

Spora: A Journal of Biomathematics

Volume 7

Article 1

2021

Flattening the Curve: The effects of intervention strategies during COVID-19

Kelly A. Reagan

Virginia Commonwealth University, reaganka2@vcu.edu

Rachel J. Pryor

Virginia Commonwealth University, rachel.pryor@vcuhealth.org

Gonzalo M. Bearman

Virginia Commonwealth University, gonzalo.bearman@vcuhealth.org

David M. Chan

Virginia Commonwealth University, dmchan@vcu.edu

Follow this and additional works at: <https://ir.library.illinoisstate.edu/spora>



Part of the [Ordinary Differential Equations and Applied Dynamics Commons](#), and the [Other Immunology and Infectious Disease Commons](#)

Recommended Citation

Reagan, Kelly A.; Pryor, Rachel J.; Bearman, Gonzalo M.; and Chan, David M. (2021) "Flattening the Curve: The effects of intervention strategies during COVID-19," *Spora: A Journal of Biomathematics*: Vol. 7, 1–7. Available at: <https://ir.library.illinoisstate.edu/spora/vol7/iss1/1>

This Mathematics Research is brought to you for free and open access by ISU ReD: Research and eData. It has been accepted for inclusion in Spora: A Journal of Biomathematics by an authorized editor of ISU ReD: Research and eData. For more information, please contact ISUReD@ilstu.edu.

Flattening the Curve: The effects of intervention strategies during COVID-19

Kelly A. Reagan, B.S.¹, Rachel J. Pryor, RN, MPH²,
Gonzalo M. Bearman, MD, MPH, FACP, FSHEA, FIDSA³, David M. Chan, Ph.D.^{4,*}

*Correspondence:
Dr. David Chan, Dept. of
Mathematics and Applied
Mathematics, Virginia
Commonwealth University,
1015 Floyd Avenue,
Richmond, VA 23284-2014,
USA
dmchan@vcu.edu

Abstract

COVID-19 has plagued countries worldwide due to its infectious nature. Social distancing and the use of personal protective equipment (PPE) are two main strategies employed to prevent its spread. A SIR model with a time-dependent transmission rate is implemented to examine the effect of social distancing and PPE use in hospitals. These strategies' effect on the size and timing of the peak number of infectious individuals are examined as well as the total number of individuals infected by the epidemic. The effect on the epidemic of when social distancing is relaxed is also examined. Overall, social distancing was shown to cause the largest impact in the number of infections. Studying this interaction between social distancing and PPE use is novel and timely. We show that decisions made at the state level on implementing social distancing and acquiring adequate PPE have dramatic impact on the health of its citizens.

Keywords: COVID-19, SIR model, PPE, social distancing

1 Introduction

During pandemics, various intervention strategies may be implemented to reduce disease spread and flatten the infection curve. Flattening the curve allows for smaller peaks of infections, that are often delayed. This is critical for the success of health care services. Not only do these strategies allow for more time to prepare for the influx of patients, but caring for a smaller number of patients at one time prevents healthcare providers and systems from being overwhelmed. It is critical for the safety of patients and healthcare workers to have enough supplies during epidemics. Supplies include medications, devices for patients (e.g. ventilators), and personal protective equipment (PPE) for the healthcare providers.

The infection examined in this study is COVID-19, however, the results can be easily applied to other pandemics. COVID-19 is a disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) [19]. Common symptoms are respiratory infections, fever and

dry cough [19]. The average incubation period for COVID-19 is estimated to be five days [11], and patients usually develop symptoms within twelve days [11]. The virus is contracted from other infectious individuals from direct contact with mouth or nose droplets [19], and from a person touching an infected object or surface [11]. Social distancing is recommended to help stop the spread of the virus, which involves maintaining a minimum of six feet between people. Caley et al. [4] showed that social distancing was effective during the Spanish Influenza of 1918. Approximately 260 per 100,000 lives were likely saved as a result of social distancing [4]. Social distancing is critical in preventing infections when there exist asymptomatic carriers within a community [18] [20]. According to the Centers for Disease Control and Prevention (CDC), older adults and those with previous underlying medical conditions such as heart disease, diabetes and lung disease, are more likely to have serious complications due to COVID-19 [5].

