Professors and Practitioners: Assessing the Impact of COVID-19 in the State of Oklahoma with and Without Residents of Long-Term Care Facilities

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Objectives. Our analysis, which began as a request from the Oklahoma Governor for useable analysis for state decision making, seeks to predict statewide COVID-19 spread through a variety of lenses, including with and without long-term care facilities (LTCFs), accounting for rural/urban differences, and considering the impact of state government regulations of the citizenry on disease spread. Methods. We utilize a deterministic susceptible exposed infectious resistant (SEIR) model designed to fit observed fatalities, hospitalizations, and ICU beds for the state of Oklahoma with a particular focus on the role of the rural/urban nature of the state and the impact that COVID-19 cases in LTCFs played in the outbreak. Results. The model provides a reasonable fit for the observed data on new cases, deaths, and hospitalizations. Moreover, removing LTCF cases from the analysis sharpens the analysis of the population in general, showing a more gradual increase in cases at the start of the pandemic and a steeper increase when the second surge occurred. Conclusions. We anticipate that this procedure could be helpful to policymakers in other states or municipalities now and in the future.

When a respiratory disease (later named COVID-19 for Coronavirus disease, 2019) attributable to a novel coronavirus was first diagnosed in the United States in early 2020, initial policy efforts were directed toward containment and eradication. Such measures had been successful with a similar coronavirus (severe acute respiratory syndrome coronavirus, or SARS CoV) in 2003, which resulted in 27 cases and no deaths in the United States. The first detected cases of COVID-19 were found in individuals with a travel history to foreign locations with known circulation of the virus. Thus, early policy measures focused exclusively on travel restrictions. By late February 2020, cases were detected in individuals with no link to travel or other known cases, indicating that community spread was occurring. Yet despite this realization, numerous stumbling blocks precluded effective control, including limitations on identification of infected individuals due to lack of available testing and inadequate contact tracing. It was subsequently recognized that community spread was widely occurring within the United States notably before those sentinel
cases (Schuchat and Team, 2020). Moreover, by this point in time, international health authorities recognized that the COVID-19 virus was quite different from its predecessor, as transmission was obviously more efficient and more difficult to contain (Liu et al., 2020). With cases and fatalities emerging much more quickly than public health infrastructure could respond to and contain, unprecedented measures were taken to reduce spread, with federally endorsed and state-mandated “shutdowns” being undertaken, including closing schools, businesses, churches, and events, and restrictions on travel and nearly all commercial and non-commercial activities outside the home. These restrictions were effective in slowing emergence of the pandemic in the United States, but with great costs, economic, and otherwise.

The shutdowns were intended to be short term, with hopes that public health and health-care infrastructure could expand capacity and be better positioned to prevent spread and respond to cases when restrictions were lifted. Various targets and resources\(^1\) were created for advising state and local administrators in reopening. Unfortunately, continued increases in case diagnoses throughout the country demonstrate that the infrastructure is not in existence to limit transmission among the general population. This sustained transmission leaves limited options for policymakers, either continue to impose restrictions on citizens of their states and municipalities, or accept increased morbidity and mortality until enough of the population develops natural immunity to limit transmission (so called “herd immunity”). Early decisions on shutdown were based on incomplete information, both regarding transmission and infection outcomes. Early reports suggested a case fatality rate of 2 percent or higher (Onder, Rezza, and Brusaferro, 2020; Porcheddu et al., 2020), and reports suggested that the virus could remain infectious on inanimate objects for up to 72 hours (van Doremalen et al., 2020). More recent work has found the case fatality rate to be much lower than 2 percent (Erikstrup et al., 2020) and transmission via surface contamination to be minimal.\(^2\)

