery stores, parks, transit stations, and workplaces (33). In NYC, the data from the Google Mobility Report website (https://www.google.com/covid19/mobility/) show a significant increase in adherence to social distancing measures over time, especially in late March and April. Unacast, on the other hand, reports three metrics to measure the efficacy of social distancing measures: change in average mobility (based on distance traveled), change in non-essential visits, and difference in encounter density (31).

Since all of these sources report different metrics and values for adherence to social distancing, we estimated the input values (as reported in Table 1 in the main text) using calibration. Our calibration procedure evaluated the adherence inputs that are higher than reported mobility values by these three different sources. As explained above, this is because none of the data sources on mobility directly reported behaviors such as wearing masks and frequent hand washing. Instead, they only report data related to the reduction in the frequency of daily contacts. Our adherence parameter is thus a proxy for individuals' behaviors that reduce the transmission of SARS-CoV-2. Our calibration procedure selected the adherence to social distancing values that allowed COVAM to match observed number of cases over time. Although COVAM has the ability to adjust this parameter on a daily basis, we changed the value of this parameter infrequently to prevent overfitting as explained below.

Age-specific daily contacts and adherence to social distancing

We incorporated the effect of age on the number of daily contacts and adherence to social distancing measures into COVAM since both of these inputs depend on age group (23,24,35-37). For this purpose, we calculated the relative rates of the age-specific parameters and applied these relative rates to the overall parameter estimates on the number of daily contacts and adherence to social distancing. We followed this approach since it allowed for presenting regional data in a more compact way. For example, instead of reporting age-specific numbers of contacts and age-specific adherence to social distancing, this approach allowed us to report a single value for the daily number of contacts (e.g. 10 and 20 per day in Dane County and NYC, respectively, in the absence of social distancing) and a single value for the adherence to social distancing at different dates for a region (e.g., 70% adherence level reduces the number of contacts to 3 and 6 per day in Dane County and NYC, respectively). This approach hence helped us to more easily communicate the model inputs. This also simplified the calibration process as otherwise we would have to separately adjust adherence to social distancing measures for every age group at various time points.

In order to estimate the age-specific daily number of contacts, we used the study by Del Valle et al. (2007) (23) that reports US-based age group-specific close contacts that allow transmission of infectious diseases. Although similar data are reported by other studies, such as the one used by the POLYMOD (35), such studies were focused on European countries and therefore may not be applicable to the US setting. For example, the daily number of contacts reported in the study by Mossong et al. (2008) (35) varied between 7.95 to 19.77 contacts per day for different countries, indicating differential number of daily contacts by country. Using the study by Del Valle et al. (23), we estimated the following relative rates for the daily number of contacts for each age group (as reported in the Appendix Table in the main text) using the 20-44 age group as the reference: 85% for ages 0–19; 100% for ages 20-44; 94% for ages 45–54; 74% for ages 55–64; 46% for ages 65–74; 34% for ages 75–84; and 34% for ages over 85. This implies that, for instance, the number of daily contacts for an individual in the 75-84 age group is 66% less than that for an individual in the 20-44 age group (100%-34%=66%) in the absence of social distancing measures. Using these estimates and the age demographics, one can find the number of daily contacts for a region. For example, for NYC where the average number of daily contacts is 20 per person, we estimated that the number of daily contacts per person for individuals is 20.3 for ages 0-19, 23.8 for ages 20-44, 22.4 for ages 45-54, 17.6 for ages 55-64, 11.0 for ages 65-74; 8.1 for ages 75-84; and 8.1 for ages over 85.

We compared the relative rate estimates to those reported by Mossong et al. (2008)(35) using the 20-44 age group as the reference: 110% for ages 0–19; 100% for ages 20-44; 94% for ages 45–54; 78% for ages 55–64; 58% for ages 65–74; 50% for ages 75–84; and 50% for ages over 85. Our estimates are somewhat comparable to these estimates that use data from European countries.

For the second input on age-specific adherence to social distancing, we followed a similar approach. Namely, we used a CDC study that reported the results of a panel survey measuring public attitudes, behaviors, and beliefs related to COVID-19, stay-at-home orders, and nonessential business closures in the US. This survey included questions regarding nonadherence to social distancing as measured by keeping a 6-feet distance from others, wearing masks, and avoiding groups of 10 or more persons. Using the data reported from this study, we estimated the following relative rates for nonadherence to social distancing for each age group (as reported in the Appendix Table in the main text) using the 20-44 age group as the reference: 100% for ages 0–19; 100% for ages 20-44; 100% for ages 45–54; 86% for ages 55–64; 61% for ages 65–74; 61% for ages 75–84; and 61% for ages over 85. There were no data on the adherence rates of the 0-19 age group. As such, we assumed that their adherence rate is the same as the 20-44 age group because children are more likely to follow the same adherence practices as their parents, who are more likely to be within the 20-44 and 45-54 age groups. This implies that, for instance, the nonadherence to social distancing of an individual in the 75-84 age group is 39% less than that for an individual in the 20-44 age group (100%-61%=39%), thus, the 75-84 age group is more compliant with the social distancing compared to the younger age group.

Using these estimates, daily number of contacts, and the age demographics, one can find the number of daily contacts for a region under any overall adherence scenario. For example, for NYC where the average number of daily contacts is 20 per person, if the overall adherence to social distancing is 90% (and thus the nonadherence rate is 10%), we estimated that the number of daily contacts per person for individuals with this overall adherence is 2.54 contacts for ages 0-19; 3.17 contacts for ages 20-44, 0.99 contacts for ages 45-54; 0.63 contacts for ages 55-64; 0.20 contacts for ages 65-74; 0.08 contacts for ages 75-84; and 0.03 contacts for ages over 85. These number of daily contacts correspond to 20*10%= 2 contacts per person in a day for the overall NYC population. Note that the number of daily contacts with social distancing measures is significantly higher in younger age groups compared to older age groups due to two reasons: 1) younger individuals have more frequent interactions in the absence of social distancing measures and 2) adherence to social distancing is significantly lower in younger age groups compared to older age groups.

Baseline probability of testing

In order to estimate the baseline testing rate (75%) for the base case, we used two studies based on data from Italy and China as described below. Note that the baseline test rate in the model represents the proportion of the individuals who experience moderate symptoms severe enough to be allowed testing in the early days of pandemic when testing was severely limited. Note also that, while we used these two studies, our primary method to validate this parameter estimate was calibration as described below. We also conducted an extensive sensitivity analysis as reported in section D.1 where we replaced the baseline parameter estimate of 75% with 50% and 25% and tested the robustness of our findings to this parameter.

The first study, conducted by researchers from the University of Padua and the Red Cross, tested all 3000 residents of Vò, a town near Venice, Italy (29). The study found that 60% of the residents who tested positive did not experience any symptoms prior to the date of testing. We assumed that some of these cases did not show symptoms due to how recently they were exposed to SARS-CoV-2, whereas the remaining cases experienced mild symptoms that were not severe enough to require testing. Assuming our model's input parameters (mean incubation period being 5 days and duration for mild to moderate symptoms being 6 days, baseline R0 value estimated for the early days of pandemic in other countries, and individuals testing positive only in the last two days of the incubation period due to sufficient viral loads to result in a positive test result) we estimated that only 68% of the patients with mild to moderate symptoms would experience symptoms severe enough to seek testing and subsequently test positive. This was our first data point. We repeated the analysis by assuming that the patients could test positive in the last three days of the incubation period; therefore, more of the asymptomatic individuals could still be in the exposed-incubation stage and we estimated the test rate to be at 75%. We observed that depending on the assumption of when the individuals would test positive during the incubation period, the baseline testing rate could have been even higher. The second study from China reported the clinical characteristics of 24 asymptomatic infections who were screened among close contacts of known infections (30). This study was very useful since it tracked individuals from their initial exposure date until they completely recovered and recorded the symptoms throughout this observation period. This study reported that 3 out of 5 patients who experienced symptoms did not experience any severe symptoms (no cough, fatigue, etc.) during the period where they would experience mild to moderate symptoms. These 3 patients experienced only fever without chills where body temperatures fluctuated from 36.5°C to 38.0°C. These data implied that only 60% of the patients with mild to moderate symptoms would experience symptoms severe enough to be allowed testing and test positive in the early days of pandemic. Using these three data points, we set this parameter equal to 75%, which led to reasonable estimates for our calibration process.

Calibration and Validation

Several model input parameters involve a high level of uncertainty, including disease transmission rates, probability of testing for COVID-19, and adherence to social distancing measures. We estimated them using calibration. Adherence to social distancing measures changes on a daily basis for each region, therefore it is adjusted at regular time points as shown in Table 1 in the main text. Our modeling approach is very flexible, thus it is possible to match the observed number of cases almost perfectly by simply adjusting adherence to social distancing on a daily basis or changing the probability of testing for each day. However, we preferred to not perfectly match the observed data to prevent overfitting. For example, the model's predicted number of cases in the early days of the pandemic in Dane County is slightly higher than the observed number of cases, which is most likely due to the very limited testing in the early days. Considering a smaller probability of testing in the early days of the pandemic would allow the model to perfectly match the observed data.

COVAM Mechanics

COVAM was coded in C++ for faster computational times and flexibility. Each replication of the simulation can last from a few seconds to an hour on a standalone desktop PC depending on the population size and number of infections. Although COVAM currently represents simple behaviors for the agents, it can easily be used to represent more complex behaviors. For example, the model is able to define the adherence levels of the individuals to the outcomes associated with COVID-19, i.e. when there are many cases and/or deaths in a week, individuals could become significantly more compliant with the social distancing measures.

Comparison of COVAM to other models

Given the lack of data on SARS-CoV-2, health systems and public health officials rely on mathematical models for policy decisions such as school closures and the extent and timing of social distancing measures. Most commonly used models compartmentalize the transmission and natural history of SARS-CoV-2 infection. Examples include the susceptible–infective-recovered (SIR) model and the susceptible–exposed-infective-recovered (SEIR) model, which extends the SIR model by including a compartment representing the latent period. After the sudden rise in COVID-19 cases in the U.S., several models specific to COVID-19 were quickly developed and made available online (3-7). Some of the models provide both U.S.-wide and state-specific prediction (5). However, given the vast within-state variability in transmission dynamics and adherence to social distancing, these models are severely limited in their applicability to local settings (6). Some limitations include the assumption of a closed population, the inability to accurately represent dynamic social distancing measures with different adherence levels, and the inability to account for the effect of limited testing capacity on the number of confirmed cases. The major strength of our work is a simple and flexible model that incorporates similarities to existing compartmental models, and also allows additional granularity when simulating critical features. COVAM is thus capable of addressing complex policy questions. For example, COVAM can be used to evaluate the impact of increasing testing capacity on COVID-19. In addition, as COVAM explicitly tracks individuals, it can be used to determine the optimal timing for implementing contact tracing for containing COVID-19. As COVID-19 has spread throughout the world, estimates of disease transmissibility in terms of basic reproduction number (R0) in subpopulations have varied widely (26,27). Another strength of our ABM approach is that there is no static R0 input. Instead, COVAM directly models daily interactions and chances of viral transmission at each interaction, allowing these parameters to be varied independently at any point in time, and stratified by age group or other demographic characteristics. This allows for evaluating the impact of specific policy decisions on the epidemic.

In summary, we chose agent-based modeling to study COVID-19 transmission because:

- It more realistically represents the dynamics of COVID-19 transmission more realistically.
- It provides a more flexible tool to represent various factors, such as varying levels of adherence to social distancing over time, varying number of imported cases, time-dependent testing rate, etc.
- It allows inclusion of heterogeneous populations. For example, individuals in different age groups have different numbers of daily contacts and varying levels of adherence to social distancing, however, conventional models do not typically represent such heterogeneity in the modeled population.

A major limitation of agent-based modeling is its higher computational needs compared to more commonly used compartmental models. Compartmental models do not represent probabilistic events and therefore require little computation time whereas, due to modeling probabilistic events, our agent-based model needs to be replicated at least 100 times to obtain the final, stable estimates. Depending on the region, this requires from a minute to an hour of run time.

In addition to our model and the models described above, several other models also reported the impact of mandating and easing social distancing measures on the burden of COVID-19. Most of these studies appear in non-peer reviewed literature. All of these studies agree with our study's finding that social distancing measures drastically reduced the number of COVID-19 cases. These studies used different methods (e.g., econometric/statistical models (53-56), compartmental models (43,57-60), time-series analysis (61,62), agent-based modeling (63,64), different metrics to measure the burden of COVID-19 (e.g., number of cases (43,54-60,63,64), doubling rate (62), daily case growth rate (53,61,63), mortality (43,55,58,63), and hospitalization (43)), different methods to represent social distancing measures (e.g., most studies used a binary variable to represent whether they are implemented or not without considering varying levels of adherence over time (53-55,61-64)) and different areas of focus (overall US (55,58,61,62), non-US settings (56,57,59,63,64), selected regions (43,54,58,60)). As a result, although all of the studies agree that social distancing measures lead to a substantial reduction in COVID-19 burden, their estimates on the magnitude of this impact vary.

Urgency in the response to the COVID-19 pandemic and the publicly availability of near real-time surveillance data have changed publication norms. Modeling is being carried out by numerous types of organizations and scientists with diverse expertise. Manuscripts of wide-ranging quality and application appear in both the peer reviewed and non-peer reviewed literature. After a careful review of many papers that we found in the literature, we identified two compartmental models that appeared in non-peer reviewed literature and compared our findings to the findings of these studies. We also identified two relevant studies that used agent-based simulation modeling (63,64). One study used a compartmental and an agent-based simulation model to evaluate the benefit of mask use on COVID-19 (63). This study strongly recommended mask use requirements to stop the spread of COVID-19. They found a substantial reduction in the burden of COVID-19 when at least 80% of a population is wearing masks. They further found that early adoption of universal mask use has a major impact on COVID-19 burden. This study focused on multiple countries and used macro-level data to inform their models. Our new sensitivity analysis that disaggregates social distancing into physical distancing and mask use as presented in section D.6 agrees with the study's main conclusion that early adoption of mask use indeed reduces virus spread substantially in NYC. We believe our estimates differ from this study because our model considers other factors affecting COVID-19 cases that were not included in that study such as 1) increasing testing capacity over time, 2) imported cases into the region, and 3) accurate representation of adherence to social distancing measures that change over time. Furthermore, our study focuses on small regions whereas the cited study focuses on whole country. The use of such models at a national level assumes that people living in one region of the country interact among each other at the same rate as they interact with people from other regions in the country. The other agent-based modeling study was published in peer-reviewed literature; however, it does not consider any particular region. This model simply presents a theoretical framework to evaluate the impact of various social distancing measures, therefore direct comparison with our work is not possible (64).