The Occupational Safety and Health Administration recommends that all healthcare workers protect themselves with PPE when interacting with COVID-19 patients. Goggles or face shields, facemasks and gloves are all recommended by the CDC as PPE to prevent the transmission of SARS-CoV-2 [5]. Contact precautions or airborne precautions (depending on the patient) and eye protection should all be utilized to prevent the spread of the virus [15], as well as standard precautions like washing

¹Department of Mathematics and Applied Mathematics and the Department of Statistical Sciences and Operations Research, Virginia Commonwealth University (VCU), Richmond, Virginia, ²Business Intelligence Analyst, Department of Infection Prevention, VCU Health System, Richmond, Virginia, ³Richard P. Wenzel Professor of Medicine VCU, Richmond, Virginia; Chair, Division of Infectious Diseases, VCU, Richmond, Virginia; Hospital Epidemiologist, VCU Health System Epidemiology and Infection Control, Richmond, Virginia, ⁴Department of Mathematics and Applied Mathematics, VCU, Richmond, Virginia

hands. The demand for PPE has soared with increased prevalence of the virus. Healthcare workers have been encouraged to disinfect and reuse PPE as much as possible due to the high worldwide demand and shortages [5] [21].

A number of models use the Susceptible, Infectious, and Removed (SIR) framework to model SARS-CoV-2 transmission under various circumstances. Some include a quarantine class [21] [8] [3] [14], some include an exposed class [21] [3] [10], and other classes such as asymptomatic [21], immunized [3], and an immigrant population [14]. We do not include additional classes beyond the SIR classes to maintain simplicity. We focus on the impact of social distancing and PPE use on the time and size of the peak number of infections, regardless if those infections are asymptomatic or not. Our model includes a time-dependent transmission rate, similar to other studies [9] [12] [6] [17], but these studies do not include social distancing or PPE use. The model by Atkeson is an SIR model with social distancing included, but does not mention the interplay of PPE on the number of infections [1].

In this study we focus on the timing of initiation and termination of social distancing and PPE use in hospitals. Assuming early control of the epidemic, we consider the results of removing social distancing restrictions. Overall, we analyze the impact of these intervention strategies on the total number of infections in a moderately sized state in the United States.

2 Model

The spread of COVID-19 is complex in many respects. Many individuals are asymptomatic [18]. Spread can occur between individuals in close proximity through the air, or through contact to surfaces where the virus can remain over time [19]. Due to many factors including the inability to conduct widespread testing, it is difficult to estimate infection rates. Additionally, rates found in the literature vary over a wide range of values [13], [22], [16], [7]. Roda et al. specifically mention that modeling parameters and results vary because of the uncertainty of when the outbreak began, the complexities in defining who is infected with COVID-19 and the wide range in the case-infection ratio [16].

The focus on this study is to examine the effect of intervention strategies. In particular the strategies of social distancing, as well as the lack of availability of PPE in hospitals. Because of this focus and the uncertainty of accurate rates, we use a simple SIR (Susceptible, Infectious, and Removed) model with a time-dependent infec-

tion rate, $\beta(t)$,

$$\begin{aligned} \frac{dS}{dt} &= -\beta(t)SI \\ \frac{dI}{dt} &= \beta(t)SI - \frac{1}{d}I \\ \frac{dR}{dt} &= \frac{1}{d}I. \end{aligned} \tag{1}$$

Here d represents the length of time individuals remain infectious. We incorporate the effects of social distancing and the loss of PPE in the time-dependent infection rate, $\beta(t)$, as well as the effectiveness of each of these intervention strategies on limiting the spread of the disease. This leads to the following definition of the infection rate,

$$\beta(t) = \beta_1(t)H + \beta_2(t)(1 - H), \tag{2}$$

where H is the proportion of infections due to hospital transmission. Further for each component of this rate we define the following:

$$\beta_1(t) = \begin{cases} \beta_h E_h, & t \leq T_h \\ \beta_h, & t > T_h \end{cases} \tag{3}$$

$$\beta_2(t) = \begin{cases} \beta_s, & t \leq T_s \\ \beta_s E_s, & t > T_s \end{cases} \tag{4}$$

where β_h and β_s are the base infection rates in the hospital setting and outside the hospital setting, respectively. E_h is the effectiveness of PPEs in the hospital, and E_s is the effectiveness of social distancing in preventing the spread of the disease. T_h is when the hospital runs out of effective PPEs. T_s is the initiation time of social distancing.