While cases in the United States have continued to increase from reopening until mid-July, these cases have shifted toward younger populations than those seen during the early stages of the epidemic, and have included a larger percentage of asymptomatic individuals. This is critical, as it has been known since early in the pandemic that outcomes vary immensely with age and health status. Specifically, case fatality rates have been recognized to be magnitudes of order higher in elderly and those with comorbidities. Decisions on future policies must be made in light of these changes in case demographics and understanding in disease transmission. True rates for infection, severe disease, and death have been elusive due to a number of considerations, including asymptomatic infections, inadequate testing, and notable differences across age groups. Moreover, it seems likely that notable differences exist within age groups, depending on overall health status and living circumstance. Rapidity of spread, in particular, is associated with population density (i.e., urban versus rural). Severe disease and death has been much more frequent in individuals living in long-term care facilities (LTCF).\(^3\) The considerations of rural versus urban populations and LTCF populations are particularly important in Oklahoma. While Oklahoma is often considered a very rural state, approximately 60 percent of the state’s population is found in just two urban centers (the cities of Oklahoma City and Tulsa as well as their surrounding spheres of economic and social influence), with nearly two thirds of the

\(^1\)See (https://www.cdc.gov/media/releases/2020/s0520-cdc-resources-open.html)

\(^2\)See (https://www.who.int/news-room/commentaries/detail/transmission-of-sars-cov-2-implications-for-infection-prevention-precautions)

\(^3\)See (https://www.nytimes.com/interactive/2020/us/coronavirus-nursing-homes.html)
population residing in an urban environment. Additionally, while less than 0.5 percent of the state’s population reside in LTCF, more than 40 percent of the reported deaths have been in such residents. These LTCF residents are, in general, the most susceptible to severe outcomes from COVID-19, and are also in a setting that readily facilitates transmission. However, they benefit little from restrictions upon the general public, as they generally have limited activities and interactions outside the facility, regardless of any statewide policies. Policymakers, however, are making decisions based on overall statistics with regard to case fatality rates, hospitalization rates, and ICU/ventilator rates. Consequently, it is of interest to model the population of interest, for our situation the state of Oklahoma, with and without the LTCF residents, to observe the effect of removing these individuals from the general population. If the LTCF residents are driving the case fatality rates for the entire state, then decisions could be significantly affected by modeling the state without these residents.

Modeling Infectious Disease Spread

Modeling of infectious diseases can generally be classified as belonging to one of three methods: statistical methods for epidemic surveillance; mathematical/mechanistic state-space models, or empirical predictions based on machine learning or expert opinion (Siettos and Russo, 2013). The first category focuses primarily on identifying emerging epidemics, and much less on predicting trends after detection. The second and third categories seek to be more predictive of existing outbreaks, and thus we will limit this discussion to a comparison of mathematical/mechanistic versus empiric methods. Empirical models historically relied upon expert opinion, combined with known characteristics of the disease and population, to make predictions. More recently, models have come to rely upon computer analysis and/or artificial intelligence to identify trends and patterns in existing data. These patterns can then be used to predict future developments. The major advantage of empirical methods is the absence of a need for assumptions or parameter estimates. The major deficiency is an inability to accurately predict the impact of a novel event. For example, an empiric model may be effective at predicting disease transmission in a new country, based on what has been observed in other countries. However, it will be of limited use in predicting the effect of vaccine introduction.

Mathematical/mechanistic models can be either deterministic or stochastic, and vary tremendously in complexity. Certain disease-specific characteristics must be estimated, such as one or more values for reproductive or transmission rates. The reproductive rates provide an estimate of how many secondary cases are expected to result from each infectious individual; or simply, how many new cases are expected to result from a single-infected individual in the population. A reproductive rate can be thought of as the product of the quantity of infectious particles (bacteria, virus, etc.), which is needed to produce an infection and the probability of someone encountering that quantity. The reproductive rate is influenced by various inherent characteristics of the disease agent, such as how infectious it is, how long an infectious individual sheds the agent, route(s) of transmission of the agent, how long the agent persists in the environment, etc.). In addition, the reproductive rate is influenced by host factors, including the presence of resistance or immunity, population density and degree of interaction, and efforts to mitigate transmission (basic sanitation efforts as well as more specific interventions). Beyond estimation

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4 See [https://data.ers.usda.gov/reports.aspx?StateFIPS=40&StateName=Oklahoma&ID=17854]
5 See [https://coronavirus.health.ok.gov/sites/g/files/gmc786/f/eo_-_covid-19_report_-_7-13-20.pdf]
of the reproductive rate(s), simpler models necessitate a large number of assumptions, including random mixing of individuals within a population and uniformity in susceptibility. Greater refinement can be achieved if estimates can be substituted for these assumptions, but accurate estimates for these parameters are often lacking.

