ORIGINAL RESEARCH

Effect of Timing of and Adherence to Social Distancing Measures on COVID-19 Burden in the United States
A Simulation Modeling Approach

Oguzhan Alagoz, PhD; Ajay K. Sethi, PhD, MHS; Brian W. Patterson, MD, MPH; Matthew Churpek, MD, MPH, PhD; and Nasia Safdar, MD, PhD

Background: Across the United States, various social distancing measures were implemented to control the spread of coronavirus disease 2019 (COVID-19). However, the effectiveness of such measures for specific regions with varying population demographic characteristics and different levels of adherence to social distancing is uncertain.

Objective: To determine the effect of social distancing measures in unique regions.

Design: An agent-based simulation model.

Setting: Agent-based model applied to Dane County, Wisconsin; the Milwaukee metropolitan (metro) area; and New York City (NYC).

Patients: Synthetic population at different ages.

Intervention: Different times for implementing and easing social distancing measures at different levels of adherence.

Measurements: The model represented the social network and interactions among persons in a region, considering population demographic characteristics, limited testing availability, "imported" infections, asymptomatic disease transmission, and age-specific adherence to social distancing measures. The primary outcome was the total number of confirmed COVID-19 cases.

Results: The timing of and adherence to social distancing had a major effect on COVID-19 occurrence. In NYC, implementing social distancing measures 1 week earlier would have reduced the total number of confirmed cases from 203 261 to 41 366 as of 31 May 2020, whereas a 1-week delay could have increased the number of confirmed cases to 1 407 600. A delay in implementation had a differential effect on the number of cases in the Milwaukee metro area versus Dane County, indicating that the effect of social distancing measures varies even within the same state.

Limitation: The effect of weather conditions on transmission dynamics was not considered.

Conclusion: The timing of implementing and easing social distancing measures has major effects on the number of COVID-19 cases.

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The novel coronavirus disease 2019 (COVID-19) pandemic poses unprecedented challenges for communities and policymakers. Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the virus that causes COVID-19, is spread mainly through infectious respiratory droplets and, in closed, crowded spaces, by aerosols, but evolving knowledge of transmission dynamics makes it challenging to tailor disease control measures to specific communities. In the absence of an effective vaccine, nonpharmaceutical interventions, such as social distancing and other measures that reduce the number of close contacts during which transmission may occur, are the primary means of reducing the spread of COVID-19. These include closing schools and businesses, requiring facial coverings, and canceling large-scale events. When these measures are implemented and followed, daily counts of new COVID-19 cases decrease ("flattening the curve") (1).

The negative economic and societal consequences of social distancing warrant a "dialing back" of such policies when it is safe to do so. However, the effect of easing social distancing on the transmission of SARS-CoV-2 is unclear. A set of indicators have been proposed by the current administration to guide communities on when they may consider easing rigorous,

mandated social distancing (2). However, these lagging indicators, such as hospitals having the capacity to "treat patients without crisis care," are not ideal because once the number of new infections increases to a level at which the health care system becomes burdened by the resulting hospitalizations, reimplementation of mandated social distancing is less effective at mitigation than earlier implementation (2). The ability to predict the effect of easing of social distancing is important to provide leading indicators for the right time to do this for a particular community.

Mathematical modeling of SARS-CoV-2 transmission dynamics using the best information available allows scientists to forecast the effect of social distancing on the COVID-19 pandemic. In particular, agent-based models—a class of computational models that can simulate the actions and interactions of

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See also:

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Figure 1. Progression of COVID-19 in persons in COVAM.
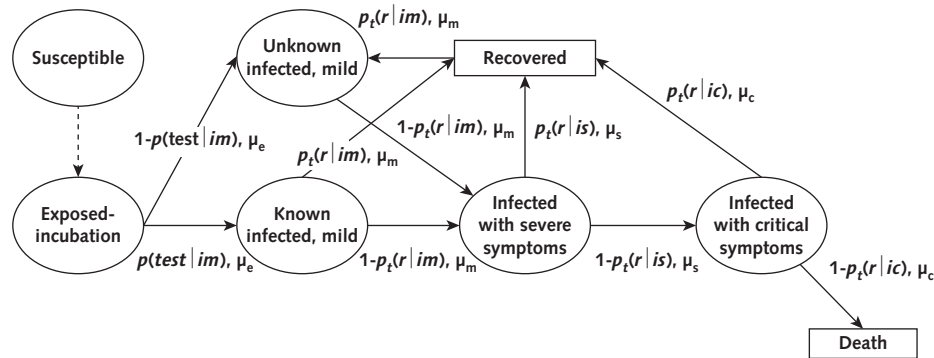
Ovals and rectangles represent the transient and absorbing states, respectively, that a person could be in; arrows show possible transitions among various states; and values on arrows represent the probability and mean duration of transitioning from one state to another. The notation used in the figure is described in the **Appendix Table** (available at Annals.org). COVAM = COVID-19 Agent-based simulation Model; COVID-19 = coronavirus disease 2019.