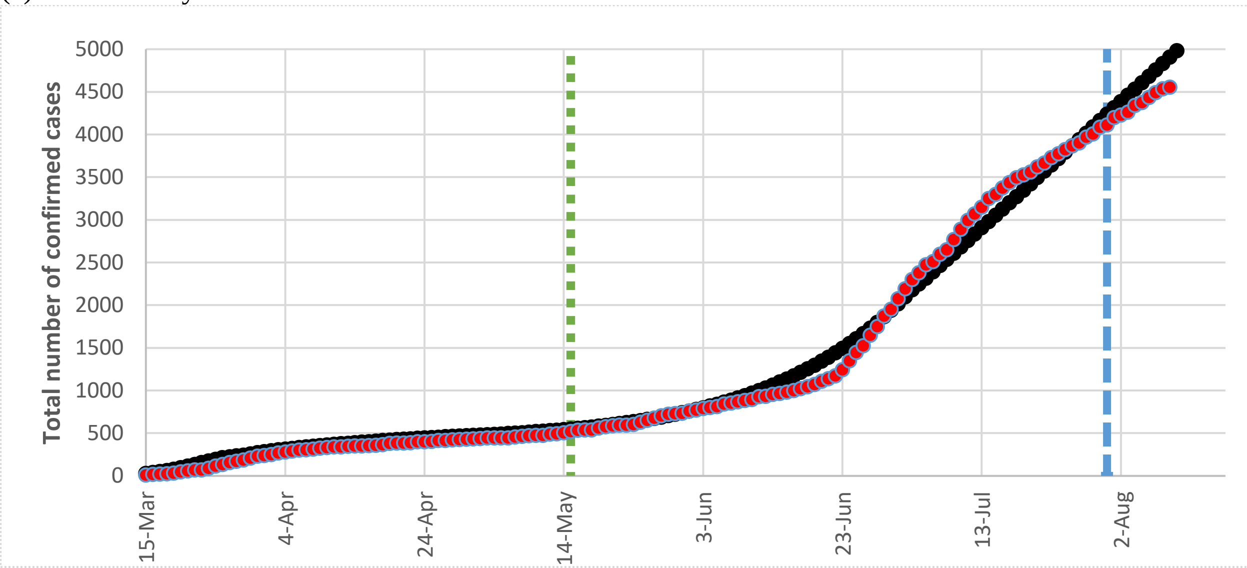
Section B. Model Validation Results

In this section, we present the results of the model validation for the base inputs. Model structure except age-specific daily number of contacts and age-specific adherence to social distancing was fixed before May 15, 2020. All model inputs specific to the three regions were fixed as of July 31, 2020 and the model's predictions were compared to the observed number of cases over time after this date. The following figures present the results of this validation experiment. All results in this section are using the average values of 100 replications. Because our computational experiments use simulated data, standard errors could be minimized by simply increasing the number of replications. We used 100 replications to obtain stable estimates around mean parameter value and small standard errors. In this set of validation experiments, COVAM's predictions were most accurate for NYC, followed by Milwaukee and then Dane County. This is primarily due to a larger number of cases in NYC. Because the number of cases is relatively low in Dane County, it is likely that small events lead to major changes in the number of cases.

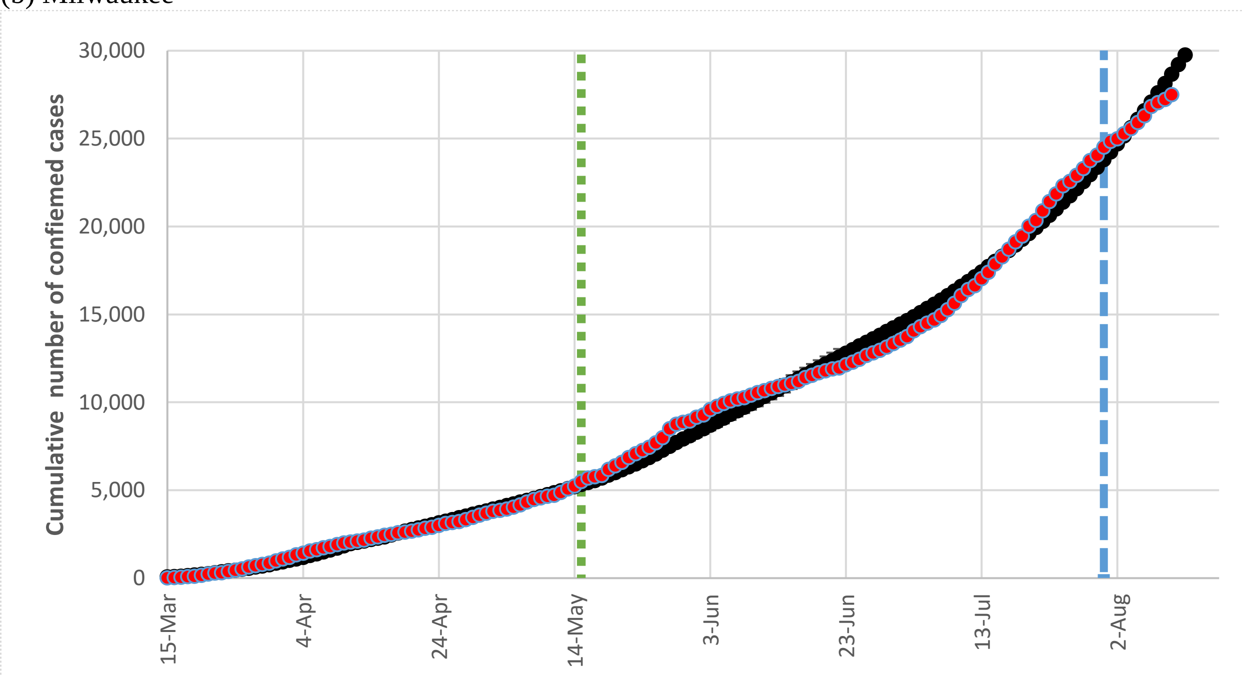
Data on actual number of confirmed cases come from Wisconsin Department of Health Services and NYC Department of Health (21,65).

Supplement Figure 1. Model validation results for the base case. In each of the following figures, red dots represent the actual observed cumulative number of confirmed cases, the black solid line represents the model's predictions, error bars around the black solid line represent 95% confidence intervals for the model's predictions based on 100 replications, the green dotted line represents the date after which model structure (except age-based daily contacts and adherence to social distancing) was fixed, and the blue dashed line represents the date after which no model input parameter was modified.

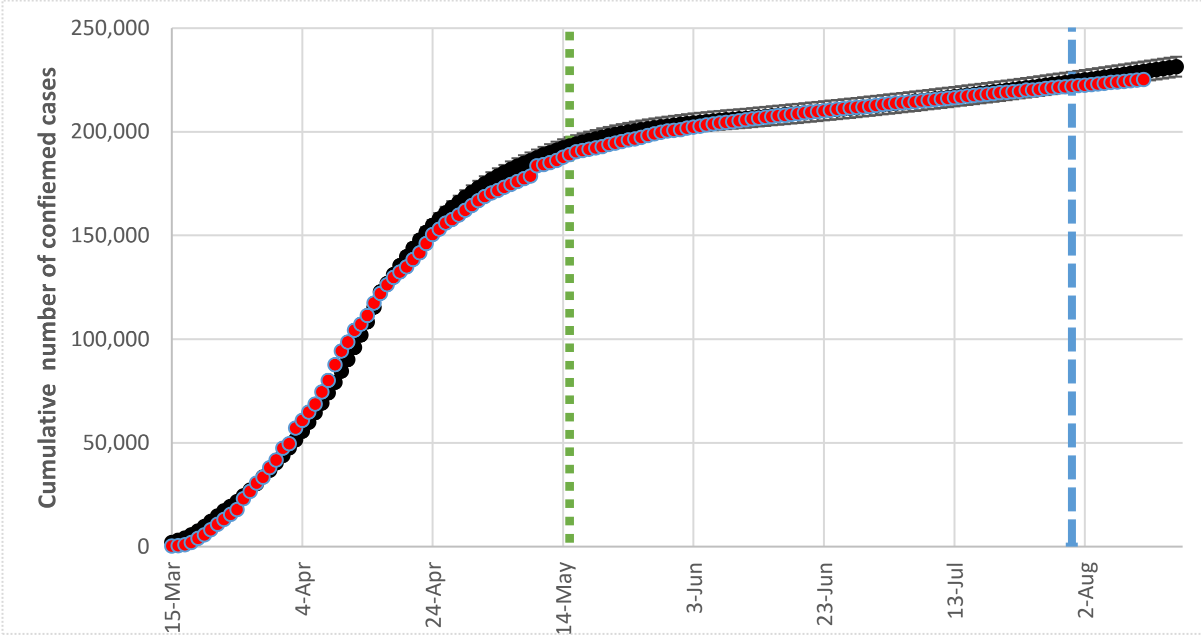
(a) Dane County



(b) Milwaukee



(c) NYC

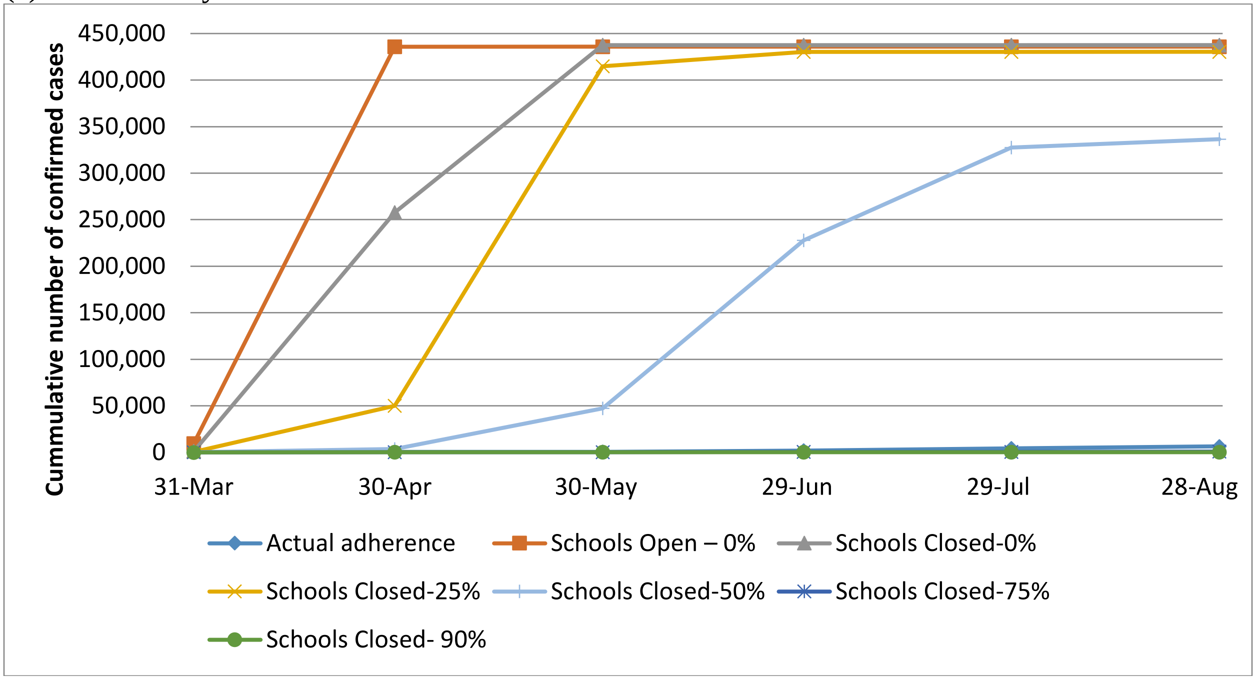


250,000
200,000
150,000
100,000
50,000
0
Cumulative number of confiemed cases
15-Mar
4-Apr
24-Apr
14-May
3-Jun
23-Jun
13-Jul
2-Aug

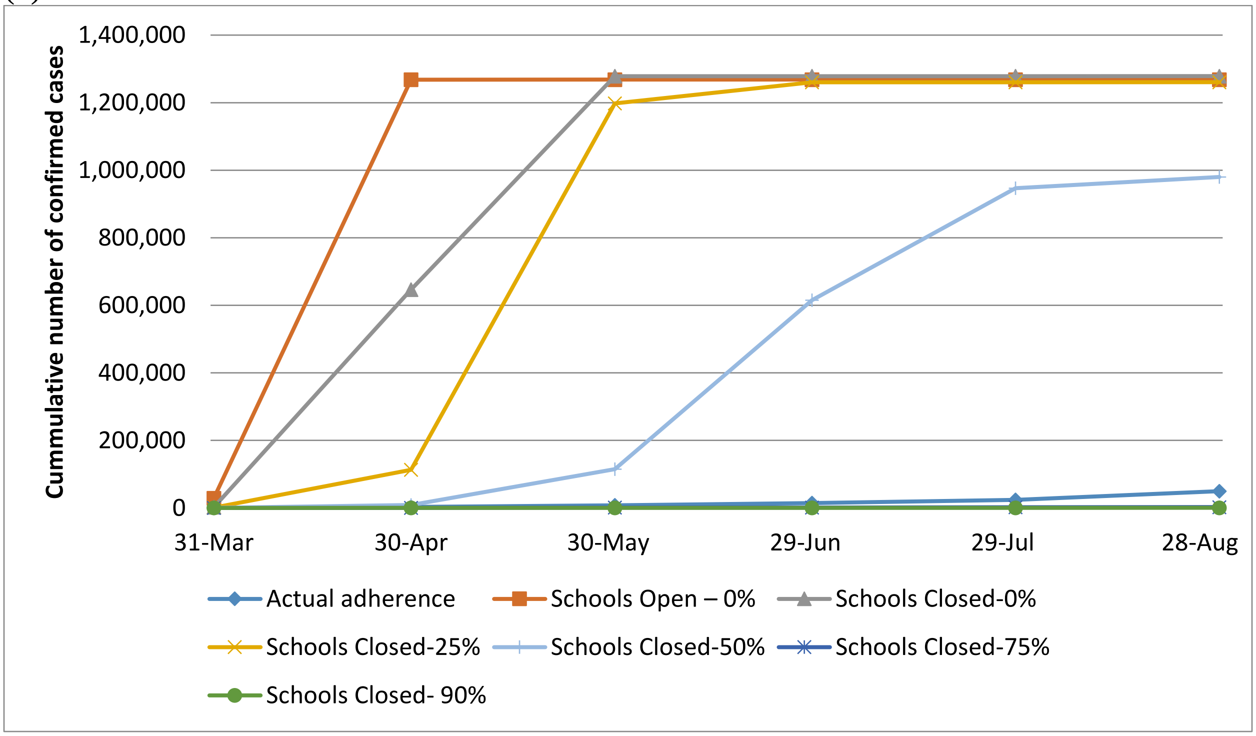
Section C. Additional Computational Experiments

Supplement Figure 2. *Impact of adherence to social distancing on the total number of confirmed cases on different dates in (a) Dane County (b) Milwaukee (c) NYC*

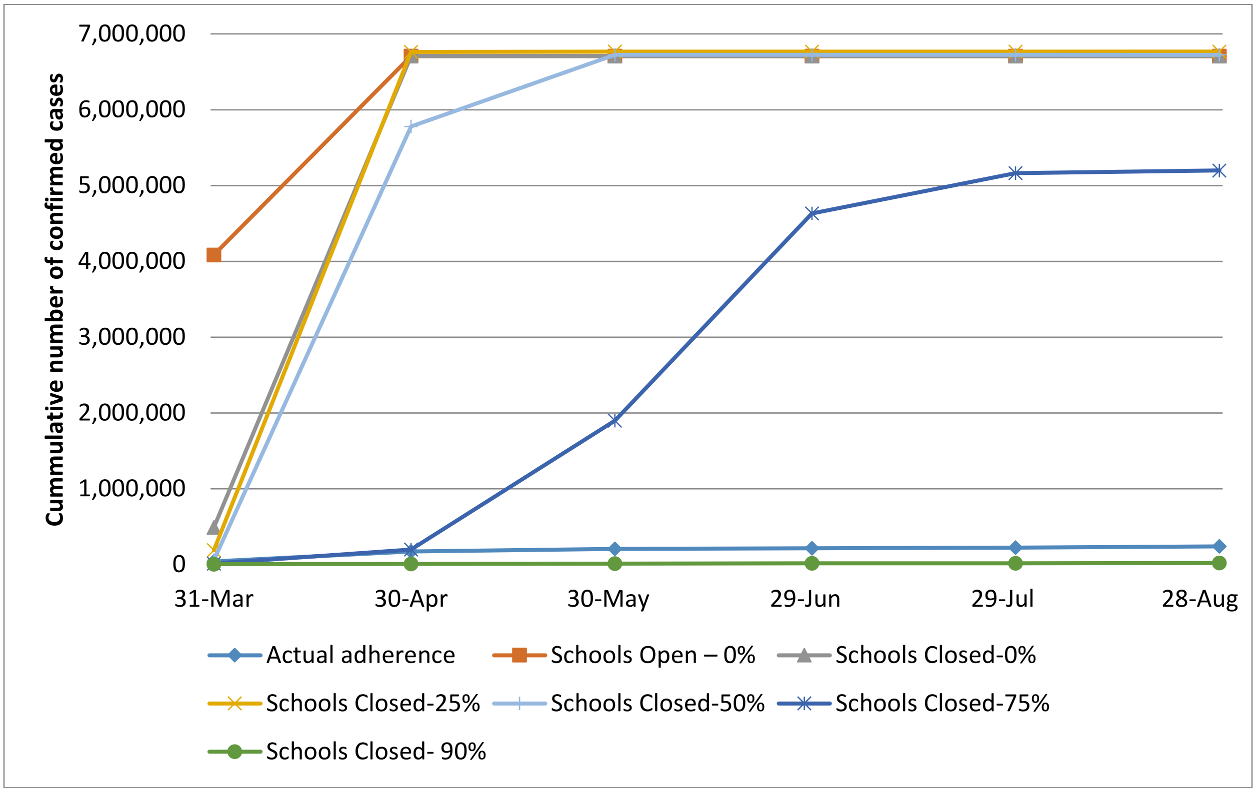
(a) Dane County



(b) Milwaukee



(c) NYC


7,000,000
6,000,000
5,000,000
4,000,000
3,000,000
2,000,000
1,000,000
0
Cummulative number of confirmed cases
31-Mar
30-Apr
30-May
29-Jun
29-Jul
28-Aug
Actual adherence
Schools Open – 0%
Schools Closed-0%
Schools Closed-25%
Schools Closed-50%
Schools Closed-75%
Schools Closed- 90%