Among the simplest mechanistic/mathematical models is a deterministic compartmental model known as SEIR. The compartments in an SEIR include susceptible (having no immunity or inherent resistance to the disease); exposed (having been exposed and contracted the disease; currently incubating the agent and not infectious); infectious (now shedding the organism and posing a risk of transmission to susceptible individuals encountered); and resistant/removed/recovered (in some form or another, no longer at risk for infection; this could be attributable to preexisting or inherent resistance, acquired immunity, or exclusion from the population). SEIR models can be modified to account for demographics or even spatial effects of disease transmission (Siettos and Russo, 2013). While increasing the complexity of the model improves accuracy, it can limit applicability of the model to other populations (assuming more detailed information about the population is not always available). Similarly, the SEIR paradigm can be made stochastic, thereby permitting introduction of multiple heterogeneous characteristics, from nonrandom mixing and interaction of people and variation in susceptibility/probability of transmission. Once again, a trade-off is required in terms of accuracy and parsimony.

The objectives of the present project are to report results of a deterministic SEIR model designed to fit observed fatalities, hospitalizations, and ICU beds for the state of Oklahoma with a particular focus on the role (i) the rural/urban nature of the state and (ii) the COVID-19 cases in LTCFs played in the outbreak. We hypothesized that the rural/urban nature of the state would yield different spread rates and pattern and that by controlling for COVID-19 cases among LTCFs, the epidemic would be much less severe. The SEIR model used different values for reproductive rates for COVID-19 transmission in rural and urban populations, and then combined the two to produce state-level predictions. Rates were also modified based on policy announcements at state and local levels to reduce transmission of the virus. Then we removed the LTCF residents from the state (both in population and hospitalization and fatality data), and modeled the state without the LTCF residents, determining what adjustments were needed to fit the observed data.

The removal of the LTCF residents was employed in an effort to allow policymakers to consider the effects of statewide mandates with regard to closures and reopening upon the population these closures and reopening measures will effect, without the confounding information on deaths and hospitalizations from the LTCF residents. We anticipate that this procedure could be helpful to policymakers in other states or municipalities now and in the future.

**Background: Building a Model at the Governor’s Request**

The team was first assembled to provide state leaders with real-time predictions of the state’s COVID deaths, hospitalizations, and ICU beds. As such, there was an extreme time constraint. The team quickly settled upon an SEIR model, and determined that the difference in interaction patterns between the rural and urban portions of Oklahoma, and the age-related differences in response to the virus were primary factors that needed to be included in our model. Consequently, the team searched the literature for data on reproductive rates, incubation period, duration of infectivity, hospitalization rates, ICU rates, and case fatality rates for other countries and areas of the United States, specifically for
COVID-19. From these, the team selected some “first guess” values for these parameters. For instance, a reproductive rate of 3.15 for the urban population and 2.61 for the rural population were initially utilized in the program. This initial stage involved a discrete-time SEIR model written in R using the following difference equations for each compartment:

\[
S_{t+1} = S_t - \lambda_t S_t E_t, \quad E_{t+1} = E_t + \lambda_t S_t - f E_t, \quad I_{t+1} = I_t + f E_t - c I_t, \quad R_{t+1} = R_t + c I_t,
\]

where \( \lambda_t = \beta_t \), \( S_t \) represents the time-varying force of infection, \( f \) is the rate at which emergent individuals become infectious, \( c \) is the rate at which people recover from COVID-19 such that they are no longer infectious to others, and \( \beta_t \) is a function of a time-varying reproductive number, specifically \( \beta_t = \frac{r_t}{P} \), with \( P \) denoting the fixed population size, and \( r_t \) denoting the effective reproductive number at time \( t \). As with other compartmental models, we assumed random mixing of the population and constant vital dynamics (i.e., no net births, deaths, or interstate migration affecting the Oklahoma population). For computational purposes, we ran the model in a discrete-time setting with a time resolution of one day. This allowed synchronization of the model output with daily figures produced by OSDH, thereby facilitating the tuning of a time-varying reproductive number \( r_t \), such that the modeled trajectory of the epidemic curve matched the most up-to-date data on cumulative cases. Specifically, optimization of the \( r_t \) track, including inflection points, was carried out by comparing the predicted cumulative count of infectious cases to the observed total case counts on a daily basis, with the objective function being defined in terms of the sum of squared differences in a logarithmic setting (to account for exponential growth curves).