The proportion of infections due to hospital transmission varies by community. This proportion is likely to be much smaller in metropolitan areas versus a community with a small population where the hospital could be the main hub of transmission. The effectiveness of PPE, E_h , may vary with the quality of PPE as well as with proper or repeated use. The effectiveness of social distancing, E_s , is likely to vary dramatically between and within communities based on how seriously the local population adhere to the rules put forth by the government. The values of E_h and E_s were simulated.

Figures 1 and 2 give examples of the infection parameter $\beta_1(t)$, $\beta_2(t)$, and β when social distancing starts on day 45 and 105, respectively, and hospitals run out of PPEs on day 100. In this example, the hospitals' proportion of infections is 15%. In Figure 1 initially β is large since there is no social distancing, and then decreases, once social distancing starts. After β drops, due to the start of social distance, it then rises again after the hospitals run out of PPEs.

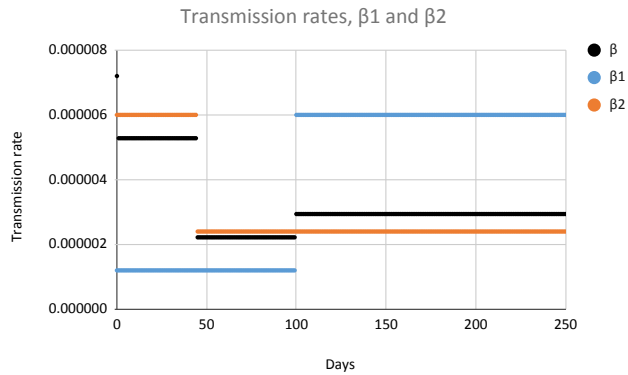


Figure 1: Social distancing begins at 45 days with modest effectiveness level and PPEs are lost at 100 days.

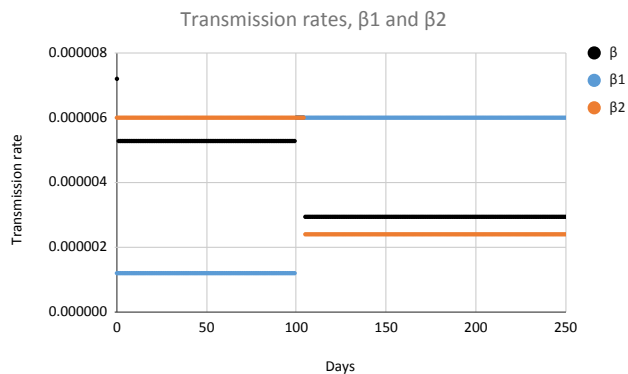


Figure 2: Social distancing begins at 105 days with modest effectiveness level and PPEs are lost at 100 days.

3 Results

In the following simulations we consider the situation at a state level where many social distancing decisions are made, as well as some decisions for acquiring PPE. We examine the median state population of 4.5 million, though similar results can be seen for different sized states. As previously mentioned, locally the parameter values vary from community to community, however here we assume the parameter values represent an average of all the communities of the state.

Parameters were chosen to exhibit a peak in the infectious class occurring around 100 days without using any intervention strategies. A peak at 100 days was chosen arbitrarily, though given the data over the first few months of the spread of COVID-19 this appears reasonable [2]. We also assumed that individuals would be infectious for two weeks, and that infections occur between close proximity between individuals. It is possible that a disease like COVID-19 may be transmitted through contact with

surfaces, though we assume that social distancing and the use of proper PPE will dramatically reduce the spread through close proximal vicinity including transfer through surfaces. We also assume for convenience that $\beta_s = \beta_h$.