Supplement Table 1. *Impact of adherence to social distancing on the total number of confirmed cases on different days*

Scenario- Adherence Level	March 31	April 30	May 31	June 30	July 31	August 31
Dane County						
Actual adherence	272	472	740	1,941	4,239	6,566
Schools Open – 0%	9,596	435,880	435,909	435,909	435,909	435,909
Schools Closed-0%	1,140	257,628	437,479	437,555	437,557	437,558
Schools Closed-25%	552	50,025	414,926	430,334	430,394	430,398
Schools Closed-50%	242	3,797	47,332	227,744	327,340	336,508
Schools Closed-75%	99	257	431	599	776	951
Schools Closed- 90%	59	99	141	183	226	269
Milwaukee						
Actual adherence	847	3726	8,093	14,231	23,803	49,967
Schools Open – 0%	29,210	1,268,390	1,268,420	1,268,420	1,268,420	1,268,420
Schools Closed-0%	2,472	646,416	1,278,370	1,278,710	1,278,710	1,278,720
Schools Closed-25%	1,194	113,499	1,197,800	1,260,420	1,260,660	1,260,670
Schools Closed-50%	531	8,958	115,271	615,432	946,786	980,048
Schools Closed-75%	232	728	1,260	1,765	2,289	2,816
Schools Closed- 90%	148	295	422	547	676	806
NYC						
Actual adherence	40,383	170,889	203,261	212,380	224,194	238,645
Schools Open – 0%	4,084,430	6,706,920	6,706,920	6,706,920	6,706,920	6,706,920
Schools Closed-0%	487,501	6,705,340	6,705,360	6,705,370	6,705,370	6,705,370
Schools Closed-25%	186,582	6,761,620	6,766,700	6,766,710	6,766,710	6,766,720
Schools Closed-50%	56,433	5,778,280	6,722,520	6,722,780	6,722,830	6,722,870
Schools Closed-75%	12,688	194,870	1,895,270	4,631,640	5,162,900	5,198,430
Schools Closed- 90%	4,671	8,800	11,818	14,554	17,350	20,103

Supplement Table 2. *Comparison of total number of confirmed cases over time when implementing social distancing on different dates*

Social distancing start date	May 15	May 31	June 15	June 30	July 15	July 31	August 15	August 31
Dane County								
1 week earlier (March 5)	295	523	998	1,969	3,295	4,716	6,055	7,477
Actual (March 12)	551	740	1,136	1,941	3,054	4,239	5,362	6,566
1-week delay (March 19)	1,810	2,022	2,450	3,320	4,515	5,785	6,974	8,242
2-week delay (March 26)	6,957	7,442	8,231	9,741	11,731	13,739	15,517	17,298
3-week delay (April 2)	26,214	27,711	29,116	31,494	34,284	36,767	38,705	40,415
4-week delay (April 9)	86,708	90,543	92,032	93,548	94,829	95,651	96,126	96,450
Milwaukee								
1 week earlier (March 5)	2,559	4,167	5,776	7,456	9,594	12,983	17,591	24,622
Actual (March 12)	5,323	8,093	11,151	14,231	18,011	23,803	31,505	42,821
1-week delay (March 19)	16,295	22,826	31,636	39,998	49,606	63,326	80,016	102,490
2-week delay (March 26)	53,860	72,147	95,771	117,670	139,094	164,829	190,756	218,909
3-week delay (April 2)	164,525	212,057	247,516	279,651	302,410	322,208	336,794	348,693
4-week delay (April 9)	409,876	481,926	506,386	519,652	525,732	528,916	530,405	531,218
NYC								
1 week earlier (March 5)	38,788	41,366	43,214	45,858	49,469	54,323	59,872	66,791
Actual (March 12)	193,291	203,261	207,741	212,380	217,698	224,194	230,941	238,645
1-week delay (March 19)	1,364,430	1,407,600	1,418,280	1,424,660	1,429,260	1,432,960	1,435,660	1,438,140
2-week delay (March 26)	4,189,700	4,198,130	4,198,740	4,199,060	4,199,340	4,199,630	4,199,900	4,200,180
3-week delay (April 2)	6,202,430	6,202,470	6,202,510	6,202,540	6,202,580	6,202,620	6,202,660	6,202,700
4-week delay (April 9)	6,680,630	6,680,630	6,680,640	6,680,640	6,680,640	6,680,640	6,680,640	6,680,650

Section D. Sensitivity Analyses

We conducted an extensive sensitivity analysis on several parameters using NYC data. In this section, we describe these experiments.

Section D.1 Sensitivity analysis on the probability of testing

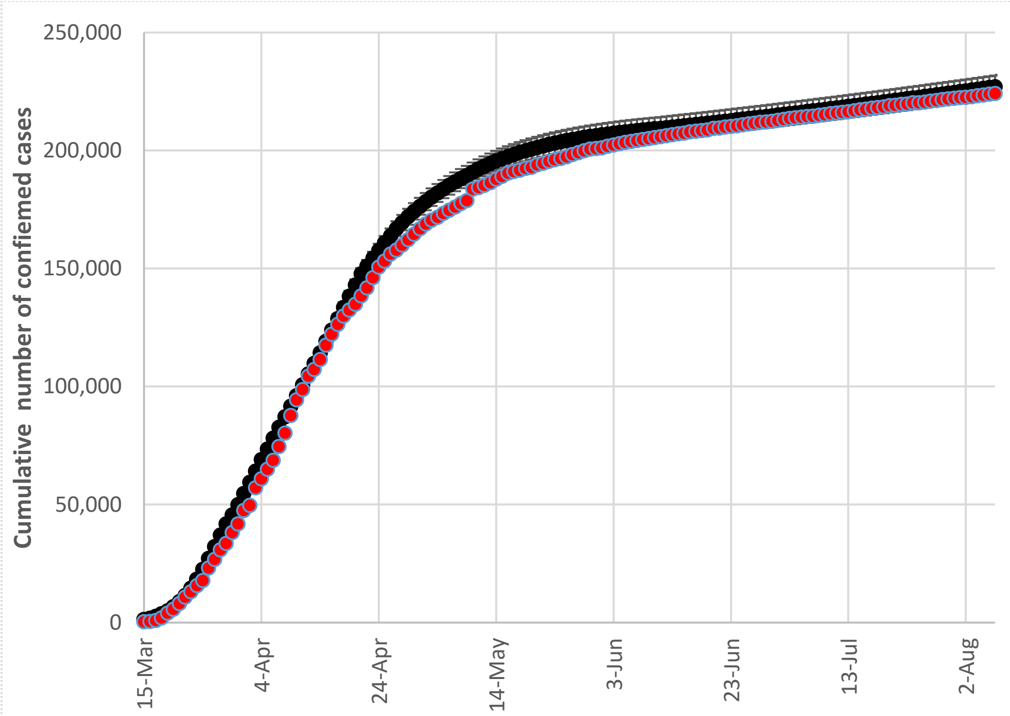
The probability of testing in the model changes over time due to increasing testing capacity in the US. Testing was severely limited especially in the early days of epidemic in the U.S.; therefore, it is likely that our initial calibration may not have estimated the input parameters correctly. For example, recent data from NYC suggest that one of every five residents tested positive for COVID-19 antibodies (66). To address the impact of uncertainty in this parameter, we did an extensive sensitivity analysis on the test rate and present the results of this analysis here.

In this sensitivity analysis, we changed the probability of testing from a baseline estimate of 75% to 25% and 50% and adjusted the parameter on adherence to social distancing measures via calibration as described in the text. Namely, we compared the model predictions to the observed number of cases in NYC by changing only adherence to social distancing measures and number of imported cases from 160 per day to 144 per day between March 4 and March 22. Our calibration resulted in the following estimates for the adherence to social distancing for each probability of testing value:

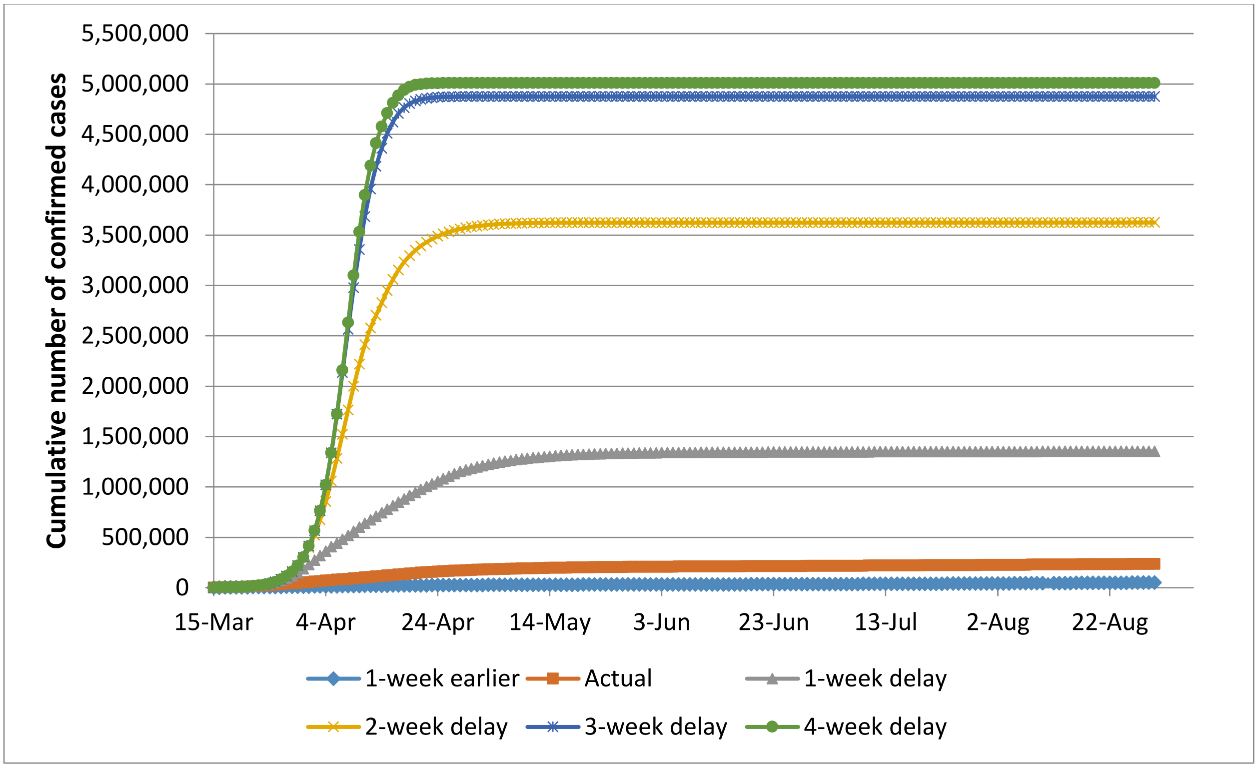
- When the probability of testing is equal to 50%, adherence level is equal to 0% between March 4 and March 11; adherence level increases linearly from 0% to 78% between March 12 and March 25; adherence level is at 85% between March 26 and April 17; adherence level is at 90% between April 18 and June 7; and adherence level is at 85% after June 8, when social distancing measures are eased.
- When the probability of testing is equal to 25%, adherence level is equal to 0% between March 4 and March 11; adherence level increases linearly from 0% to 75% between March 12 and March 27; adherence level is equal to 90% between March 28 and May 23; and adherence level is at 85% after May 24 as well as after June 8, when social distancing measures are eased.

Below, we first present the results of the validation, which show that COVAM was able to replicate the observed cumulative number of COVID-19 cases using the new set of social distancing adherence parameters and number of imported cases for different values for probability of testing. We then present the results of our experiments.

Supplement Figure 3. *Comparison of model predictions to actual NYC data when the probability of testing is equal to 50%*



Supplement Figure 4. *Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when the probability of testing is equal to 0.50*



Supplement Table 3*. Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when the probability of testing is equal to 0.50*

Social distancing implementation date	May 15	May 31	June 15	June 30	July 15	July 31	August 15	August 31
1 week earlier (March 5)	29,402	31,407	32,855	34,941	37,727	41,514	45,825	51,161
Actual (March 12)	196,542	206,297	210,502	214,697	219,311	224,600	229,800	235,585
1-week delay (March 19)	1,308,430	1,337,830	1,344,120	1,347,380	1,349,530	1,351,240	1,352,530	1,353,740
2-week delay (March 26)	3,621,970	3,623,530	3,623,690	3,623,830	3,623,970	3,624,110	3,624,260	3,624,400
3-week delay (April 2)	4,874,720	4,874,730	4,874,740	4,874,750	4,874,760	4,874,780	4,874,790	4,874,800
4-week delay (April 9)	5,008,000	5,008,000	5,008,000	5,008,000	5,008,000	5,008,000	5,008,000	5,008,010

Supplement Table 4. *Comparison of total number of confirmed cases over time for different adherence levels in NYC when the probability of testing is equal to 0.50*

Scenario- Adherence Level	March 31	April 30	May 31	June 30	July 31	August 31
Actual adherence	49,956	174,217	206,297	214,697	224,600	235,585
Schools Open – 0%	1,060,800	5,0152,90	5,015,290	5,015,290	5,015,290	5,015,290
Schools Closed-0%	330,771	5,016,150	5,016,180	5,016,190	5,016,190	5,016,190
Schools Closed-25%	127,358	5,080,150	5,086,990	5,086,990	5,087,000	5,087,000
Schools Closed-50%	38,993	4,251,540	5,099,030	5,099,280	5,099,320	5,099,350
Schools Closed-75%	9,003	142,135	1,437,530	3,587,880	4,020,520	4,050,680
Schools Closed- 90%	3,397	6,550	8,909	11,045	13,223	15,355