This model was run separately for urban and rural population components, and produced unique projections for each. Following output of the predicted compartmental counts and cumulative counts (including cumulative cases and cumulative deaths), we used an Excel spreadsheet to combine the resulting urban and rural values from the R program. The Excel spreadsheet also incorporated age-stratified case fatality and hospitalization rates.

Once this model was developed, the team then utilized the daily Oklahoma data provided by the Executive Order reports to compare the predictions from the model with the actual observed data. This allowed the team to investigate adjustments to the age-stratified rates, as well as the effective reproductive rates, the incubation period, and the duration of infectivity. During this period, the team was providing real-time predictions for the state government, so the modifications were done quickly with an emphasis on fitting the past several weeks as closely as possible, so that the predictions for the next several weeks would be more accurate and valuable for policy making. Additionally, during this time frame the team was able to incorporate an appropriate reduction in the effective reproductive rates that corresponded with the statewide shutdown orders.

During the first week of May 2020, the state of Oklahoma began reopening and the Governor’s COVID-19 Task Force requested updated model results less frequently. This allowed the team to focus on adjusting the model to fit the overall behavior of the COVID-19 spread in the state, rather than focusing primarily on the recent past. The details of this resulting model are discussed below.

As discussed previously, the team decided to utilize an SEIR model for modeling the virus. Additionally, the team decided to utilize differing transmission rates for the urban and rural populations. This introduced the additional assumption that the urban and rural populations do not interact, another assumption that is obviously incorrect, although again the benefits were assumed to outweigh this limitation.

After deciding on these particulars, the team next faced the task of determining a start date for the virus in Oklahoma. The first verified case in Oklahoma was diagnosed
on March 6 and an executive order was issued directing protection of the vulnerable populations.\textsuperscript{6} However, we hypothesized that the virus was circulating in Oklahoma before this (Schuchat and Team, 2020). For this reason, the team chose to utilize a start date of February 9 and to drop multiple cases into both rural and urban populations. We began the model with 30 initial and simultaneous cases for the rural population and 60 for the urban population. We also utilized population counts of 1,335,480 and 2,607,599 for the rural and urban populations, respectively.\textsuperscript{7} As mentioned previously, the team also utilized basic reproductive rates of 3.15 and 2.61 for the urban and rural populations, respectively, at the beginning of the virus spread for the state.

Given that the shutdown drastically affected the population mixing patterns, the team estimated the magnitude and implementation dates for these changes. Several sensitivity analyses were run to investigate a variety of possibilities with the aim of adjusting the model to more closely match the observed number of reported cases of COVID-19 (further described below).

It should be noted that the urban population of Oklahoma is dominated by Tulsa and Oklahoma City. On March 17, the mayors of Oklahoma City and Tulsa issued emergency orders to close bars, gyms, and theaters, and to limit restaurants to take-out and delivery orders.\textsuperscript{8} Consequently, the team chose to decrease the effective reproductive rate for the urban population on March 17 by 30 percent (to 2.205).

Subsequently, on March 24, the governor of Oklahoma issued a Safer at Home order.\textsuperscript{9} This action was assumed to impact the rural population, although it did not add many restrictions that were not already in place in Oklahoma City and Tulsa. Thus, the team chose to decrease the reproductive rate for the rural population on March 24 by 22 percent (to 2.0358).