autonomous agents, such as humans—provide a flexible and simulation-based method to better represent transmission dynamics in a complex system. Although other models are available, including those providing predictions for every U.S. state, these models have several limitations that limit their generalizability (3–7). For example, they assume a closed population and ignore "imported" infections, they do not accurately consider imperfect adherence levels to the dynamic social distancing measures, and most do not incorporate the effect of limited testing capacity into the number of confirmed cases (3–6).

We present an agent-based model that represents the social network and interactions among persons in a region, considering local population demographic characteristics, population density, the daily number of contacts in the absence of social distancing measures, and adherence to social distancing measures. Our model, the COVID-19 Agent-based simulation Model (COVAM), allows transmission from asymptomatic patients, accounts for imported cases during the early days of the pandemic, and considers the possibility that some patients with mild to moderate symptoms never receive confirmatory testing for COVID-19. This study shows how COVAM can inform decision making on how social distancing measures may be adjusted to control the spread of SARS-CoV-2 and prevent a return to exponential growth in COVID-19 cases in 3 unique urban communities.

METHODS

Persons in COVAM have unique attributes, such as age, and interact with each other in ways that transmit SARS-CoV-2. We use a time step of 1 simulated day to update the status of these persons and to represent interactions. We assume all persons in the model are susceptible to COVID-19 at the beginning of the simulation—that is, no vaccine is available, and there is no preexisting immunity. Details of the modeling approach and parameter estimation are provided in section A of the **Supplement** (available at Annals.org) and are briefly summarized here.

All persons in COVAM are categorized into 1 of 8 possible states representing their COVID-19 status (**Figure 1**). We consider transmission by exposed patients during the last several days of the incubation period and allow some to never be tested positive for COVID-19 even when they have mild symptoms, which reflects limited testing capacity and variation in sensitivity of the diagnostic tests in the earlier days of the pandemic in the United States (8–12).

The simulation starts with 1 (or more) exposed person. At the beginning of each day, the contagious person randomly interacts with other persons in the community. For each interaction, there is a possibility that the contagious person exposes the susceptible persons to SARS-CoV-2.

Input Parameters

To maximize model generalizability, we derived input parameter estimates from relevant results in peer-reviewed literature and used data from Dane County, Wisconsin, to calibrate several parameters (**Appendix Table**, available at Annals.org [13–20]). There are 2 sets of parameters governing the transmissibility of SARS-CoV-2 in COVAM. The first is the number of close contacts per day without any intervention, which represents the social network effect and is independent of the respiratory agent that is transmitted. This parameter depends on population density and age group and is estimated using the literature and calibration, as explained below. The second parameter is the probability that contagious, exposed patients transmit SARS-CoV-2 to a susceptible person when a close contact occurs. The theoretical basic reproductive number (R_0) corresponding to these parameter estimates was 3.34 for Dane County without any social distancing measures, which was within the range of R_0 values reported in the literature (1.5 to 6.5) (26, 27).

Adherence to Social Distancing Measures

The effectiveness of social distancing measures depends on how closely a population follows them and the type of measures that are implemented at different times. For example, in New York, mass gathering restrictions started on 12 March 2020, initial business closures were recommended on 16 March, educational facilities were closed on 18 March, and nonessential services closed and a statewide stay-at-home order was issued on 22 March (5). In COVAM, adherence to social distancing is represented by adjusting the number of contacts per person using cellphone mobility data published by several sources (31–34). For instance, the estimated average number of daily close contacts per person in New York City (NYC) is 20; therefore, a 70% adherence level reduces the number of such contacts to 6 per person per day, leading to slower transmission. The number of close contacts and adherence to social distancing change by age group because social distancing literature and COVID-19–specific studies show that younger persons are more likely to have more contacts and lower adherence to social distancing measures than older persons (23, 24, 35–37). It is important to note that adherence to social distancing measures in COVAM is a proxy for several behaviors that reduce the transmissibility of SARS-CoV-2, including infrequent travel, keeping at least 6 feet apart during person-to-person interactions, frequent handwashing, and wearing masks.