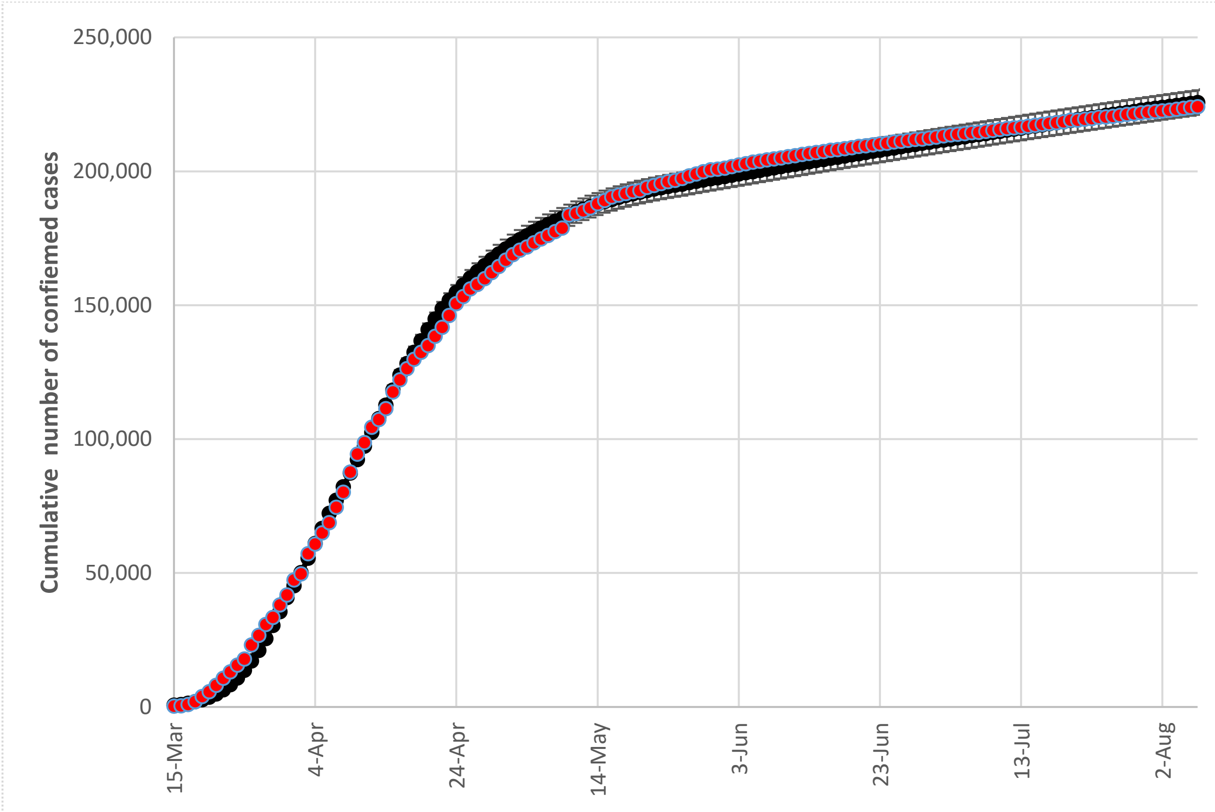
Supplement Table 5. *Comparison of total number of confirmed cases over time when easing social distancing on different dates in NYC when the probability of testing is equal to 0.50*

Total number of infections by	**Easing social distancing measures on June 1**			**Easing social distancing measures on June 8**		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	222,424	232,984	252,690	219,486	223,383	229,223
July 31	235,081	311,539	652,169	229,363	267,872	411,401
August 31	248,413	551,064	2,450,460	240,325	414,008	1,635,540

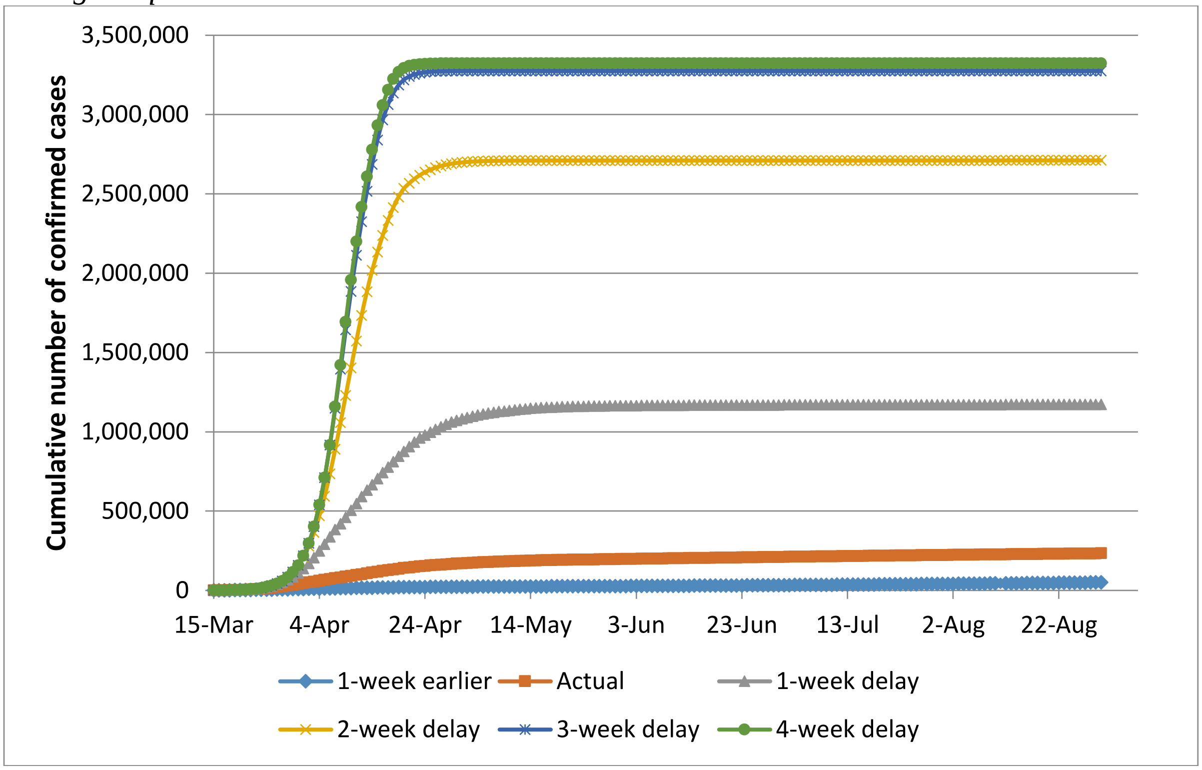
Total number of infections by	**Easing social distancing measures on June 15**			**Easing social distancing measures on July 1**		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	217,973	219,153	220,665	217,033	217,033	217,033
July 31	225,725	245,085	304,153	221,480	225,259	232,271
August 31	235,007	335437	1,012,510	228,240	258,073	396,056

DAE: Drop in adherence rates after easing social distancing measures. A value of 5%, 10%, and 15% DAE implies that adherence to social distancing measures after the date of easing is at 85%, 80%, and 75%, in NYC, respectively

Supplement Figure 5. *Comparison of model predictions to actual NYC data when the probability of testing is equal to 25%*



Supplement Figure 6*. Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when the probability of testing is equal to 0.25*



Supplement Table 6*. Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when the probability of testing is equal to 0.25*

Social distancing implementation date	May 15	May 31	June 15	June 30	July 15	July 31	August 15	August 31
1 week earlier (March 5)	25,564	27,736	30,274	33,349	36,981	41,386	46,003	51,367
Actual (March 12)	188,674	197,610	204,398	210,841	216,945	223,109	228,543	234,099
1-week delay (March 19)	1,150,090	1,164,780	1,168,090	1,169,710	1,170,670	1,171,380	1,171,910	1,172,460
2-week delay (March 26)	2,710,560	2,710,860	2,710,920	2,710,980	2,711,040	2,711,100	2,711,160	2,711,220
3-week delay (April 2)	3,274,910	3,274,920	3,274,920	3,274,930	3,274,930	3,274,940	3,274,940	3,274,950
4-week delay (April 9)	3,323,040	3,323,040	3,323,040	3,323,040	3,323,040	3,323,040	3,323,040	3,323,040

Supplement Table 7. *Comparison of total number of confirmed cases over time for different adherence levels in NYC when the probability of testing is equal to 0.25*

Scenario-Adherence Level	March 31	April 30	May 31	June 30	July 31	August 31
Actual adherence	40,872	169,125	197,610	210,841	223,109	234,099
Schools Open – 0%	551,075	3,324,120	3,324,120	3,324,120	3,324,120	3,324,120
Schools Closed-0%	174,089	3,326,660	3,326,710	3,326,710	3,326,710	3,326,710
Schools Closed-25%	68,277	3,398,400	3,406,980	3,406,980	3,406,980	3,406,990
Schools Closed-50%	21,594	2,726,560	3,416,190	3,476,430	3,476,460	3,476,480
Schools Closed-75%	5,295	89,483	980,278	2,545,710	2,879,680	2,902,520
Schools Closed- 90%	2,122	4,301	5,996	7,529	9,100	10,640

Supplement Table 8. *Comparison of total number of confirmed cases over time when easing social distancing on different dates in NYC when the probability of testing is equal to 0.25*

Total number of infections by	**Easing social distancing measures on June 1**			**Easing social distancing measures on June 8**		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	222,323	243,087	278,843	216,667	225,349	237,738
July 31	298,915	613,445	1,485,940	275101	457953	963,254
August 31	499,580	1,906,200	3,198,330	435,196	1,556,920	3,035,810

Total number of infections by	**Easing social distancing measures on June 15**			**Easing social distancing measures on July 1**		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	213,187	216,137	219,672	210,841	210,841	210,841
July 31	257,669	358,469	612,119	234,156	254,808	291,107
August 31	383,645	1,204,260	2,725,280	304,737	606,768	1469,260

DAE: Drop in adherence rates after easing social distancing measures. A value of 5%, 10%, and 15% DAE implies that adherence to social distancing measures after the date of easing is at 80%, 75%, and 70%, in NYC, respectively

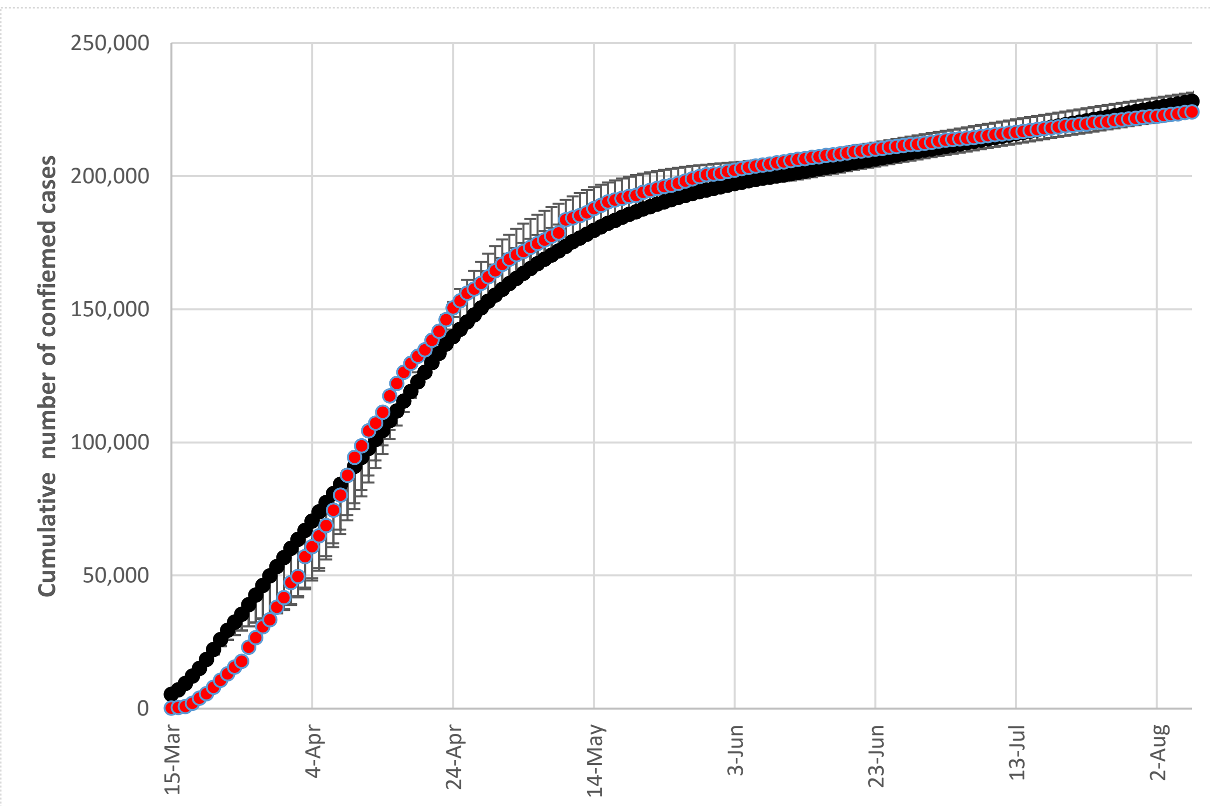
Section D.2 Sensitivity analysis on transmission rates

We conducted a sensitivity analysis on transmission rates similar to the one described in section D.1. We halved the probability of transmission from a patient with mild to moderate symptoms (replaced the baseline estimate of 0.0418 with 0.0209) and recalibrated several model parameters including probability of testing, number of daily contacts, number of initial infections, and adherence to social distancing measures. Our calibration resulted in the following values for these input parameters:

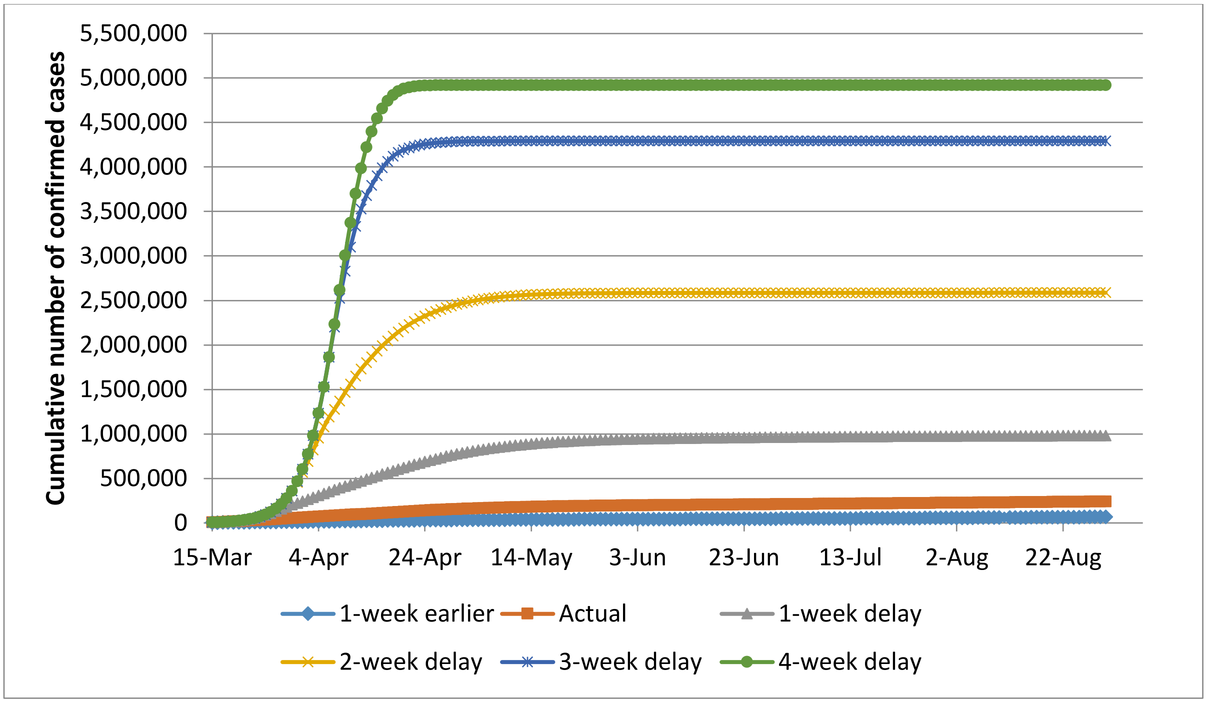
- Baseline probability of testing: 50%
- Number of initial infections: 1600 compared to the baseline estimate of 16, reflecting the theory that the pandemic in NYC started much earlier than previously thought[45]
- Adherence level is equal to 0% between March 4 and March 11; adherence level increases linearly from 0% to 80% between March 12 and March 20; adherence level is equal to 80% between March 21 and April 19; adherence level is equal to 85% between April 20 and June 7; and adherence level is equal to 80% after June 8.

Below, we first present the results of the validation, which show that COVAM was able to replicate the observed cumulative number of COVID-19 cases using the new set of input parameters for this sensitivity analysis. We then present the results of our experiments.