To examine the effects of these intervention strategies, the simulations are divided into three categories of effectiveness of social distancing; high (75%), moderate (60%) and modest (40% effective). The percent of effectiveness represent the reduction of the base infection rate outside of the hospital setting, $1 - E_h$. We also look at the difference in the level of hospital transmission from low proportion of 5% to a high proportion of 15%. It is clear that some of the transmission of the disease is due to transmission through contact within hospitals. Since many infected individuals, as well as non-infected individuals, will visit hospitals over the time of the epidemic in relatively close quarters, hospitals can be one of the main hubs of transmission. It is not clear what percentage this transmission would be within a particular community. In general the percentage will change over time and will be affected by the hospital’s protocols and availability of PPE. In any particular community at a particular time the actually percentage could easily fall outside of this range, however, for this study we will assume that the percentage remains relatively constant at this percentages.

To examine the effects of social distancing, we initiate social distancing at different points in time, after 45, 60, 75, 90 and 105 days of the initial outbreak. The effects of initiation social distancing after the peak of infections are fairly modest. These initiation times were chosen based on the peak number of infectious individual occurred around 100 days. To explore the loss of PPE, we consider the cases where there is an early loss of PPE at 50 days, and a loss near the peak of the number of infectious individuals at 100 days. It was assumed that once PPE ran out, supplies were not replenished to any significant degree within the time frame of the simulations.

3.1 Highly effective social distancing

Individuals need to obtain food and other goods, and at times medical care, which makes social distancing impossible to achieve at extremely high percentages. In this situation we assume highly effective social distancing reduces the infection parameter by 75%. We observe in Figure 3 postponing social distancing results in a dramatic increase in the peak number of infections. Starting social distancing before day 75 results in a peak of approximately 225,000, whereas after 75 days, peaks of 1,000,000 or more occur. This is due to the spread of the disease has gone past the point of control. Delays in peaks allow for healthcare agencies both time to prepare and with lower peaks the ability to better handle the patient load.

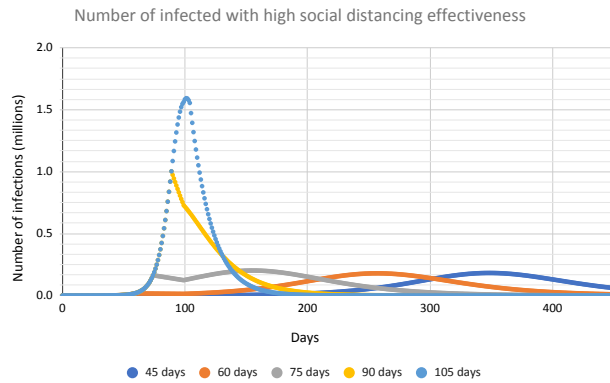


Figure 3: The social distancing effectiveness is 75%, hospital transmission is 15% and the hospital runs out of PPEs at 100 days.

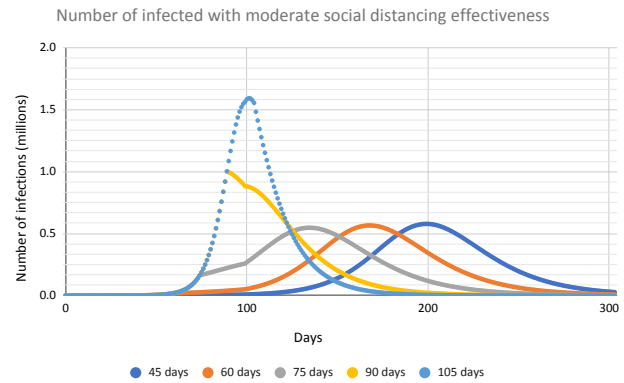


Figure 5: The social distancing effectiveness is 60%, hospital transmission is 15% and the hospital runs out of PPEs at 100 days.