Calibration and Validation

We used a simple calibration procedure using earlier surveillance data from Dane County to fine-tune several input parameters that involve uncertainty (Appendix Table). We used the reported COVID-19 data from Dane County until 15 May 2020 to test whether our initial parameter estimates replicated the number of cases accurately. After this date, we modified the structure of the model to incorporate the age-specific number of close contacts and age-specific adherence inputs. We did not change any of the parameters after 31 July 2020 and compared the model's projections with the actual number of cases after this date.

Application to Dane County

The input parameters used for the computational experiments for Dane County are presented in Table 1. Briefly, we incorporated the population demographic characteristics in terms of age groups, the number of persons imported into Dane County, and adherence to social distancing measures. The model has the ability to add different numbers of imported cases daily; however, we kept the number of initial imported cases the same to prevent overfitting. We considered that adherence to social distancing measures in Dane County decreased on 14 May 2020 because the Wisconsin Supreme Court struck down the governor's stay-at-home order on this date (39).

Application to Milwaukee Metropolitan Area

We adapted COVAM to Milwaukee to cross-validate our model and test its predictive accuracy. The population density of the Milwaukee metropolitan (metro) region is approximately 3 times that of Dane County (1341 vs. 438 per square mile) (38). Therefore, the Milwaukee metro area also provided a useful comparator region for COVAM to test whether the effect of timing and adherence to social distancing measures on COVID-19 differed between regions within the same state. Our objective was to modify as few parameters as possible to prevent overfitting. We used the same simulation settings as those in Dane County, except for 4 changes (Table 1): the epidemic was initiated with 3 exposed patients instead of 1; 6 imported cases were added to account for the larger population; demographic characteristics were adjusted using Milwaukee population data; and the adherence input was adjusted proportionately to cellphone mobility data, which indicated lower adherence in Milwaukee (31–33).

Application to NYC

New York City was among the first epicenters of the COVID-19 pandemic in the United States. Thus, the relative maturity of the epidemic in NYC made it a good test case to evaluate COVAM's predictive accuracy for later stages of the pandemic. As before, to maximize generalizability and avoid overfitting, we used the same simulation settings as those in Dane County, except for 4 changes (Table 1): 160 imported cases were added between 5 March and 22 March 2020 and 32 imported cases were added after 22 March to account for the greater number of visitors and daily commuters to NYC; demographic characteristics were adjusted using NYC population data; adherence to social distancing measures was adjusted because cellphone data showed higher adherence in NYC than in Dane County (31–33, 40); and the number of contacts per person per day was set to 20 because of substantially higher population density (27 755 vs. 438 per square mile) and reports from the social network analysis literature that population density increases the number of close contacts (41, 42).

Policy Analyses

We used COVAM to evaluate the effect of 3 aspects of social distancing. First, to evaluate the effect of adherence, we compared a scenario in which social distancing was not implemented with scenarios in which it was implemented at the beginning of the simulation and adherence was consistently at 25%, 50%, 75%, and 90%. Second, to evaluate the effect of timing of implementation, we tested scenarios in which social distancing was implemented 1 week earlier and 1 to 4 weeks later than the actual date. Finally, to evaluate the effect of the timing of easing of social distancing, we tested scenarios in which measures were eased on different dates (this was done only for NYC, where social distancing measures were eased on 8 June 2020). We assumed that after the measures were eased, adherence decreased by 5, 10, and 15 percentage points because of heightened community awareness. In NYC, a decrease of 5 percentage points reduced adherence from 90% to 85% after social distancing measures were eased.