On March 28, Oklahoma City and Tulsa issued emergency proclamations for a shelter in place order, and the team chose to drop the urban reproductive rate to 50 percent of the original basic reproductive rate prior to any citywide or state activity restrictions (to 1.575). As this was a very serious proclamation, it was assumed that this would also impact the rural populations in the state, although not as much as the urban population, and with a delay in response. Consequently, we chose to decrease the rural reproductive rate to 61 percent of the original basic reproductive rate prior to any citywide or state activity restrictions (to 1.5921)

Finally, on April 1 the Governor issued a statewide shutdown order,\textsuperscript{10} and the team chose to decrease the urban reproductive rate to two-ninth of the original reproductive rate (to 0.7) on April 8, assuming that it would take approximately a week for residents to actually adopt the shutdown order. The team also chose to drop the rural reproductive rate to 0.7 on April 15, again assuming that the adoption of the shutdown order would have an increased delay for the rural population. However, we assumed that the reproductive rates would be the same for the urban and rural populations, as the reproductive rate during a shutdown would appear to be unaffected by the urban–rural distinction.

On April 22, the governor announced his “Open Up and Recovery Safely (OURS)” plan, which involved various dates and stages for the state to reopen. Again, we believed that the urban population would implement reopening quicker than the rural population.

\textsuperscript{6}See (https://www.cdc.gov/coronavirus/2019-ncov/hcp/duration-isolation.html)
\textsuperscript{7}See (https://www.recoverytrial.net/files/recovery_dexamethasone_statement_160620_final.pdf)
\textsuperscript{8}See (https://www.ok.gov/odmhsas/documents/ZORRO%20-%20Quality%20Services%20in%20Rural%20Areas%20Workgroup%20Presentation.pdf)
\textsuperscript{9}See (https://www.sos.ok.gov/documents/executive/1912.pdf)
\textsuperscript{10}See (https://www.okc.gov/Home/Components/New/News/3293/18?npage=5).
Assessing COVID-19 Impact in Oklahoma

It was also surmised that the main effect of “opening up” would not be observed until phase 2 of the plan was reached on May 15. Consequently, the effective reproductive rate was increased to 1.05 on May 15 for the urban population, and on May 20 for the rural population. As more time passed, the population of the state increased their movement and interaction patterns, so on May 31, the effective reproductive rates were increased to 1.5 for the urban population, and 1.4 for the rural population. Finally, the urban effective reproductive rate was further increased to 2.0 and the rural effective reproductive rate to 1.9 on June 20, representing further increases in interaction patterns among the state’s residents.

The SEIR model also required a value for the latent periods and the duration of infectiousness. Various values for these parameters were considered at the beginning of the team’s modeling process, and the team quickly settled on a latency of five days. This value was generally consistent with the literature at the time (Lauer et al., 2020; Li et al., 2020), assuming that infectivity coincided with onset of symptoms. More recent publications suggest infectivity may precede symptom onset (He et al., 2020a, 2020b), although shedding appears to be highest at symptom onset (To et al., 2020). The model adopted a duration of shedding of seven days. While shedding has been documented to persist longer than this, the significance of low viral burden is unclear, and it is generally considered that effective transmission is limited after 10 days. The seven-day duration would also reflect a general reduction in the risk of transmission due to self-isolation by symptomatic individuals.

With these parameters determined, the SEIR model provides a daily prediction for new infectious people that can be utilized to empirically derive predictions for hospitalizations and fatalities. This determination requires a plethora of parameters, including asymptomatic rates, hospitalization rates, and case fatality rates. The literature is clear that these rates are quite different for different age ranges, so the team decided to utilize age-stratified rates. Table 1 summarizes our base rates for these age stratifications. These are termed the “base” rates as it was necessary to consider adjustments to some of these rates for various time periods. For instance, the case fatality rates were higher at the beginning of the epidemic, and then lowered with improved therapeutic treatments. It should be noted that the case fatality rates in Table 1 are the percentage of symptomatic cases that result in a fatality.

The team used these age-stratified rates and the results from the SEIR model to predict the daily hospitalizations and case fatalities. Adjustments were made to these base rates as follows: hospitalization rates were extremely high at the beginning of the pan-

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TABLE 1

| Age Group          | Asymptomatic (%) | Hospitalized (%) | Symptomatic Case Fatality Rate |
|--------------------|------------------|------------------|-------------------------------|
| 85 and older       | 25               | 18               | 6                             |
| 65–84              | 45               | 9                | 3                             |
| 50–64              | 65               | 4                | 0.4                           |
| 30–49              | 85               | 3                | 0.0175                        |
| Under 30           | 90               | 1                | 0.00625                       |