Supplement Figure 7*. Comparison of model predictions to actual NYC data when the transmission rate is halved*



Supplement Figure 8. *Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when the transmission rate is halved*



Supplement Table 9. *Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when transmission rate is halved*

Social distancing implementation date	May 15	May 31	June 15	June 30	July 15	July 31	August 15	August 31
1 week earlier (March 5)	38,325	41,977	44,480	47,543	51,367	56,290	61,583	67,933
Actual (March 12)	181,025	195,472	202,860	209,811	216,934	224,751	232,116	240,156
1-week delay (March 19)	894,104	939,577	954,498	963,544	969,817	974,594	977,918	980,747
2-week delay (March 26)	2,567,690	2,582,990	2,584,810	2,585,430	2,585,830	2,586,210	2,586,530	2,586,890
3-week delay (April 2)	4,291,690	4,291,850	4,291,910	4,291,970	4,292,030	4,292,090	4,292,150	4,292,210
4-week delay (April 9)	4,919,870	4,919,880	4,919,890	4,919,890	4,919,900	4,919,910	4,919,920	4,919,920

Supplement Table 10. *Comparison of total number of confirmed cases over time for different adherence levels in NYC when the transmission rate is halved*

Scenario- Adherence Level	March 31	April 30	May 31	June 30	July 31	August 31
Actual adherence	56,818	155,404	195,472	209,811	224,751	240,156
Schools Open – 0%	1,489,190	5,011,150	5,011,150	5,011,150	5,011,150	5,011,150
Schools Closed-0%	466,910	4,999,920	5,000,730	5,000,740	5,000,740	5,000,750
Schools Closed-25%	173,850	4,980,230	5,038,420	5,038,440	5,038,460	5,038,480
Schools Closed-50%	50,715	2,623,060	4,814,370	4,829,180	4,829,330	4,829,430
Schools Closed-75%	11,372	57,302	207,886	555,608	1,151,040	1,734,160
Schools Closed- 90%	4,628	6,587	8,019	9,392	10,799	12,205

Supplement Table 11. *Comparison of total number of confirmed cases over time when easing social distancing on different dates in NYC when the transmission rate is halved*

Total number of infections by	**Easing social distancing measures on June 1**			**Easing social distancing measures on June 8**		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	213,485	225,386	244,575	209,811	214,581	221,243
July 31	232,148	303,496	528,795	224,751	264,370	373,445
August 31	250,615	478,986	1,573,070	240,156	383,042	1,070,930

Total number of infections by	**Easing social distancing measures on June 15**			**Easing social distancing measures on July 1**		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	207,751	209,367	211,226	206,409	206,409	206,409
July 31	219,740	241,314	292,068	213,660	218,298	225,920
August 31	232,735	321,499	716,895	222,785	252,174	347,669

DAE: Drop in adherence rates after easing social distancing measures. A value of 5%, 10%, and 15% DAE implies that adherence to social distancing measures after the date of easing is at 80%, 75%, and 70%, in NYC, respectively

Section D.3. Sensitivity analysis on the number of imported cases

The imported cases in COVAM are included to explain two situations: 1) In the early days of the pandemic, these represent the cases that provided the seed of the epidemic in a region; 2) These also represent the interactions between individuals who do and do not live in the modeled region but have close contacts due to commuting and/or traveling. A molecular epidemiology study conducted by Mount Sinai Hospital's Icahn School of Medicine found that SARS-CoV-2 was likely circulating as early as February in the NYC area whereas our simulation starts on March 4 (67). Therefore, using imported cases helps our model to introduce initial seeds for the pandemic. Note that our base case assumption of 160 imported cases per day is assumed to last only between March 4 and March 22. After March 22, due to strong travel restrictions, we reduced this number to 32 per day throughout the simulation. This is because NYC as well as other simulated regions are not closed populations – there was not a strict quarantine enforced in any of the regions and thus there continued to be interactions with neighboring regions where COVID-19 activity was very high. For example, in the model representing the Milwaukee metro area, the model does not explicitly represent the Chicago area where there is high level of COVID-19 activity. We use imported cases to account for the interactions between people living in the Chicago area and those living in the Milwaukee metro area.

While we provide the details on how this parameter is estimated, our primary method to validate this input was calibration. We started estimating the value of this input using Dane County data. We found that when there are 3 imported cases per day in Dane County starting on March 4, 2020, there would be a total of 57 imported cases among a total of 225 reported confirmed cases as of March 27, 2020. This implies that 25% of the confirmed cases are imported cases. Even if NYC has the same level of travel in and out of the city, given NYC's large population (approximately 16 times the population of Dane County), we would have to assume that the number of imported cases in NYC would be 16*3=48 per day. We compared the airline traffic data of passengers traveling into NYC (JFK, LaGuardia, and Newark airports, 69 million passengers annually) and into Dane County (Dane County Regional Airport, 2.3 million passengers annually) to find that NYC airline travel is 30 times higher than Dane County. Considering the different population sizes, this implies approximately twice as much outside travel into the NYC area as compared to Dane County. This implied that the number of imported cases in the early days of the pandemic when there were no travel restrictions should be at least 90 per day for NYC. We then considered a higher number of imported cases due to several close communities in and around the NYC area, such as New Jersey, where the prevalence of SARS-CoV-2 was very high. We considered that commuting via public transportation was higher in NYC (39% for NYC, versus 4.6% for Dane County and 3% for the Milwaukee area according to US Census data) (68). These data implied that we would have to assume a high number of imported cases. Our calibrations found that an estimate of 160 imported cases per day provided a very good input to explain the huge spike in NYC in the early days of the pandemic.

Alternatively, we could have used a larger number of initial infections and smaller number of imported cases. In fact, the sensitivity analysis in this section assumed a higher initial number of infections and lower number of imported cases in order to test the effect on our main findings.

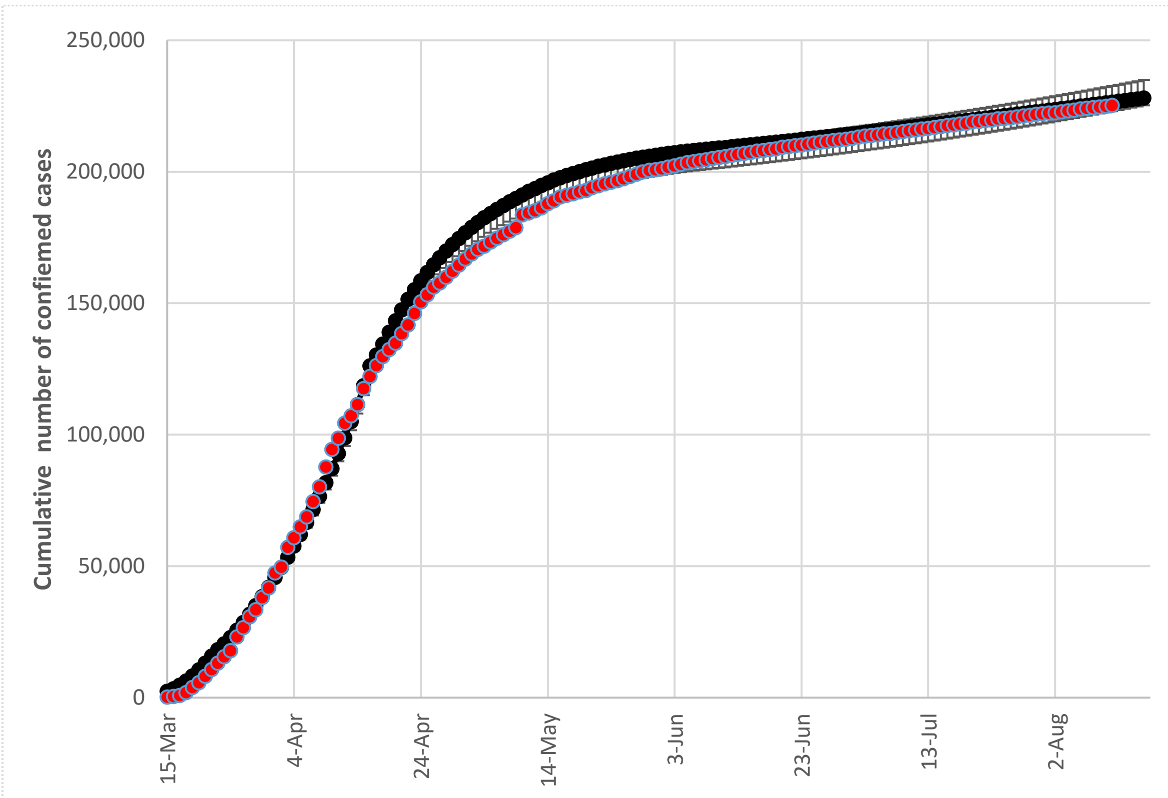
More specifically, we followed the same approach as in section D.1 and found the following parameter sets for our sensitivity analysis on the number of imported cases:

- Number of initial exposures is equal to 320 (compared to base case estimate of 16)

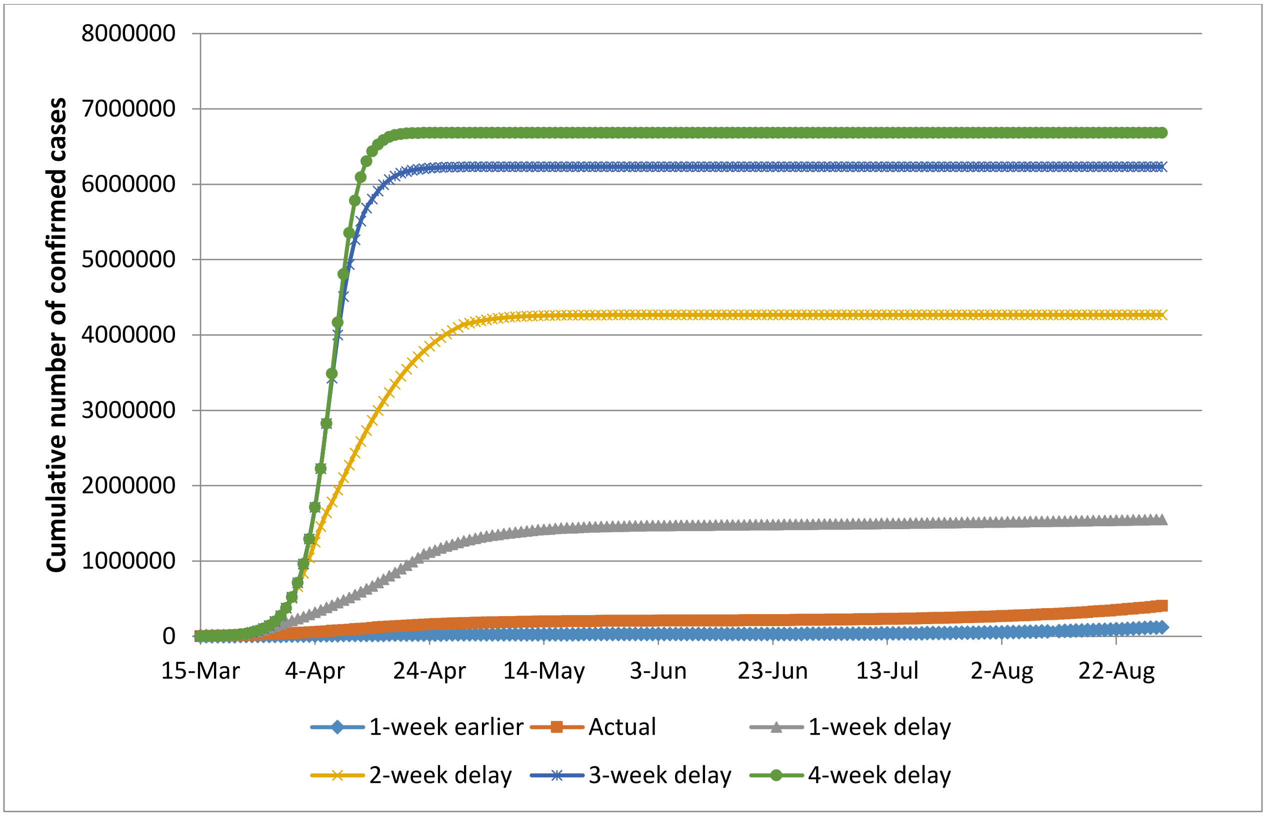
- Number of imported cases between March 4 and March 22 is equal to 48 per day (compared to base case estimate of 160)
- Number of imported cases after March 22 is equal to 16 per day (compared to base case estimate of 32)

We set all other input parameters to their values in the base case. Below, we first present the results of the validation, which show that COVAM was able to replicate the observed cumulative number of COVID-19 cases using the new set of input parameters for this sensitivity analysis. We then present the results of our experiments. Our findings on the impact of timing and adherence to social distancing did not change.

Supplement Figure 9. *Comparison of model predictions to actual NYC data when the number of imported cases is reduced*



Supplement Figure 10. *Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when number of imported cases is reduced*



Supplement Table 12*. Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when the number of imported cases is reduced*

Social distancing implementation date	May 15	May 31	June 15	June 30	July 15	July 31	August 15	August 31
1 week earlier (March 5)	28,208	29,849	31,035	33,638	39,306	51,865	75,760	126,298
Actual (March 12)	196,852	206,301	210,608	218,130	232,568	261,694	312,472	410,464
1-week delay (March 19)	1,424,920	1,467,240	1,478,000	1,488,430	1,500,770	1,515,990	1,532,400	1,552,460
2-week delay (March 26)	4,258,220	4,265,500	4,265,960	4,266,170	4,266,350	4,266,540	4,266,710	4,266,880
3-week delay (April 2)	6,233,250	6,233,280	6,233,300	6,233,320	6,233,330	6,233,350	6,233,370	6,233,390
4-week delay (April 9)	6,681,950	6,681,950	6,681,950	6,681,950	6,681,950	6,681,950	6,681,950	6,681,960

Supplement Table 13. *Comparison of total number of confirmed cases over time for different adherence levels in NYC when the number of imported cases is reduced*

Scenario- Adherence Level	March 31	April 30	May 31	June 30	July 31	August 31
Actual adherence	42,055	174,664	206,301	218,130	261,694	410,464
Schools Open – 0%	1,851,940	6,706,510	6,706,510	6,706,510	6,706,510	6,706,510
Schools Closed-0%	518,168	6,704,630	6,704,640	6,704,640	6,704,640	6,704,650
Schools Closed-25%	176,770	6,766,680	6,772,300	6,772,300	6,772,310	6,772,310
Schools Closed-50%	45,222	5,518,530	6,734,090	6,734,420	6,734,440	6,734,460
Schools Closed-75%	7,914	117,081	1,295,620	4,260,850	5,145,360	5,210,190
Schools Closed- 90%	2,461	4,389	5,913	7,292	8,666	10,039

***Supplement Table 14**. Comparison of total number of confirmed cases over time when easing social distancing on different dates in NYC when the number of imported cases is reduced*

Total number of infections by	Easing social distancing measures on June 1			Easing social distancing measures on June 8		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	228,232	248,854	285,292	218,130	215,340	233,006
July 31	308,828	678,902	1,913,480	261,694	296,052	884,223
August 31	568,627	2,913,060	5,715,510	410,464	1,033,500	4,971,500

Total number of infections by	Easing social distancing measures on June 15			Easing social distancing measures on July 1		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	213,828	215,340	217,150	211,730	211,730	211,730
July 31	238,132	296,052	455,813	218,562	224,761	235,809
August 31	324,445	1,033,500	3,547,800	246,422	367,676	843,280

DAE: Drop in adherence rates after easing social distancing measures. A value of 5%, 10%, and 15% DAE implies that adherence to social distancing measures after the date of easing is at 80%, 75%, and 70%, in NYC, respectively