Table 1. Input Parameters Used to Apply COVAM to Dane County, Milwaukee Metro Area, and New York City

Parameter	Description	Value for Dane County	Value for Milwaukee Metro Area*	Value for New York City	Source
Population	Number of persons living in the region	542 364	1 576 236	8 398 748	U.S. census data (38)
Simulation start date	Date when the simulation starts	4 March 2020	4 March 2020	4 March 2020	Not applicable
Number of initial exposures	Number of persons exposed to COVID-19 at the beginning of the simulation	1	3	16	Calibration
Number of imported cases and dates	Number of persons exposed to COVID-19 from outside the region per day and dates of importation of cases	3 per day between 5 March and 25 March 2020 1 per day afterward	6 per day between 5 March and 3 April 2020 3 per day afterward	160 per day between 5 March and 22 March 2020 32 per day afterward	Calibration
Number of close contacts per person per day without any social distancing intervention	Number of people that a person has a close contact with that provides a transmission opportunity. This parameter assumes that schools are closed.	10	10	20	Calibration and literature (22, 23)
School effect	Percentage increase in the number of daily close contacts when schools are open	40%	40%	40%	Literature (22)
Adherence to social distancing	Percentage of persons following the social distancing guidelines, which is equivalent to a percentage drop in average number of contacts per person	4–11 March: 0% 12–25 March: increased linearly from 0% to 90% 26 March–30 April: 80% 1–13 May: 70% 14 May–29 June: 60% 30 June–end of simulation: 70%	4–11 March: 0% 12–22 March: increased linearly from 0% to 60% 23 March–7 April: 60% 8–12 April: 80% 13 April–13 May: 70% 14–25 May: 60% 26 May–29 June: 70% 30 June–end of simulation: 65%	4–11 March: 0% 12–20 March: increased linearly from 0% to 80% 21 March–12 April: 80% 13 April–7 June: 90% 8 June–end of simulation: 90%	Cellphone data and calibration (31–33)
Probability of testing	Probability that a patient with mild to moderate symptoms will test positive for COVID-19	75% until 15 April 80% between 15 April and 10 May 90% afterward	75% until 15 April 80% between 15 April and 10 May 90% afterward	75% until 15 April 80% between 15 April and 10 May 90% afterward	Literature and calibration (29, 30)
Demographic characteristics	Percentage of persons in age groups	Age 0–19 y: 20.8% Age 20–44 y: 46.5% Age 45–54 y: 10.3% Age 55–64 y: 10.2% Age 65–74 y: 7.4% Age 75–84 y: 3.3% Age ≥85 y: 1.5%	Age 0–19 y: 28.6% Age 20–44 y: 36.2% Age 45–54 y: 13.7% Age 55–64 y: 8.5% Age 65–74 y: 6.6% Age 75–84 y: 4.7% Age ≥85 y: 1.0%	Age 0–19 y: 23.2% Age 20–44 y: 38.6% Age 45–54 y: 13.0% Age 55–64 y: 11.7% Age 65–74 y: 7.1% Age 75–84 y: 3.4% Age ≥85 y: 1.9%	U.S. census data (38)

COVAM = COVID-19 Agent-based simulation Model; COVID-19 = coronavirus disease 2019.
* Consists of 4 counties: Milwaukee County, Waukesha County, Washington County, and Ozaukee County.

We did both a parametric and a structural sensitivity analysis for NYC. Our parametric sensitivity analysis tested the effect of uncertainty in 3 input parameters: probability of testing, transmission rates, and number of imported cases. Our structural sensitivity analysis evaluated 3 different scenarios: hospital transmission was allowed; the number of daily close contacts differed for persons with and without known infection status; and the number of daily contacts varied widely to represent superspreader events. In all of these sensitivity analyses, we recalibrated model parameters and reevaluated all of the scenarios. We ran 100 replications for each experiment and report only mean values because the SEs were very low.

Role of the Funding Source

RESULTS

In COVAM, the observed number of COVID-19 cases, and thus SARS-CoV-2 transmission dynamics, was accurately replicated in the short term over time in Dane County, Milwaukee, and NYC (**Supplement Figure 1**, available at Annals.org). Our first set of ex-

periments showed that adherence to social distancing has a substantial effect on the cumulative number of cases (**Supplement Figure 1** and **Supplement Table 1**, available at Annals.org). For example, compared with 50% adherence, no social distancing other than closing schools increased the total number of cases from 56 433 to 487 501 in NYC in just 26 days (by 31 March).

Figure 2 presents the change in the number of cases when social distancing measures were implemented earlier or later than the actual date. We found that even a 1-week delay in implementation would have had a major effect on the total number of confirmed infections over time in each region. For example, implementing the measures 1 week earlier in NYC could have reduced the number of cases by 80%, from 203 261 to 41 366 by 31 May, whereas a 1-week delay could have increased the number of confirmed cases by almost 7-fold, to 1 407 600 (**Figure 2**; **Supplement Table 2**, available at Annals.org). The effect of implementing social distancing measures depends highly on the region because each has different levels of adherence and transmission (**Supplement Table 2**). For example, implementing the measures 1 week later in Dane County could have increased the number of cases by 36% as of 31 July (4239 to 5785), whereas the same scenario in NYC could have increased the number of cases by 539% (224 194 to 1 432 960). Compared with Dane County, in the Milwaukee metro area, a delay in implementation had a differential effect on the number of cases.