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See (https://www.governor.ok.gov/articles/press_releases/governor-stitt-announces-latest-covid-19-actions)
demic, including a broad characterization of “persons under investigation.” Thus, initial hospitalization rates were considered to be 400 percent of base rates, and declined approximately 21 percent per day from February 10 until reaching base rate at April 1. The fatality rate was assumed to be higher at the beginning, and declining with earlier diagnosis and improved treatment. As such, initial case fatality rate was assumed to be 135 percent of base case fatality rate, and declined 2.5 percent per day from February 10 until reaching base rate at April 1. Further reductions in case fatality rate were recognized, including results from the RECOVER trial that demonstrated up to a 33 percent reduction in fatality with dexamethasone treatment. This lead us to reduce case fatality rates further, to 80 percent of base rate, effective June 1.

Figure 1 shows the results of the predicted hospitalizations and fatalities, along with the actual values. The model utilizes the science of disease progression via the SEIR model and provides a reasonable fit for the observed data. It should be noted that data involved with this virus are notorious for being extremely variable, and often prone to errors, but the team was still able to fit the overall state reasonably well after incorporating reproductive rate changes on the dates of the various statewide and metropolitan mandates and actions. Consequently, this model illustrates that the overall pattern of disease spread in the state has been modeled sufficiently. This allowed the team to examine the fit of this model for the subpopulation of LTCFs.

Controlling for Long-Term Care Facilities

Fairly early in the progression of the epidemic, it was determined that the LTCFs were affected disproportionately compared to the rest of the population. As these facilities generally contain older individuals, often in compromised health and who are more likely to succumb to the virus, this is completely reasonable. Additionally, public health policy decisions such as a shelter in place order, a mask ordinance, or relaxing these restrictions,
arguably have minimal effect upon residents of LTCFs. Consequently, it seems reasonable that policymakers should consider removing these individuals from any data that are being utilized to inform these public health policy decisions.

To assess the effect of removing these individuals from the state data, the team created a model excluding residents of LTCF. First, the number and age distribution of LTCF residents were obtained from the Long-Term Care Service within the Oklahoma State Department of Health. These values were then removed from the model’s age stratification percentages for the state. The subtraction from the urban and rural estimates was done in a manner proportionate to the age demographics for the state (i.e., the number of LTCF residents older than 85 years of age were apportioned to rural vs. urban equal to the general distribution of residents older than 85 years of age). This resulted in a modest but not inconsequential reduction in the overall percentage of the non-LTCF state population in the older age categories, and an equal modest increase in the percentage of non-LTCF state population in the younger age categories. The number of daily deaths and hospitalizations for individuals in LTCF was collected from the state’s surveillance data. These values were then subtracted from the daily values for the entire state to obtain the hospitalization and fatality counts in the non-LTCF state population.

The team then examined what changes in values for hospitalization and case fatality rates were needed to bring the model into alignment with the observed data for the non-LTCF state population. The trend of this model appeared reasonable for both hospitalizations and fatalities, but the predicted values were too high for this new population. Consequently, the base age-stratified rates for hospitalizations and fatalities had to be adjusted for the non-LTCF state population in order for the SEIR model to fit this new population well. Those adjusted base age-stratified rates are presented in Table 2.

Note that the asymptomatic rates did not change. However, the hospitalization rate for the 85 years and older age group was reduced by 50 percent (from 0.18 to 0.09), and by 33.3 percent (from 0.09 to 0.06) for the 65- to 84-year age group. Additionally, the case fatality rate for the 85 years and older age groups was reduced by 66.7 percent (from 0.06 to 0.02), and by 53.3 percent (from 0.03 to 0.014) for the 65- to 84-year age group. This is a dramatic decrease in these rates, and obviously would impact decisions. The predicted results for the non-LTC state population, along with the actual observed values is presented, along with these same results for the whole state population for comparison, in Figures 2 and 3.

Note that the model still fits the non-LTC population, but that the progression of the virus is much less extreme in the early stages than for the whole state. As “shutdown” orders arguably do not affect the LTCF residents, removing these individuals from data used to
determine the timing of these orders seems reasonable. From Figures 2 and 3, it seems plausible that if policymakers had been presented with the non-LTC population data, then the timing of the statewide activity restrictions might have been different, with perhaps better results, although of course decisions are always improved based on retrospection, using data not available at the time.