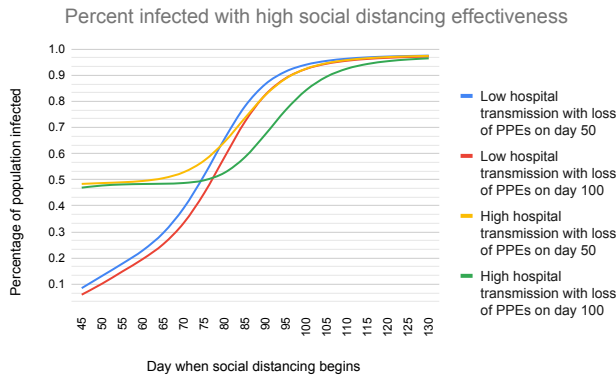


Figure 4: The percentage of the total population infected when social distancing has a high effectiveness level.

Comparing β in Figure 1 and 2 we see the effect of a delayed social distancing from initiating on day 45 in the former and on day 105 in the latter. The former situation has a lower overall β between day 45 and 105. This decrease in beta during this time results in the delay in the peak infections seen in Figure 3. In general initiating social distancing 15 days earlier results in a delay in the peak by almost 100 days, unless it starts near 100 days which is when the peak occurs without any social distancing.

We see similar results in Figure 4 where the overall percentage of people who become infected rises well above 50% when social distancing starts after day 75. This quickly becomes over 90% of the population having been infected in most cases where social distancing is started after 90 days. Also seen in Figure 4 is the importance of hospital protocols and PPEs where there is high hospital transmission. In the case with low transmission and early social distancing, the epidemic can be controlled to

very low levels. Starting social distancing later abates the effect of hospital transmission since eventually each situation eventually reaches the same effective β .

In Figure 4 we also see the effects of losing PPEs. For low hospital transmission the percent eventually infected drops 3% to 10% for a given day of initiation of social distancing. In the high hospital transmission case the percent can drop nearly 20% in some instances. However, when initiation starts early or very late there is difference between the early loss of PPEs on day 50, or when PPEs are lost near the peak of the infection on day 100.

3.2 Moderately effective social distancing

In the case with moderately effective social distancing, with a reduction of 60% in the infection parameter, we see in some cases more than twice the size in infection peaks than in the highly effective case, such as in Figure 5. This decrease in the effectiveness results in the peaks with early social distancing range from 550,000 to 600,000 individuals, whereas the with late social distancing the peaks are again over 1,000,000. Overall this is a significant rise in the peak number of cases with this drop in effectiveness.

There are still delays in the peak with early initiation of social distancing, though the delays are noticeably shorter. In the highly effective case the peaks occurred around 340, 250, and 150 days for social distancing initiation occurring on day 45, 60 and 75, respectively. In the moderately effective scenario the peaks occur approximately on days 200, 170 and 140. Overall these peaks are delayed by approximately a month for implementing 15 days earlier. This is around a third of the delay in the highly effective case.

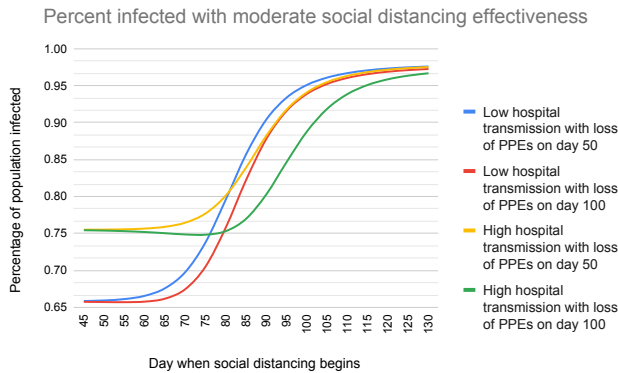


Figure 6: The percentage of the total population infected when social distancing is moderately effective.

In Figure 6 around day 85 we see an increase in the percentage of the population infected eventually by the virus. However in this case, due to the effectiveness of social distancing, the benefits to the overall percentage of infected is reduced where a majority of the population will eventually become infected. The effect of low and high hospital transmission are relatively small.

The effect of losing PPE is evident in Figure 6 where under low hospital transmission a reduction of 3% to 5% is typical depending on the day of initiation of social distancing. In the case of high hospital transmission the percent reduction may range as large as 13%, though again there is little effect whether initiation occurs early or late.