Earlier easing of the social distancing measures would have had major detrimental effects on the total number of COVID-19 cases in NYC, especially when there was a significant decrease in adherence after easing (**Table 2**). Easing of the measures on 1 June instead of the actual date (8 June) and a decrease in adherence of 5 percentage points would have increased the total number of confirmed cases from 224 194 to 230 932 as of 31 July. If adherence had decreased by 15 percentage points after social distancing measures were eased on 8 June, the number of cases could have increased from 224 194 to 439 728 by 31 July (**Table 2**), showing the importance of personal behaviors that prevent transmission of SARS-CoV-2, such as face mask use after the measures are eased. The decrease in adherence after easing has a more pronounced effect on the number of cases than the date of easing (**Table 1**).
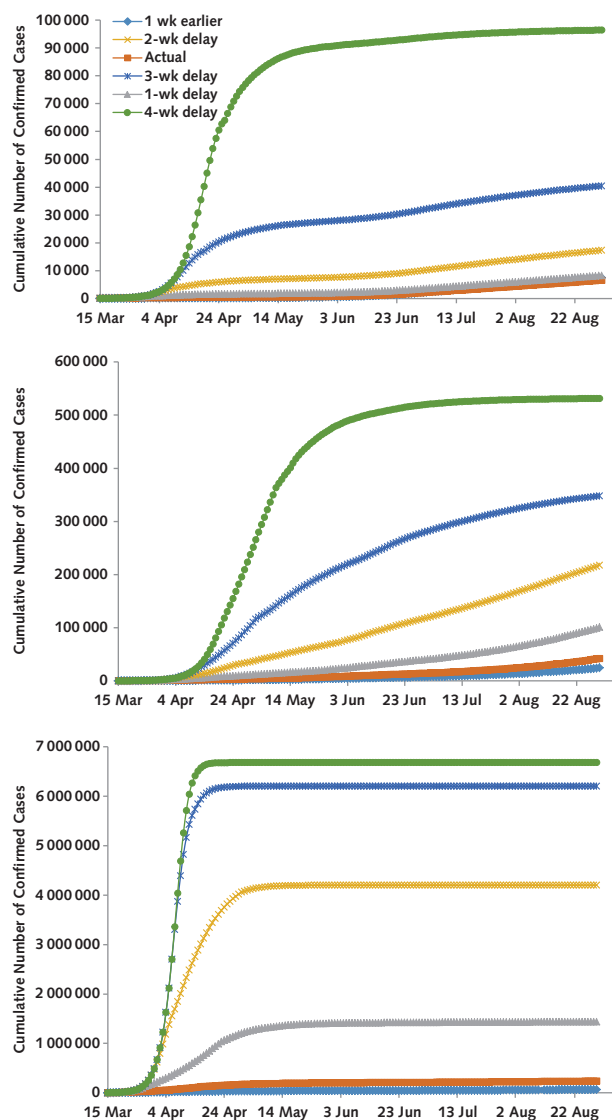
The sensitivity analyses showed that the overall trends in base-case runs would still hold (**Supplement Figures 3** to **18** and **Supplement Tables 3** to **24**, available at Annals.org).

Discussion

In this study, we used agent-based simulation modeling to estimate the effect of the timing of implementation and easing of social distancing measures and adherence to them in 3 urban communities. We found that the timing of implementation of social distancing and adherence had a large effect on the number of

cases that varied widely by region. The effect in NYC was large compared with Dane County and the Milwaukee metro area. This finding shows the importance of considering implementation of reopening policies at the regional level, as the results in Dane County and the Milwaukee metro area differed considerably despite being in the same state. We also found that maintaining a high level of adherence after easing of social distancing measures has a major effect on the number of cases, implying that cities and regions should strongly encourage the community to maintain behaviors that reduce the transmissibility of SARS-CoV-2, such as wearing masks. COVAM's accuracy in predicting the current outbreak and ability to esti-

Figure 2. Comparison of total number of confirmed cases time for implementation of social distancing at different dates in Dane County (*top*), Milwaukee metropolitan area (*middle*), and New York City (*bottom*).