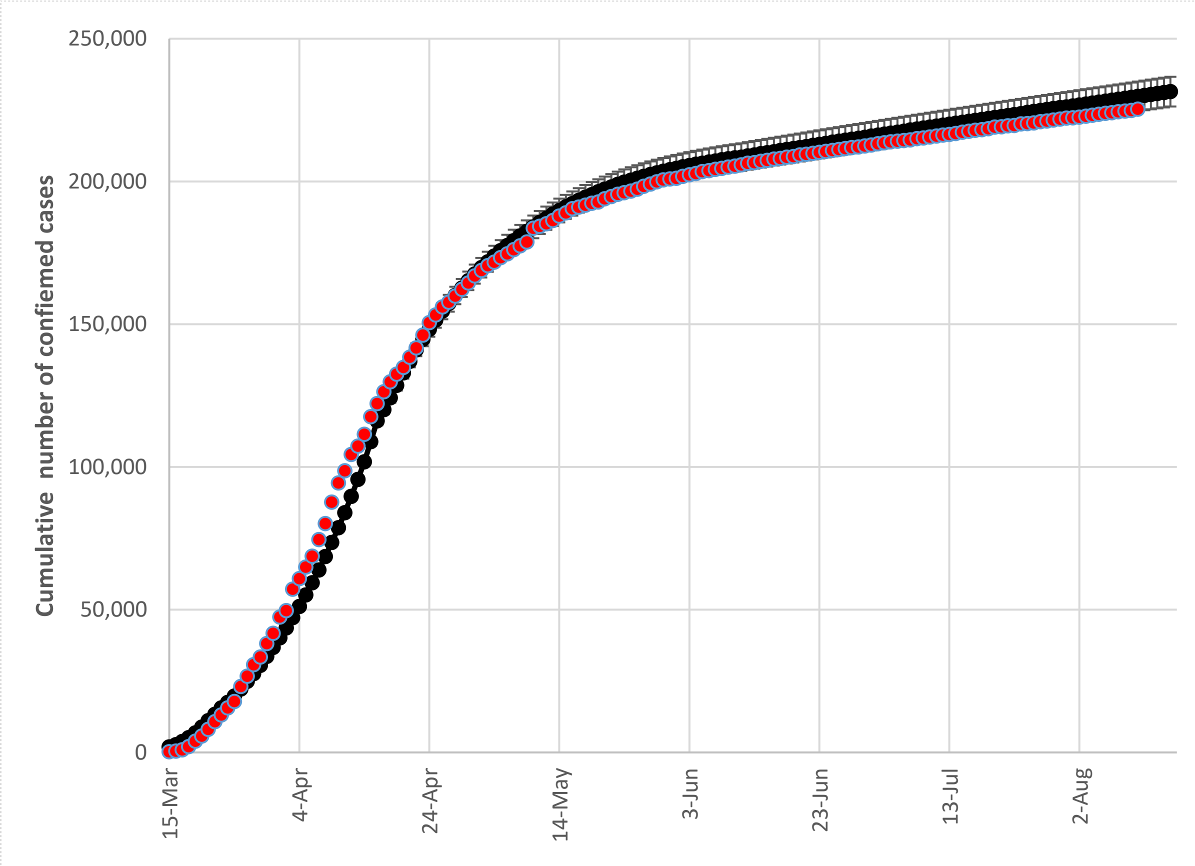
Section D.4 Sensitivity analysis when hospital transmission is allowed

In our base case, we assumed no SARS-CoV-2 transmission within the hospital setting. Case reports indicate that SARS-CoV-2 transmission to healthcare workers is occurring, especially in settings where contact occurs without appropriate PPE (69). A review of the recent literature, however, indicates that with appropriate PPE (as is now generally the case in US healthcare settings) transmission by this route is likely not occurring at rates which would substantially affect our model's findings for the general population (70-72). To ensure that this is the case, we conducted a sensitivity analysis in which hospital transmission was allowed. For this purpose, we set the probability of transmission from hospitalized patients to healthcare workers to 20% of the transmission from non-hospitalized patients and report the results of this experiment. We assumed this probability of transmission as reported by previous studies on seasonal influenza (22). We then recalibrated the model parameters and found the following values:

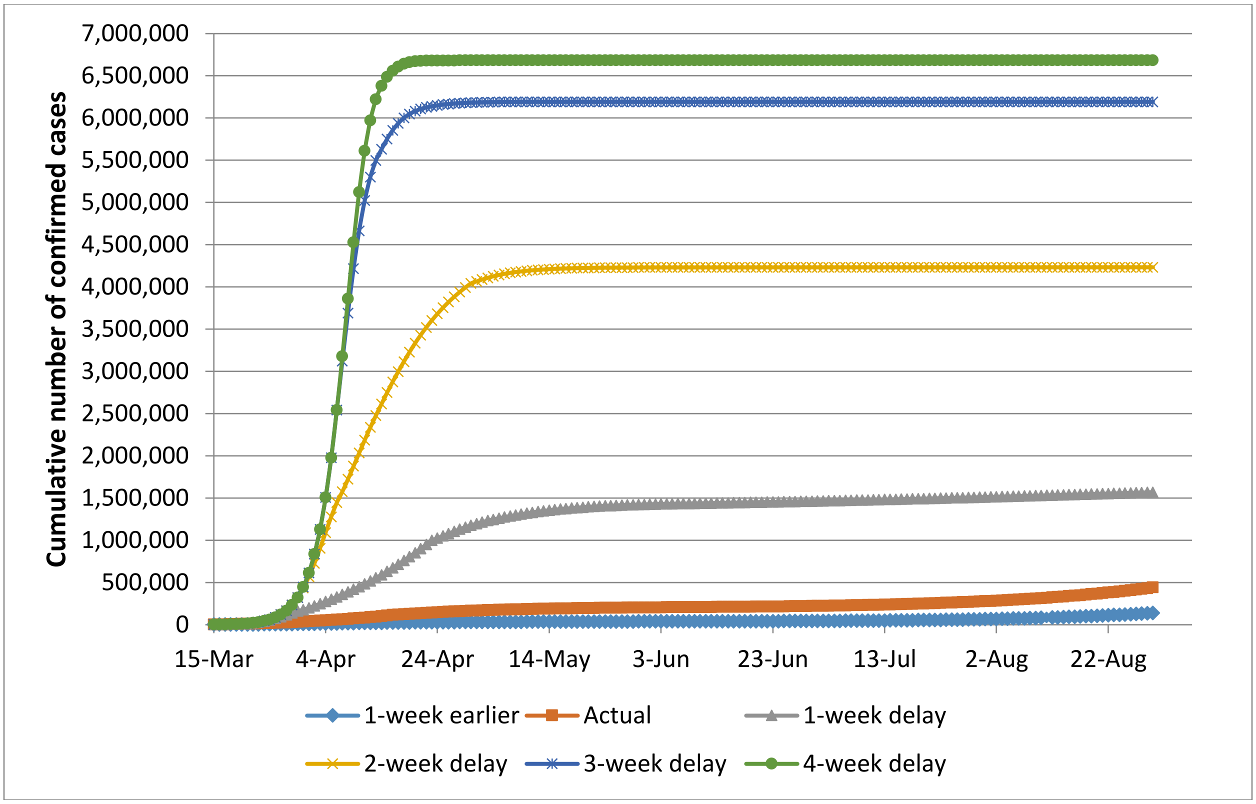
- Number of imported cases between March 4 and March 22 is equal to 136 per day (compared to base case estimate of 160)
- Number of imported cases after March 22 through the end of simulation is equal to 16 per day (compared to base case estimate of 32)
- Adherence to social distancing after June 8 is 86% (compared to base case estimate to 85%).

Below, we first present the results of the validation, which show that COVAM was able to replicate the observed cumulative number of COVID-19 cases using the new set of input parameters for this sensitivity analysis. We then present the results of our experiments, which show that our main findings/conclusions did not change with this sensitivity analysis.

Supplement Figure 11. *Comparison of model predictions to actual NYC data when hospital transmission is added to the model*



Supplement Figure 12. *Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when hospital transmission is added to the model*



Supplement Table 15. *Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when the hospital transmission is added to the model*

Social distancing implementation date	May 15	May 31	June 15	June 30	July 15	July 31	August 15	August 31
1 week earlier (March 5)	36,757	39,264	40,966	44,469	51,601	66,406	92,769	145,452
Actual (March 12)	191,100	204,120	210,625	221,351	240,736	277,957	338,964	449,803
1-week delay (March 19)	1,363,180	1,424,980	1,444,210	1,463,820	1,485,880	1,512,290	1,539,740	1,571,770
2-week delay (March 26)	4,214,100	4,230,450	4,231,860	4,232,320	4,232,560	4,232,760	4,232,930	4,233,120
3-week delay (April 2)	6,191,920	6,192,060	6,192,080	6,192,100	6,192,120	6,192,140	6,192,160	6,192,180
4-week delay (April 9)	6,682,130	6,682,130	6,682,130	6,682,130	6,682,130	6,682,130	6,682,140	6,682,140

Supplement Table 16. *Comparison of total number of confirmed cases over time for different adherence levels in NYC when hospital transmission is added to the model*

Scenario- Adherence Level	March 31	April 30	May 31	June 30	July 31	August 31
Actual adherence	36,796	165,187	204,120	221,351	277,957	449,803
Schools Open – 0%	1,451,640	6,709,630	6,706,930	6,706,930	6,706,930	6,706,930
Schools Closed-0%	446,173	6,708,660	6,708,940	6,708,940	6,708,940	6,708,940
Schools Closed-25%	170,585	6,775,480	6,784,040	6,784,040	6,784,040	6,784,040
Schools Closed-50%	51,479	5,746,720	6,769,030	6,769,750	6,769,770	6,769,780
Schools Closed-75%	11,525	188,410	1,997,850	4,896,620	5,413,570	5,446,820
Schools Closed- 90%	4,204	7,637	9,643	11,240	12,764	14,313

Supplement Table 17. *Comparison of total number of confirmed cases over time when easing social distancing on different dates in NYC when hospital transmission is added to the model*

Total number of infections by	Easing social distancing measures on June 1			Easing social distancing measures on June 8		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	234,451	263,549	315,665	221,351	230,376	243,784
July 31	334,697	797,599	2,269,250	277,957	476,639	1,013,870
August 31	620,823	3,115,000	5,795,300	449,803	2,047,850	5,198,880

Total number of infections by	Easing social distancing measures on June 15			Easing social distancing measures on July 1		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	215,526	217,837	220,660	212,491	212,491	212,491
July 31	247,867	328,778	551,919	221,728	230,613	247,092
August 31	350,594	1,213,200	3,949,710	254,445	408,786	1,023,310

DAE: Drop in adherence rates after easing social distancing measures. A value of 5%, 10%, and 15% DAE implies that adherence to social distancing measures after the date of easing is at 81%, 76%, and 71%, in NYC, respectively

Section D.5 Sensitivity analysis when number of daily contacts is affected by knowledge about infection status

We conducted a structural sensitivity analysis on the assumption that individuals with known and unknown COVID-19 status have the same number of daily contacts. We did not consider a different number of daily close contacts between individuals with and without known infections in the base case due to several reasons. First, there was a major delay in reporting and confirming the results of the testing, especially in the earlier days of the pandemic. Therefore, individuals who tested positive often received these results several days after they were tested. There is a possibility that individuals did not modify their behaviors during this wait period. For example, a recent study conducted a large, 50-state survey and reported that the median waiting time for nasal swab results nationally was 3 days and mean waiting time was 4.1 days (73). A report by the Department of Health and Human Services found that while 45% of the tests were completed in 3 days in early July, 56% of the tests were completed within 3 days by the end of July (74). Second, the contagious period appears to be highest in the early days of the illness. Therefore, there would be a need to change the transmission potential of the individuals by day of transmission; currently there are not sufficient data for this (25). Finally, there are no reliable data on the impact of testing on contact rates (versus self-isolation for symptoms alone). Thus, we did not consider this scenario in the base case to simplify the analysis.

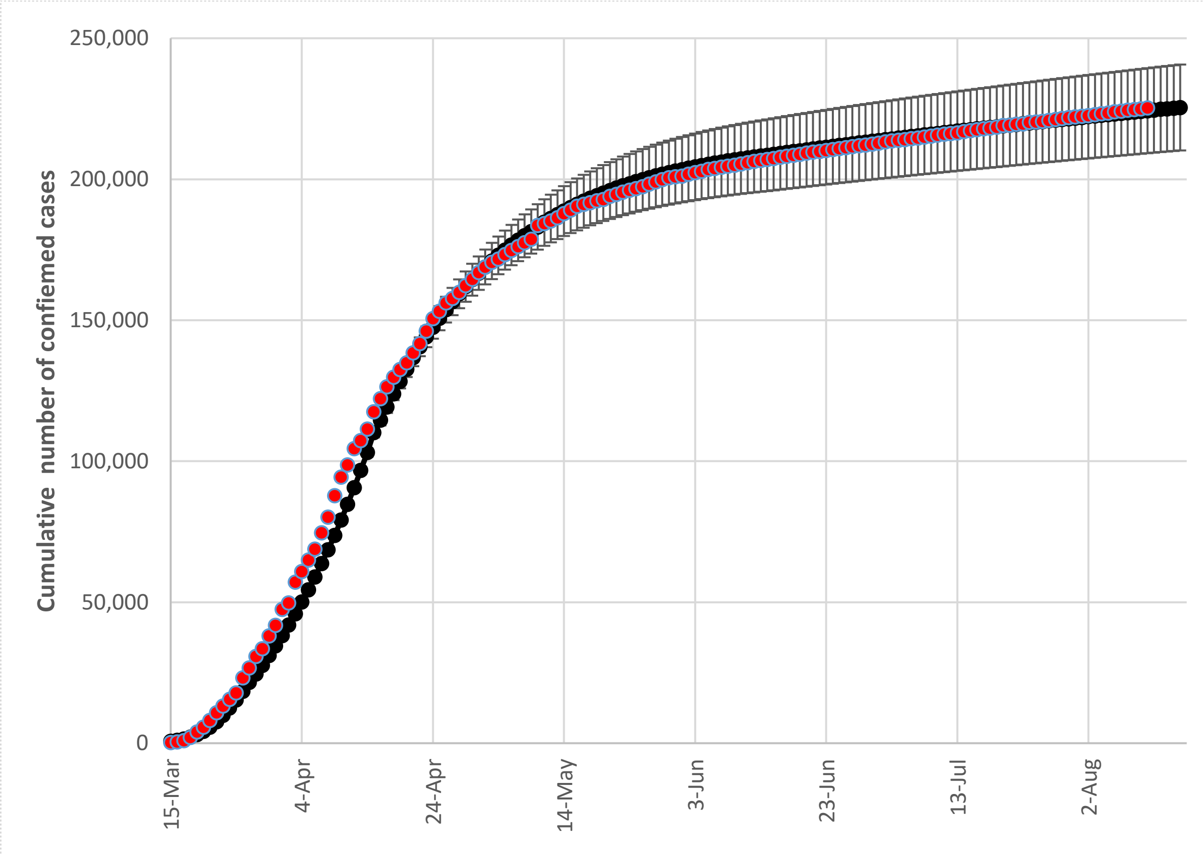
In this sensitivity analysis, we now differentiate the number of contacts for individuals with known and unknown infections. We conducted this experiment to confirm that our assumption that there is no difference in contact patterns between known and unknown infection status did not introduce a bias to our findings. For this purpose, we made the following assumptions compared to the base case:

- Individuals who are tested positive know about their COVID-19 status 3 days after experiencing mild to moderate symptoms. This assumption is made to account for delay in getting the test results.
- Individuals with known infections reduce their daily number of contacts by 50% after they learn about their infection status. We were not able to find any data on the rate of reduction in the number of contacts after individuals learn about their COVID-19 status. As such, we made this assumption to account for the cases where some individuals do not change their behavior after a known infection. While some individuals will reduce their non-household interactions, they will still keep their household contacts.