Modest effective social distancing

For modest effective social distancing the overall effect are unsurprisingly relatively small. In Figure 7 the number of infections at the peak are at or above 1,000,000 individuals. It is interesting to observe that there is a small increase in the peak number of infections with an earlier delay in initiation of social distancing. The cause of the increase in the size of the peak is due to the higher infection rate that occurs after day 100, and the fact that on day 100 there is a larger susceptible population for the situations with earlier initiation, see Figure 7.

The delay in peak infectious individuals exhibited here is on the order of about 10 days for each 15 day increment of earlier initiation of social distancing. This delay can be important in order to prepare, though the with large scale of the peaks of infectious individuals the benefits are small compared to the cases of moderate and high effectiveness.

In Figure 8 nearly the entire population acquires the infection. The effect of high and low hospital transmission and when the low of PPE occur is relatively small when compared to the entire population, though the trends are

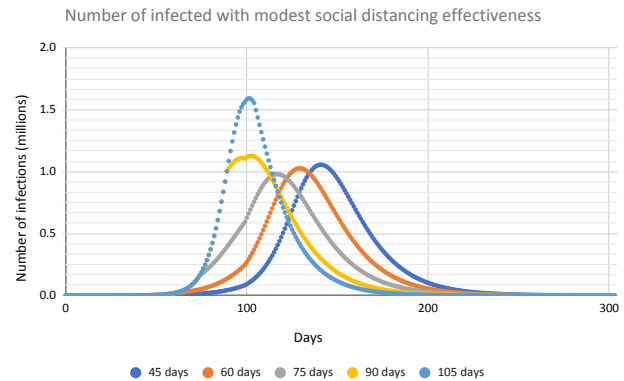


Figure 7: The social distancing effectiveness is 40%, hospital transmission is 15% and the hospital runs out of PPEs at 100 days.

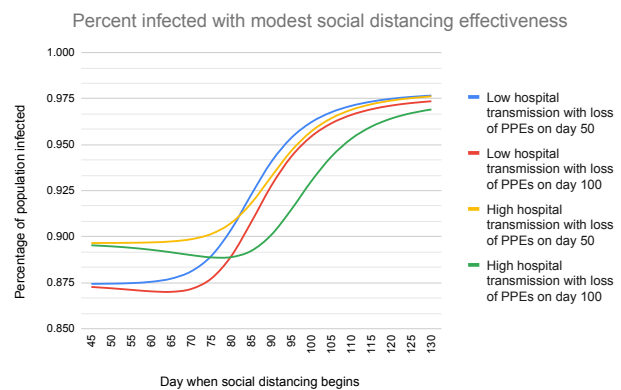


Figure 8: The percentage of the population when social distancing has a modest effectiveness level.

similar to the other cases. There is a dip in the percentage of infected with the delay in loss of PPE on day 100, this is again due to the higher infection rate on a large susceptible population.

3.3 Impact of terminating social distancing

Finally we examine the situation where social distancing is terminated after being initiated. In particular we consider the case where social distancing starts on day 45 and then is terminated on days 150, 200, 250, and 300. The results are seen in Figure 9. In each case of termination, a relatively large peak soon follows the termination. Without termination the peak is a little over 200,000, though the peak grows to over 1.5 million with early termination after 150 days, and to near 700,000 for the late termination on day 300. Each additional delay of 50 days does

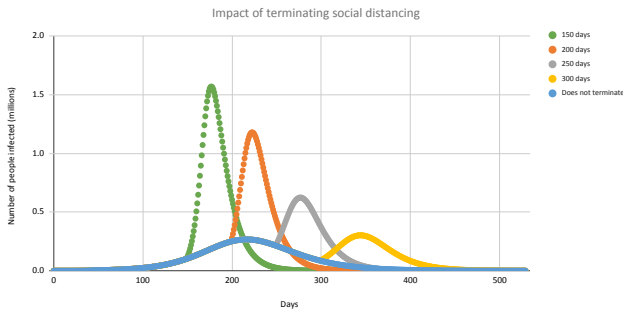


Figure 9: The social distancing effectiveness is 60%, hospital transmission is 15% and the hospital does not run out of PPEs.