Table 2. Effect of Easing of Social Distancing Measures on the Total Number of Confirmed Cases on Different Dates in New York City

Date	Measures Eased on 1 June			Measures Eased on 8 June		
	5% DAE*	10% DAE*	15% DAE*	5% DAE*	10% DAE*	15% DAE*
30 June	215 612	227 701	250 284	212 380	216 782	223 512
31 July	230 932	321 048	728 275	224 194	269 766	439 728
31 August	248 247	620 935	2 097 610	238 645	452 219	1 994 590
	Measures Eased on 15 June			Measures Eased on 1 July		
30 June	210 685	212 067	213 784	209 627	209 627	209 627
31 July	219 945	243 378	313 699	215 152	219 944	229 027
31 August	232 342	357 264	1 202 310	224 050	263 995	444 037

DAE = drop in adherence after easing of social distancing measures.
* DAE of 5%, 10%, and 15% implies that adherence to social distancing measures after the date of easing is 85%, 80%, and 75%, respectively.

mate the effect of easing social distancing measures at the regional level shows its unique value for informing current and future policies. Our findings show that one-size-fits-all strategies are suboptimal and that context- and region-specific policies are needed when considering implementing and easing social distancing measures.

Our findings are consistent with those of other studies that focused on the effect of social distancing measures on COVID-19 burden. One study found that a reduction of 75% in nonhousehold contacts would be needed to handle the peak hospitalization demand in the Austin, Texas, metro area (43). In contrast, our model estimated that 70%, 70%, and 85% adherence to social distancing measures in Dane County, Milwaukee, and NYC, respectively, would be needed to keep the pandemic in a steady state. Another study reported that 57% of infections in the United States as of 3 May 2020 could have been avoided if social distancing measures had been implemented just 1 week earlier (44). We found that implementing social distancing measures 1 week earlier would have reduced the number of infections by 46%, 52%, and 80% in Dane County, Milwaukee, and NYC, respectively, as of 15 May 2020.

Some opponents of social distancing policies cite achievement of herd immunity as a reason for easing current measures (45). However, herd immunity is possible only if infection with SARS-CoV-2 results in lasting immunity, which is unknown at this time. Moreover, the correlates of protective immunity to SARS-CoV-2 have yet to be identified (45). In the absence of these data, social distancing is the most effective tool to prevent further spread of SARS-CoV-2. To date, social distancing measures and adherence to them have halted exponential growth in daily case counts of COVID-19. However, SARS-CoV-2 continues to spread, and many U.S. cities and urban communities have yet to return to pre–exponential growth levels of transmission. COVAM showed that premature easing of social distancing measures and low adherence to them could result in a rapid return to exponential growth of COVID-19 cases in communities.

Closing schools and businesses has major adverse economic and health consequences. Despite acknowledging the growing evidence that children and adolescents play a role in disease transmission, the American Academy of Pediatrics notes the importance of in-school learning and the negative effects that school closures had on children in the spring of 2020 (46). These include social isolation, worsening of mental and physical health, and learning deficits without adequate resources. Business closures caused substantial job losses in many sectors and led to major issues in the supply chain of essential items, including medical supplies (47). Precautions to control the COVID-19 pandemic have led to worse health outcomes for other diseases as well. For example, a recent commentary by the director of the National Cancer Institute noted that reduced screening and delays in diagnosis due to the COVID-19 pandemic are expected to lead to almost 10 000 excess deaths from breast and colorectal cancer in the United States over the next decade (48). It is critical that local decision makers determine region-specific policies that weigh the competing risks for COVID-19 transmission and negative economic, health, and social effects of business and school closures.

Our study has limitations, most of which are due to limited data and uncertainty about SARS-CoV-2. We made simplifying assumptions, such as that asymptomatic patients transmit the disease at the same rate as symptomatic patients and weather does not affect SARS-CoV-2 transmissibility, whereas several studies suggest otherwise (49, 50). Furthermore, COVAM uses adherence to social distancing as a proxy for several factors contributing to disease transmission, including fewer close contacts because of limited travel and precautions that prevent transmission during a close contact, such as wearing masks. Therefore, COVAM may not accurately estimate the effect of personal precautions on transmission.