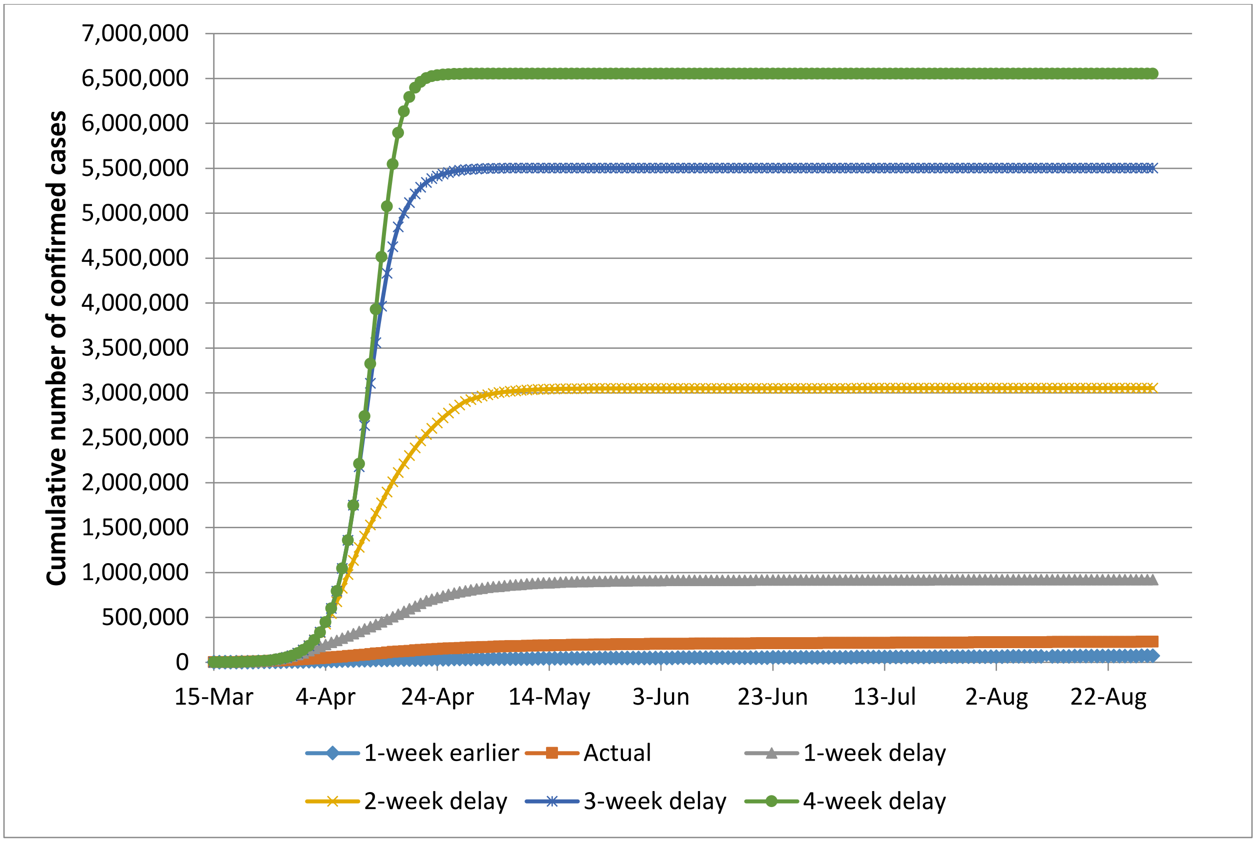
In our calibration, we did not change any input parameters except the adherence to the social distancing measures. Our calibration resulted in the following values for adherence to social distancing: it is equal to 0% between March 4 and March 11; increases linearly from 0% to 72% between March 12 and March 21; is equal to 74% between March 22 and April 8; is equal to 85% between April 8 and June 7; and is equal to 82% after June 8.

Compared to our base case assumptions, we found that differential contact patterns between individuals with and without known infection slightly reduced our calibrated adherence to social distancing input. We found that none of our model's results changed with this assumption.

Supplement Figure 13*. Comparison of model predictions to actual NYC data when number of contacts is reduced after known infection*



Supplement Figure 14. *Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when number of contacts is reduced after known infection*



Supplement Table 18*. Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when number of contacts is reduced after known infection*

Social distancing implementation date	May 15	May 31	June 15	June 30	July 15	July 31	August 15	August 31
1 week earlier (March 5)	44,190	48,908	52,082	55,389	59,058	63,304	67,604	72,500
Actual (March 12)	189,943	202,895	208,836	213,452	217,573	221,678	225,219	228,799
1-week delay (March 19)	889,329	909,881	914,521	916,715	918,261	919,696	920,944	922,212
2-week delay (March 26)	3,043,150	3,050,140	3,050,820	3,051,250	3,051,680	3,052,140	3,052,550	3,053,010
3-week delay (April 2)	5,503,360	5,503,510	5,503,610	5,503,710	5,503,810	5,503,910	5,504,010	5,504,110
4-week delay (April 9)	6,552,510	6,552,530	6,552,540	6,552,560	6,552,570	6,552,600	6,552,610	6,552,630

Supplement Table 19*. Comparison of total number of confirmed cases over time for different adherence levels in NYC when number of contacts is reduced after known infection*

Scenario- Adherence Level	March 31	April 30	May 31	June 30	July 31	August 31
Actual adherence	34,508	164,374	197,657	213,452	221,678	228,799
Schools Open – 0%	412,935	6,690,830	6,690,830	6,690,830	6,690,840	6,690,840
Schools Closed-0%	136,848	6,698,300	6,699,990	6,700,000	6,700,020	670,0030
Schools Closed-25%	58,461	6,435,160	6,620,130	6,620,180	6,620,240	6,620,290
Schools Closed-50%	21,306	1,816,810	5,916,950	5,970,280	5,970,730	5,970,990
Schools Closed-75%	6,923	32,313	87,537	185,187	324,422	469,807
Schools Closed- 90%	3,846	6,695	8,621	10,440	12,347	14,265

***Supplement Table 20**. Comparison of total number of confirmed cases over time when easing social distancing on different dates in NYC when number of contacts is reduced after known infection*

Total number of infections by	Easing social distancing measures on June 1			Easing social distancing measures on June 8		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	161,245	138,210	139,752	160,121	134,768	133,326
July 31	177,802	178,216	259,336	172,996	161,032	200,687
August 31	203,924	291,522	831,521	194,513	245,421	589,769

Total number of infections by	Easing social distancing measures on June 15			Easing social distancing measures on July 1		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	160,011	133,104	130,584	162,029	132,413	129,455
July 31	170,136	150,448	167,991	167,747	139,242	139,551
August 31	188,122	211,348	426,067	180,106	168,020	230,276

DAE: Drop in adherence rates after easing social distancing measures. A value of 5%, 10%, and 15% DAE implies that adherence to social distancing measures after the date of easing is at 77%, 72%, and 67%, in NYC, respectively

Section D.6 Sensitivity analysis when physical distancing and other risk reduction behaviors such as mask use are disaggregated

We conducted a structural sensitivity analysis on the assumption that adherence to social distancing measures and other behaviors that reduce the risk of transmission such as wearing masks and frequent hand washing are bundled together. While we acknowledge that the two types of behaviors are distinct from each other, we made this assumption to simplify the presentation of the adherence data. Moreover, while there are almost daily data regarding reductions in individuals' traveling behaviors, there are not any reliable temporal data on hand washing and facial mask use, which may change over time. We believe that this was a reasonable assumption, as risk-averse individuals are likely to engage in risk reduction behaviors such as social distancing and using masks. However, we have now included a sensitivity analysis to estimate the effects when the model does not bundle the two behaviors. In this section, we present the details and the results of these experiments.

We can disaggregate social distancing measures into the following two components: 1) physical distancing via less frequent traveling or keeping at least 6-feet distance during interactions and 2) other risk reduction behaviors including wearing face masks. First, we need to estimate the proportion of the population that is following physical distancing and the proportion of the population that is not following physical distancing but is wearing masks. Second, we need to estimate the effectiveness of keeping at least 6-feet distance during interactions as well as the effectiveness of wearing masks. A recent study reported the results of a comprehensive systematic review and meta-analysis to estimate the effectiveness of physical distancing and the use of face masks/eye protection for avoiding person-to-person virus transmission (75). The study found that face mask use reduces the risk of transmission by 85% (noting that the type of mask impacts the rate of reduction in transmission risk) whereas keeping a 1 meter distance during an interaction reduces the risk of transmission by 82%. We could use these data to implement the differential impact of physical distancing and wearing masks. However, while cellphone data provides some information about the proportion of the population that is traveling less, there is not reliable information on the proportion of the population that follows other risk reduction behaviors such as mask use and frequent hand washing. Several self-reported surveys estimated this input parameter, but given that these behaviors change over time, such data may not be sufficient to accurately inform the model.

In our sensitivity analysis, we have now made the following changes to the model to disaggregate these two main behaviors. We redefined adherence to social distancing measures using two parameters: 1) adherence to physical distancing measures and 2) proportion of the population that is not following physical distancing measures but is following recommended risk reduction behaviors. We assumed that the risk of infection drops by 85% for the former group whereas it drops by 82% for the latter group while keeping the overall adherence level to be equal to the adherence input estimated for the base case.

We then ran the following two scenarios:

- Scenario 6.1: 25% of the reduction in the number of contacts due to social distancing measures is attributed to the adherence to the physical distancing whereas the rest is attributed to the wearing face masks
- Scenario 6.2: 75% of the reduction in the number of contacts due to social distancing measures is attributed to the adherence to the physical distancing whereas the rest is attributed to the wearing face masks

For both scenarios, we kept all other input parameters the same and compared the model's predictions. Supplement Figure 15 shows the results of this experiment, which imply that there is no difference between the two scenarios. Therefore, as long as the overall adherence level estimated by our base case remains the same, the results do not change even if these two types of behaviors are not bundled.

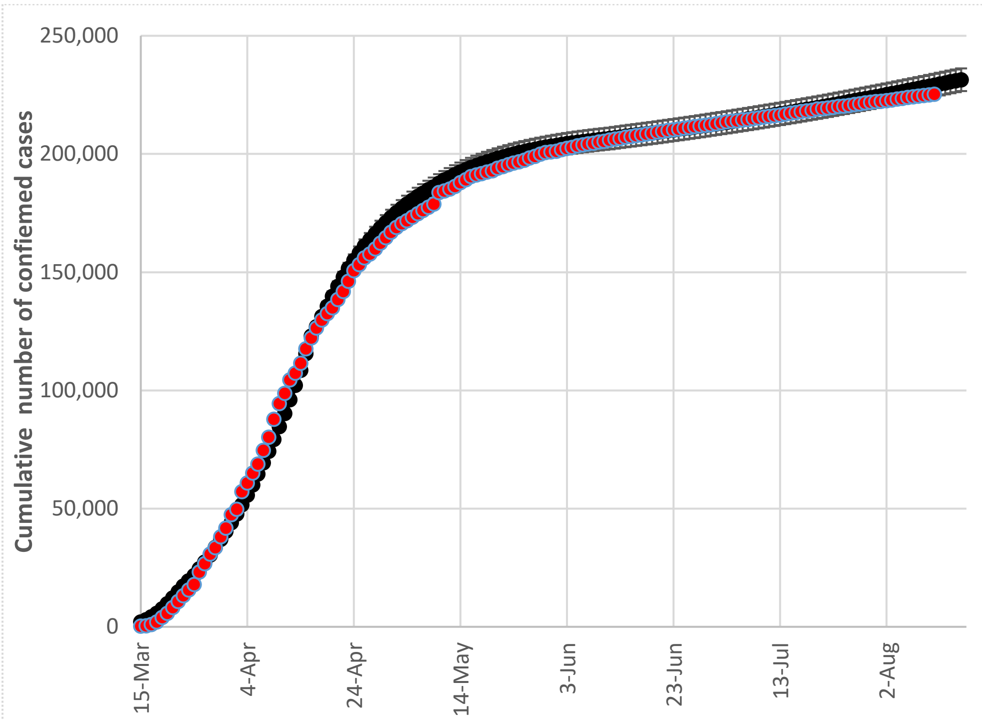
To demonstrate the potential use of COVAM where these two distinct sets of behaviors are disaggregated, we conducted the following experiments:

- Scenario 6.3: only 40% of the individuals adhere to the physical distancing measures from March 4 until the end of the simulation. Everyone is required to wear face masks, but adherence to face mask use is equal to 90% from March 4 until the end of the simulation. All other input parameter values are the same as in the base case.
- Scenario 6.4: adherence to physical distancing is equal to 90% from March 4 until the end of the simulation, and adherence to mask use is 50% from March 4 until the end of the simulation. All other input parameter values are the same as in the base case.

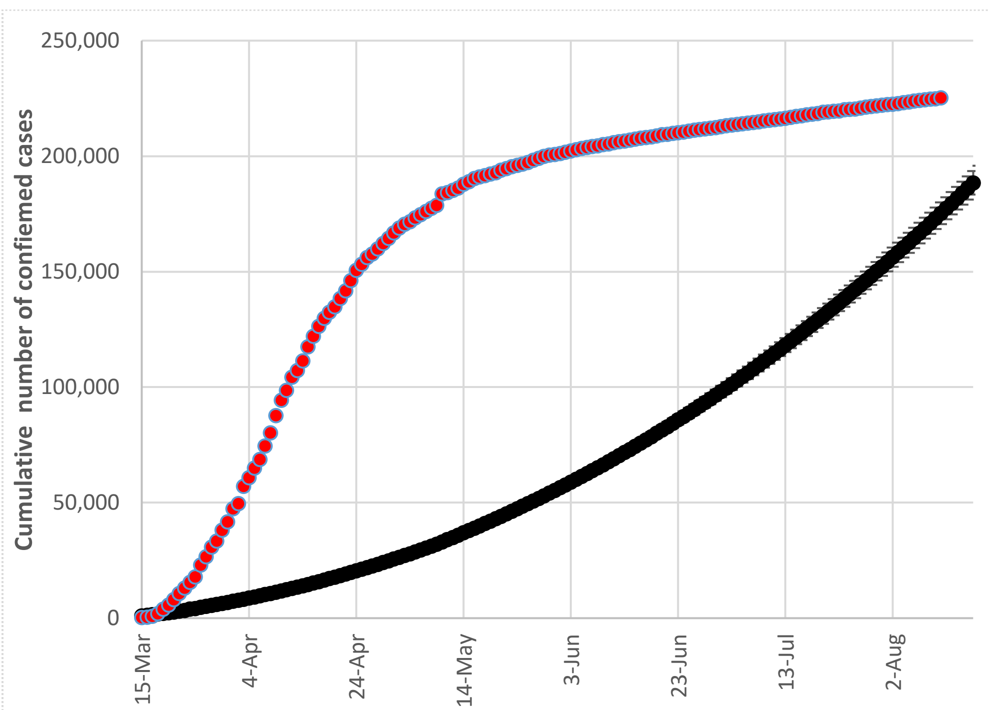
We present the results of this experiment, which show that implementing face mask use with high fidelity could have prevented many infections in the short time. Scenario 6.3 and Scenario 6.4 have a comparable number of confirmed cases over time, implying that a high level of adherence to face mask use may help to limit the use of physical distancing measures, such as closing businesses, with the goal of controlling COVID-19 pandemic. This experiment also demonstrates the differential impact of adherence to physical distancing and face mask use on the number of confirmed COVID-19 cases over time.