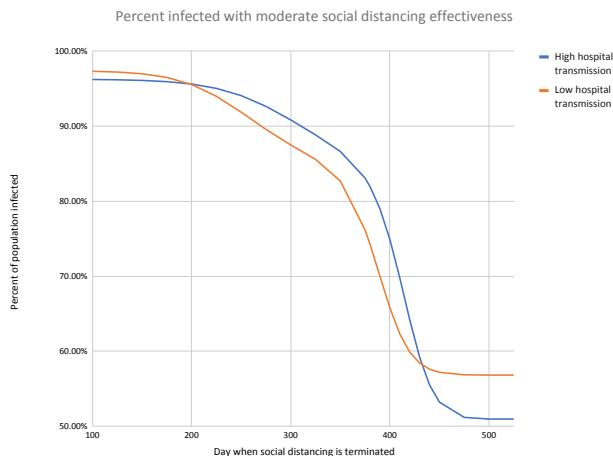


Figure 10: This represents the percent of the population eventually infected under moderately effective social distancing beginning on day 45 and being terminated. PPEs are assumed to be plentiful.

have noticeable drop in the peak as well as a delay in the timing of the peak.

Figure 10 shows that the earlier that social distancing is terminated, the higher the percentage of the population is infected when social distancing begins at day 45. There are modest differences in the low and high hospital transmission cases. This does show that ending social distancing before day 300 results in about 90% of the population acquiring the virus. Whereas waiting an additional 150 days results in about 55% of the population getting infected. This is a dramatic difference in our state population of 4.5 million people.

4 Discussion

Our model is unique because it analyzes the interaction between social distancing and the loss of PPE. In the initial outbreak of the epidemic there were a small number of hospitals and healthcare facilities that ran out of PPE, however, during the end of 2020 and beginning of 2021 there was large surge of cases that has overwhelm many hospitals. Our model uses average values for statewide estimates, which does not allow for local predictions. We also do not include other factors such as contact tracing and vaccination. Our goal is to analyze the effect of intervention strategies instead of fitting a model to data.

We developed an SIR model with a time-dependent infection parameter that focuses on the intervention strategies, social distancing and PPE use within hospitals. Our simulations examine a state population of 4.5 million, and assume an average value for the infection rate. Due to change from initiation and termination of social distancing as well as hospitals running out of PPE, we observe dramatic variation in when the peak number of infectious individuals occur and the size of this peak.

The death rate of COVID-19 is unknown, and we do not calculate deaths here, though one could assume a percentage of those infected. In cases where a large percent of the population has been infected would likely result in a large number of deaths. These deaths have ranging impact on individual families as well as the economy as a whole. Decisions of when to initiate and terminate social distancing as well as obtaining adequate quantities of PPE are critical to dealing with pandemics and ameliorate their outcomes.

It is clear of the importance of hospitals having sufficient equipment to reduce the transmission of the disease within hospitals. However, it is also important that the effectiveness of social distancing is critical in reducing the number of infections. Ineffective social distancing has little effect on the spread of the disease within the population. Public education of social distancing is vital to save lives and to not burden the health system within each community. Our model is relevant now because an increase in contact tracing could spot where cases are most prominent such as in hospitals or in communities where social distancing is or maybe not being implemented.

Author Contributions

Kelly Reagan: conceptualization, software, investigation, resources, writing (original draft), writing (review and editing), visualization. Rachel Pryor: writing (review and editing). Gonzalo Bearman: writing (review and editing). David Chan: conceptualization, methodology, software, validation, writing (original draft), writing (review and editing), supervision, project administration.