There are also limitations related to the modeling approach. Our calibration procedure used a simple trial–error approach, as opposed to a full-scale calibration in which all plausible combinations of the input parameter values are tested (51). Owing to the computational intensity of a more formal and detailed calibration procedure, our calibration may not have identified the best parameter combinations. As with any other modeling technique, agent-based modeling has limitations, including greater computational needs compared with more commonly used compartmental models because of modeling of probabilistic events, as well

as more complex development given that agent-based models typically require stylistic programming to represent events more realistically.

In conclusion, our model shows that delayed implementation of, lower adherence to, and premature easing of social distancing generally resulted in increased cases of COVID-19 in urban areas of the United States. However, the magnitude of effect varied substantially by region. These findings highlight the importance of region-specific considerations, and ideally modeling, as inputs to making policy decisions for a given region.

From University of Wisconsin-Madison, Madison, Wisconsin (O.A., A.K.S.); University of Wisconsin-Madison, School of Medicine and Public Health, Madison, Wisconsin (B.W.P., M.C.); and University of Wisconsin-Madison, School of Medicine and Public Health, and the William S. Middleton Memorial Veterans Hospital, Madison, Wisconsin (N.S.).

Corresponding Author: Oguzhan Alagoz, PhD, University of Wisconsin-Madison, 1513 University Avenue, Madison, WI 53706; e-mail, alagoz@engr.wisc.edu.

Current author addresses and author contributions are available at Annals.org.

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Current Author Addresses: Dr. Alagoz: University of Wisconsin-Madison, 3242 Mechanical Engineering Building, 1513 University Avenue, Madison, WI 53706.

Dr. Sethi: University of Wisconsin-Madison, Room 601 WARF, 610 Walnut Street, Madison, WI 53726.

Dr. Patterson: University of Wisconsin-Madison, School of Medicine and Public Health, 800 University Bay Drive, Madison, WI 53705.

Dr. Churpek: University of Wisconsin Medical Foundation, 8007 Excelsior Drive, Madison, WI 53717.

Dr. Safdar: University of Wisconsin Medical Foundation Centennial Building, 1685 Highland Avenue, Madison, WI 53705-2281.

Author Contributions: Conception and design: O. Alagoz, A.K. Sethi, M. Churpek, N. Safdar.

Analysis and interpretation of the data: O. Alagoz, A.K. Sethi, B.W. Patterson, M. Churpek.

Drafting of the article: O. Alagoz, A.K. Sethi.

Critical revision of the article for important intellectual content: O. Alagoz, A.K. Sethi, B.W. Patterson, N. Safdar.

Final approval of the article: O. Alagoz, A.K. Sethi, B.W. Patterson, M. Churpek, N. Safdar.

Provision of study materials or patients: O. Alagoz.

Statistical expertise: O. Alagoz.

Obtaining of funding: O. Alagoz, N. Safdar.

Administrative, technical, or logistic support: O. Alagoz, A.K. Sethi, N. Safdar.

Collection and assembly of data: O. Alagoz.