Finally, near the end of June the state saw a sharp increase in hospitalizations. Eventually this led to a mask ordinance for Tulsa and Oklahoma City, the two major metropolitan areas of the state. However, note that this increase is much more dramatic for the non-LTCF population. This is reasonable, as the increase is likely due to the lifting of the shelter in place order, which arguably would not have had much effect on the LTCF population.
In this instance, the elected officials from Tulsa and Oklahoma City might have been alarmed even earlier if they had seen the more dramatic increase in hospitalizations from the non-LTCF population, and perhaps have enacted the mask ordinance for these cities even earlier. Earlier implementation may have increased any benefits that resulted from this ordinance.

Conclusions

This report describes efforts to develop, and results of, a modified SEIR model for the SARS-CoV-2 or COVID-19 pandemic in Oklahoma in early 2020. The model was able to closely fit the shape of the curves representing hospitalizations and fatalities in the state population from March through end of June 2020. This model is sufficiently simple, yet is still reasonably robust, and all parameter estimates are within reason of values derived from empiric observation. While this model should not be considered to have provided ideal estimates of all examined parameters, it is apparent that the combination of estimates chosen provides results that are overall consistent with empiric data. It also provides a platform to examine the differing demographic distributions between rural and urban populations of the state of Oklahoma, and assess impacts of differing policies, practices, or transmission dynamics in these different populations. Finally, it is also amenable to exclusion of a small portion of the state population from the model to examine what role that subpopulation plays in disease occurrence and outcomes. For this particular project, our group chose to focus on LTCF residents, as it was noted this subpopulation was disproportionately impacted throughout the nation and the state of Oklahoma during early stages of the COVID-19 pandemic. Doing so was relatively easy, given data available from state agencies. This selective elimination allowed us to more fully appreciate the disproportionate impact on the LTCF residents. Specifically, it was widely reported that greater than 50 percent of deaths in Oklahoma were among LTCF residents. However, it was still telling to note that removal of that population resulted in a 66 percent drop in the fatality rate among Oklahomans older than age 85 but not in an LTCF. This unique approach provides an estimate for the impact of the disease on the non-LTCF population of the state that may be useful to policymakers to consider in future decisions related to COVID-19.

Our model and approach have several limitations worth noting. As stated previously, numerous parameter estimates are needed. Some are widely available and considered reliable, including the age distribution of Oklahoma’s population. Others, in particular those related to the disease, are less certain, but are based on best estimates either from Oklahoma or from COVID-19 surveillance data more broadly. It is important to note that these do not have to be particularly accurate to permit many conclusions following selective removal of specific subpopulations. In many instances, the magnitude of change is as important as a particular value. It should also be noted that there are numerous assumptions to any SEIR model, and these are increased by our modifications. Namely, we modeled the rural and urban populations independently, assuming no functional interaction between those populations. Indeed, even determining the percentage of the population that is “rural” versus “urban” is not without controversy or difficulty. Our model sought to be consistent with classification standards used by several sources, and again, the magnitude of effect can be appreciated even in the absence of ideal accuracy. It should also be noted that we did not use case counts as a metric of comparison or validation. The model generates a projected daily case count, but it is known that testing in Oklahoma has always been inadequate
to consider the number of cases detected as reflective of true numbers of cases. This was particularly true early in the pandemic, including the time interval examined here.

In conclusion, we demonstrated that the impact of COVID-19 in terms of hospitalization and deaths in Oklahoma during early 2020 was disproportionately focused on LTCF populations. More importantly, we were able to develop a model that estimates how removal of this particular subset of the population permits quantification of parameters in the remainder of the state. Removal of the LTCF population from Oklahoma resulted in a 66 percent reduction in the case fatality rate among individuals older than 85 years of age, a 50 percent reduction in hospitalization rates in that age group, and a greater than 50 percent reduction in case fatality among those aged 65–84. This is in no way meant to reduce the importance of the impacts on the LTCF population, nor the remaining population of Oklahoma. Rather, it has the potential to make more informed decisions on policy as well as preparedness in the COVID-19 pandemic.

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