References

- [1] Atkeson, A. (2020). What will be the economic impact of COVID-19 in the US? Rough estimates of disease scenarios. Technical report, National Bureau of Economic Research.
- [2] Bhardwaj, R. (2020). A predictive model for the evolution of COVID-19. *Transactions of the Indian National Academy of Engineering*, 5(2):133–140.
- [3] Bouchnita, A. and Jebrane, A. (2020). A multi-scale model quantifies the impact of limited movement of the population and mandatory wearing of face masks in containing the COVID-19 epidemic in Morocco. *Mathematical Modelling of Natural Phenomena*, 15:31.
- [4] Caley, P., Philp, D. J., and McCracken, K. (2008). Quantifying social distancing arising from pandemic influenza. *Journal of the Royal Society Interface*, 5(23):631–639.
- [5] CDC (2020). Coronavirus disease 2019 (COVID-19). <https://www.cdc.gov/coronavirus/2019-ncov/index.html>.
- [6] Chen, Y.-C., Lu, P.-E., Chang, C.-S., and Liu, T.-H. (2020). A time-dependent SIR model for COVID-19 with undetectable infected persons. *IEEE Transactions on Network Science and Engineering*, 7(4):3279–3294.
- [7] Cherniha, R., Davydovych, V., et al. (2020). A mathematical model for the COVID-19 outbreak and its applications. *Symmetry*, 12(6):990.
- [8] Crokidakis, N. (2020). COVID-19 spreading in Rio de Janeiro, Brazil: do the policies of social isolation really work? *Chaos, Solitons & Fractals*, page 109930.
- [9] Götz, T. (2020). First attempts to model the dynamics of the coronavirus outbreak 2020. *arXiv preprint arXiv:2002.03821*.
- [10] Kočańczyk, M., Grabowski, F., and Lipniacki, T. (2020). Dynamics of COVID-19 pandemic at constant and time-dependent contact rates. *Mathematical Modelling of Natural Phenomena*, 15:28.
- [11] Lauer, S. A., Grantz, K. H., Bi, Q., Jones, F. K., Zheng, Q., Meredith, H. R., Azman, A. S., Reich, N. G., and Lessler, J. (2020). The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: estimation and application. *Annals of internal medicine*.
- [12] Liu, Z., Magal, P., Seydi, O., and Webb, G. (2020). Predicting the cumulative number of cases for the COVID-19 epidemic in China from early data. *arXiv preprint arXiv:2002.12298*.
- [13] Mandal, M., Jana, S., Nandi, S. K., Khatua, A., Adak, S., and Kar, T. (2020). A model based study on the dynamics of COVID-19: Prediction and control. *Chaos, Solitons & Fractals*, 136:109889.
- [14] Mishra, B. K., Keshri, A. K., Rao, Y. S., Mishra, B. K., Mahato, B., Ayesha, S., Rukhaiyyar, B. P., Saini, D. K., and Singh, A. K. (2020). COVID-19 created chaos across the globe: Three novel quarantine epidemic models. *Chaos, Solitons & Fractals*, page 109928.
- [15] OSHA (2020). United States Department of Labor. <https://www.osha.gov/SLTC/covid-19/controlprevention.html#health>.
- [16] Roda, W. C., Varughese, M. B., Han, D., and Li, M. Y. (2020). Why is it difficult to accurately predict the COVID-19 epidemic? *Infectious Disease Modelling*, 5:271–281.
- [17] Waqas, M., Farooq, M., Ahmad, R., and Ahmad, A. (2020). Analysis and prediction of COVID-19 pandemic in Pakistan using time-dependent SIR model. *arXiv preprint arXiv:2005.02353*.
- [18] Whitehead, S. and Feibel, C. (2020). CDC director on models for the months to come: 'this virus is going to be with us'. <https://www.npr.org/sections/health-shots/2020/03/31/824155179/cdc-director-on-models-for-the-months-to-come-this-virus-is-going-to-be-with-us>.
- [19] WHO (2020). Coronavirus. https://www.who.int/health-topics/coronavirus#tab=tab_1.
- [20] Wilder-Smith, A. and Freedman, D. (2020). Isolation, quarantine, social distancing and community containment: pivotal role for old-style public health measures in the novel coronavirus (2019-nCoV) outbreak. *Journal of travel medicine*, 27(2):taaa020.
- [21] Wu, J., Tang, B., Bragazzi, N. L., Nah, K., and McCarthy, Z. (2020). Quantifying the role of social distancing, personal protection and case detection in mitigating COVID-19 outbreak in Ontario, Canada. *Journal of Mathematics in Industry*, 10(1):1–12.
- [22] Zhang, Z., Zeb, A., Hussain, S., and Alzahrani, E. (2020). Dynamics of COVID-19 mathematical model with stochastic perturbation. *Advances in Difference Equations*, 2020(1):1–12.