Parameter	Description	Notation	Mean Value	Reference
Progression and duration				
Incubation period	Time between exposure and occurrence of symptoms	μ_e	5 d	CDC and literature (13-16)
Duration of mild symptoms	Time between beginning of mild symptoms and beginning of severe symptoms or recovery	μ_m	6 d	CDC and literature (3, 13, 17, 18)
Duration of severe symptoms (hospitalization)	Time between beginning of severe symptoms and beginning of critical symptoms or recovery	μ_s	6 d	CDC and literature (3, 13, 17, 18)
Duration of critical symptoms (ICU stay)	Time between beginning of critical symptoms and death or recovery	μ_c	10 d	CDC and literature (3, 13, 17–19)
Probability of recovery after mild symptoms	Probability that an infected patient with mild symptoms (who also has tested positive) will recover once the mild symptomatic phase is over. This parameter is a function of age.	$p_t(r\|im)$	Age 0–19 y: 98% Age 20–44 y: 82% Age 45–54 y: 75% Age 55–64 y: 75% Age 65–74 y: 64% Age 75–84 y: 55% Age ≥85 y: 49%	CDC (20)
Probability of recovery after severe symptoms	Probability that an infected patient with severe symptoms will recover once the severe symptomatic phase is over. This parameter is a function of age.	$p_t(r\|is)$	Age 0–19 y: >99% Age 20–44 y: 82% Age 45–54 y: 68% Age 55–64 y: 69% Age 65–74 y: 63% Age 75–84 y: 53% Age ≥85 y: 65%	CDC (20)
Probability of recovery after critical symptoms	Probability that an infected patient with critical symptoms will recover once the critical symptomatic phase is over. This parameter is a function of age.	$p_t(r\|is)$	Age 0–19 y: >99% Age 20–44 y: 95% Age 45–54 y: 92% Age 55–64 y: 75% Age 65–74 y: 72% Age 75–84 y: 64% Age ≥85 y: 9%	CDC and Wisconsin Department of Health Services (20, 21)
Probability that an infected patient with critical symptoms needs ventilator support	Probability that an infected patient with critical symptoms will need mechanical ventilator support during their ICU stay	$p(v\|is)$	46%	Literature (14)
Transmission				
Number of contacts per person without any social distancing intervention	Number of people that a person has a close contact with that likely produces a transmission opportunity. This parameter represents the number of such contacts and assumes no intervention is implemented.	n_c	10	Calibration and literature (22, 23)
Relative rate for the number of daily contacts per age group	The number of daily contacts changes by age group. This parameter represents the relative rate of the number of contacts for each age group compared with the 20–44 y age group, which has the highest number of daily contacts.	rr_{dc}	Age 0–19 y: 85% Age 20–44 y: 100% Age 45–54 y: 94% Age 55–64 y: 74% Age 65–74 y: 46% Age 75–84 y: 34% Age ≥85 y: 34%	Literature (23)
Relative rate for nonadherence to social distancing per age group	Nonadherence to social distancing changes by age group. This parameter represents the relative rate of nonadherence to social distancing for each age group compared with the 20–44 y age group, which has the highest rate of nonadherence.	rr_{na}	Age 0–19 y: 100% Age 20–44 y: 100% Age 45–54 y: 100% Age 55–64 y: 85% Age 65–74 y: 61% Age 75–84 y: 61% Age ≥85 y: 61%	CDC (24)
Number of days an exposed patient is contagious	Exposed persons could be contagious before showing symptoms. This parameter represents the number of days in the end of the incubation period and before showing mild symptoms when exposed patients transmit the disease.	d	2	Literature (11, 25)
Probability that an exposed patient will transmit SARS-CoV-2 to a susceptible person with a close contact	Probability that an asymptomatic patient in the last few days of the incubation period will transmit SARS-CoV-2 to a susceptible person who is in close contact	$p(c\|e)$	0.0418	Calibration and literature (26-28)

Continued on following page

Parameter	Description	Notation	Mean Value	Reference
Probability that a patient with mild to moderate symptoms who has not been tested positive will transmit SARS-CoV-2 to a susceptible person with a close contact	Probability that a patient with mild to moderate symptoms who has not been tested positive for SARS-CoV-2 will transmit it to a susceptible person who is in close contact	$p(c|im-)$	0.0418	Calibration and literature (26-28)
Probability that a patient with mild to moderate symptoms who tested positive for SARS-CoV-2 will transmit it to a susceptible person with a close contact	Probability that a patient with mild to moderate symptoms who tested positive for SARS-CoV-2 will transmit it to a susceptible person who is in close contact	$p(c|im+)$	0.0418	Calibration and literature (26-28)
Relative transmissibility of a patient with severe symptoms compared with a patient with mild to moderate symptoms who tested positive	This parameter describes the probability that a patient with severe infection transmits the disease ($p(c|is)$) relative to that for a patient with mild to moderate symptoms who tested positive ($p(c|im+)$)	$\dfrac{\ln(1-p(c|is))}{\ln(1-p(c|im+))}$	0%	Not applicable
Relative transmissibility of a patient with critical symptoms compared with a patient with mild to moderate symptoms who tested positive	This parameter describes the probability that a patient with critical infection transmits the disease ($p(c|ic)$) relative to that for a patient with mild to moderate symptoms who tested positive ($p(c|im+)$)	$\dfrac{\ln(1-p(c|is))}{\ln(1-p(c|im+))}$	0%	Not applicable
Diagnostic testing				
Baseline probability of testing with mild to moderate symptoms	The baseline probability that a patient with mild to moderate symptoms will test positive for COVID-19, assuming limited testing capacity and cases where patients do not have mild symptoms that cause them to request testing; additional testing capacity increases this probability	$p(test|im)$	75%	Literature and calibration (29, 30)

CDC = Centers for Disease Control and Prevention; COVID-19 = coronavirus disease 2019; ICU = intensive care unit; SARS-CoV-2 = severe acute respiratory syndrome coronavirus 2.