Supplement Figure 15. *Comparison of model predictions to actual NYC data when adherence to physical distancing and other behaviors that reduce the risk of transmission are not bundled*

(a) Scenario 6.1

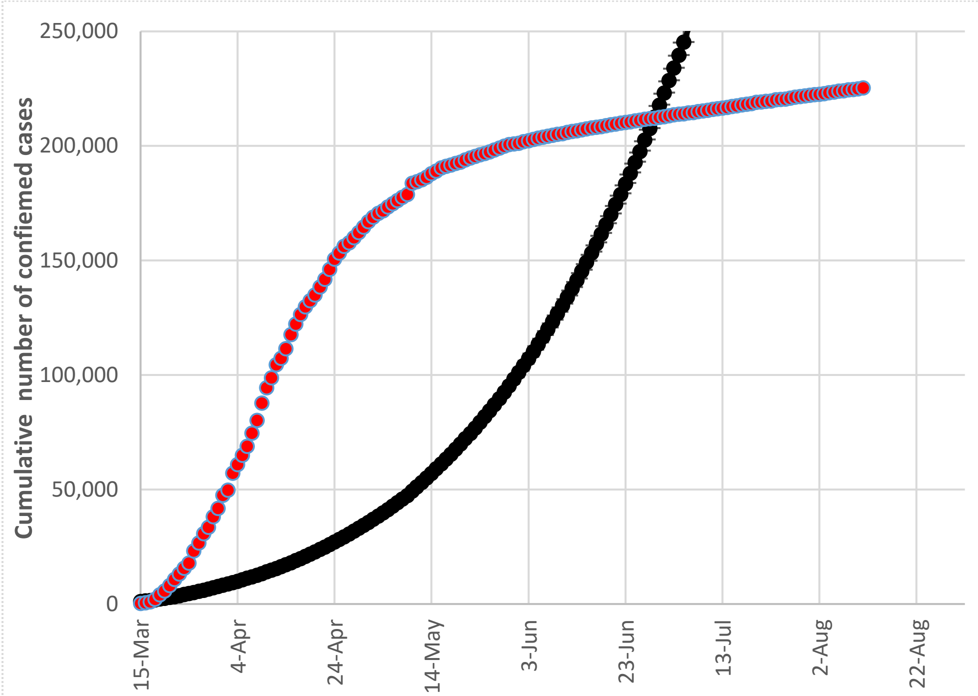


(b) Scenario 6.2

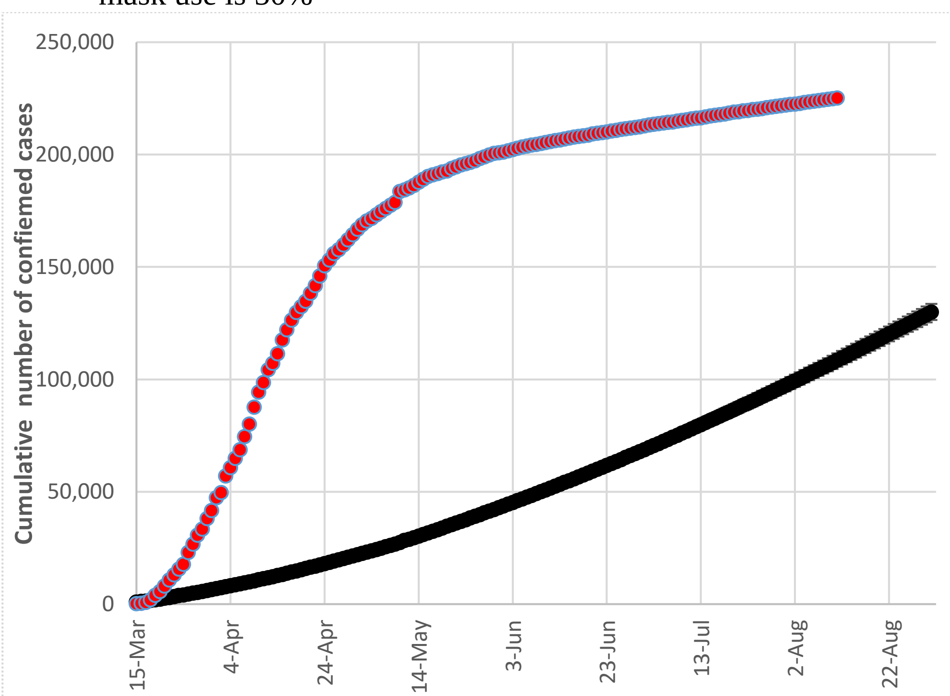


Supplement Figure 16. *Model predictions when adherence to adherence to physical distancing and adherence to face mask use are observed at different levels*

(a) Scenario 6.3-adherence to physical distancing measures is 40% and adherence to face mask use is 90%



(b) Scenario 6.4-adherence to physical distancing measures is 90% and adherence to face mask use is 50%



Section D.7 Sensitivity analysis when different numbers of superspreader individuals are modeled

We conducted a structural sensitivity analysis to evaluate the potential role of "superspreaders," individuals with a large number of daily contacts. Our base case did not specifically evaluate the potential role of superspreaders because we do not have any reliable data to estimate the proportion of superspreaders in our specific regions. However, in this sensitivity analysis, we explicitly model superspreaders by creating an additional population that represents superspreaders while keeping the average number of daily contacts under various adherence rates the same. Our base case model has different numbers of daily contacts for different age groups, therefore some (i.e. older) age groups have a small number of daily contacts whereas other (i.e. younger) age groups have a high number of daily contacts. We defined several categories of "superspreaders," individuals who contact more than 10, 20, and 40 people in a given day. We use a triangular distribution to model two different scenarios: 1) A "high variance" scenario in which individuals are assigned a daily number of contacts following a triangular distribution with a parameter set of (0,0, 3*average number of daily contacts). The mean value for this triangular distribution is equal to the average number of daily contacts. 2) A "low variance" scenario in which individuals are assigned a daily number of contacts following a triangular distribution with a parameter set of (average number of daily contacts, average number of daily contacts, average number of daily contacts). The low variance scenario corresponds to our base case.

We conducted this experiment for NYC. Supplement Table 21 shows the distribution of the individuals with different numbers of daily contacts under these two scenarios. Note that the number of spreaders with the daily number of contacts less than 2 is higher in the high variance scenario, since we had to reduce the number of daily contacts for many other individuals due to a large number of "superspreaders" to keep the average number of daily contacts the same.

Supplement Table 21*. Comparison of contagious individuals with different number of daily contacts under high variance and low variance scenario*

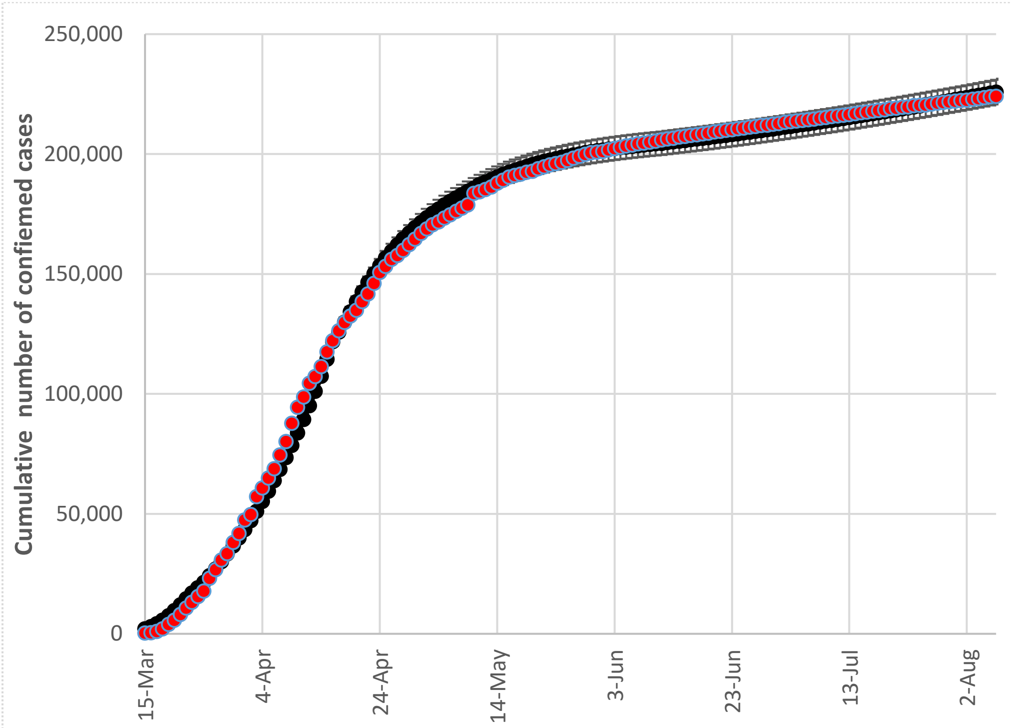
Spreader type (i.e. contagious individuals with the number of daily contacts)	Proportion of the contagious individuals in this category under high variance scenario	Proportion of the contagious individuals under low variance scenario (base case)	Proportion of the infections caused by this group of spreaders under high variance scenario	Proportion of the infections caused by this group of spreaders under low variance scenario
<2	22.43%	29.81%	7.63%	6.50%
2 to 5	48.94%	40.26%	28.60%	40.76%
5 to 10	27.85%	22.09%	36.72%	48.65%
10 to 20	0.55%	7.44%	23.84%	2.24%
20 to 40	0.23%	0.32%	2.13%	1.85%
>40	0.00%	0.07%	1.08%	0.00%

We also estimated that the proportion of infections caused by superspreaders in each scenario and reported them in Supplement Table 21. As shown in the table, individuals who have more than 10 daily contacts are responsible for 27% of the infections in the high variance whereas they are responsible for only 4% of the infections in the low variance scenario. The ability of COVAM to estimate the proportion of the infections caused by "superspreaders" demonstrates an additional benefit of using agent-based models since such an estimation is not possible via compartmental models. If data on the number of superspreaders in a region is available, COVAM may help to evaluate the impact of controlling superspreader events on the number of confirmed cases.

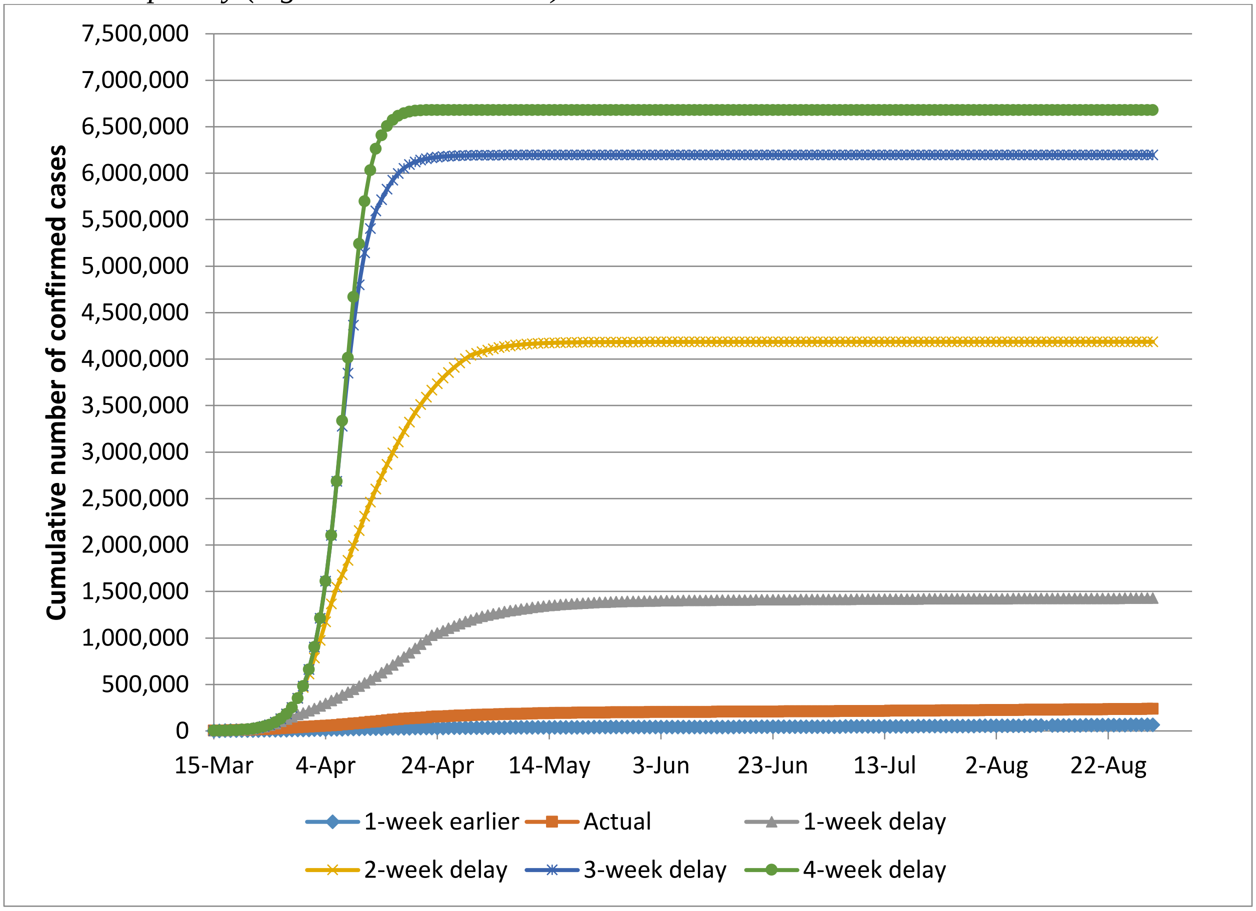
We then tested whether using a high variance instead of a low variance changed any of the model results. The figures below show the results of this experiment for NYC. We found that the trends observed under our base case did not change under the high variance scenario. This is because COVAM models adherence proportional to all individuals. For example, consider two individuals: Individual #1 has 40 contacts and Individual #2 has 5 contacts per day. A 70% adherence reduces the number of daily contacts for Individual #1 and Individual #2 from 40 to 28 and from 5 to 1.5, respectively. Therefore, as long as the average number of daily contacts remains the same, changing the spread of number of contacts does not substantially change the results in our model.

It is likely that controlling superspreaders may be implemented differently than what we assumed in the base case. Instead of applying the proportional reduction to the daily number of contacts equally between superspreaders and "low-spreaders" as we currently do, one can simply reduce the number of contacts for superspreaders and "low-spreaders" from the observed levels to 0. For example, for the example described above, both Individual #1 and Individual #2 could end up having 0 contacts per day. This represents the situation of canceling a large gathering versus canceling a number of small gatherings. In that case, we would expect the impact of adherence to social distancing to be different. We tested this hypothesis by running the following experiment. We randomly reduced the number of daily contacts from its current level to 0 for 5% of all individuals (low-spreaders and superspreaders equally likely) and compared the results of the high-variance and low-variance scenarios. We found that implementing adherence to social distancing measures this way led to a 31% reduction in the number of confirmed cases under the high variance scenarios and a 30% reduction in the number of confirmed cases under the low variance scenario. We observe that although a high variance has led to a larger impact of social distancing measures compared to a low variance, the difference was very small.

***Supplement Figure 17**. Comparison of model predictions to actual NYC data when superspreaders are modeled explicitly (high variance scenario)*



Supplement Figure 18. *Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when superspreaders are modeled explicitly (high variance scenario)*



Supplement Table 22. *Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when superspreaders are modeled explicitly (high variance scenario)*

Social distancing implementation date	May 15	May 31	June 15	June 30	July 15	July 31	August 15	August 31
1 week earlier (March 5)	38,601	41,187	43,028	45,639	49,229	54,069	59,570	66,485
Actual (March 12)	191,489	201,314	205,710	210,495	216,043	222,693	229,580	237,334
1-week delay (March 19)	1,354,050	1,397,130	1,407,960	1,414,450	1,419,110	1,422,880	1,425,700	1,428,200
2-week delay (March 26)	4,176,180	4,184,800	4,185,460	4,185,770	4,186,050	4,186,350	4,186,630	4,186,900
3-week delay (April 2)	6,195,840	6,195,890	6,195,930	6,195,960	6,196,000	6,196,040	6,196,080	6,196,120
4-week delay (April 9)	6,680,330	6,680,330	6,680,330	6,680,340	6,680,340	6,680,340	6,680,340	6,680,350

Supplement Table 23. *Comparison of total number of confirmed cases over time for different adherence levels in NYC when superspreaders are modeled explicitly (high variance scenario)*

Scenario- Adherence Level	March 31	April 30	May 31	June 30	July 31	August 31
Actual adherence	39,984	169,286	201,314	210,495	222,693	237,334
Schools Open – 0%	1,548,790	6,706,480	6,706,480	6,706,480	6,706,480	6,706,480
Schools Closed-0%	482,720	6,705,550	6,705,570	6,705,580	6,705,580	6,705,580
Schools Closed-25%	185,036	6,762,380	6,767,550	6,767,560	6,767,560	6,767,570
Schools Closed-50%	56,044	5,768,740	6,722,910	6,723,170	6,723,220	6,723,260
Schools Closed-75%	12,656	194,231	1,890,590	4,628,470	5,162,320	5,198,030
Schools Closed- 90%	4,673	8,798	11,816	14,523	17,317	20,099

Supplement Table 24. *Comparison of total number of confirmed cases over time when implementing social distancing measures on different dates in NYC when superspreaders are modeled explicitly (high variance scenario)*

Total number of infections by	**Easing social distancing measures on June 1**			**Easing social distancing measures on June 8**		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	213,722	225,753	248,022	210,495	214,966	221,804
July 31	229,327	319,603	724,327	222,693	269,183	442,423
August 31	246,648	621,206	3,061,610	237,334	455,653	2,015,180

Total number of infections by	**Easing social distancing measures on June 15**			**Easing social distancing measures on July 1**		
	DAE 5%	**DAE 10%**	**DAE 15%**	**DAE 5%**	**DAE 10%**	**DAE 15%**
June 30	208,769	210,196	211,976	207,668	207,668	207,668
July 31	218,501	242,730	316,249	213,450	218,554	228,127
August 31	231,140	360,940	1,234,760	222,630	264,437	453,116

DAE: Drop in adherence rates after easing social distancing measures. A value of 5%, 10%, and 15% DAE implies that adherence to social distancing measures after the date of easing is at 85%, 80%, and 75%, in NYC, respectively

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