

## Supplementary Material for “An Agent Based Modeling of COVID-19: Validation, Analysis, and Recommendations”

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### 1. Supplementary Tables for Ford County, Kansas, USA:

Name	Value
min_age	1
max_age	77
min_name_length	3
max_name_length	7
min_family_size	1
max_family_size	5
n_workgroup	4000
n_transport	1000
transport_seat_limit	40
n_events	335
n_persons	33619
n_infected_init	2
awareness_start	1
quarantine_start	1
quarantined_person_ratio	0.4

Table 1: Part 1 of location-specific data for Ford county including total population, initial cases, average family size, life expectancy, lock-down declaration etc.

Name	Minimum age	Maximum age	Percentage	Total number
Student	4	25	0.32	10758

Service	18	65	0.488	16406
Doctor	30	65	0.005	168
Unemployed	10	77	0.187	6286

Table 2: Part 2 of location-specific data for Ford county including percentage of the total population belonging to different professions.

Task	Minimum start time	Maximum start time	Minimum duration	Maximum duration	Profession	Minimum probability	Maximum probability
Stay Home	0	0	7	8	Service	1	1
Stay Home	0	0	6	7	Driver	1	1
Stay Home	0	0	7	8	Doctor	1	1
Go to Work	7	8	1	2	Service	0.4	1
Go to Work	6	7	1	1	Driver	0.4	1
Go to Work	7	8	1	2	Doctor	0.8	1
Work	8	10	8	9	Service	0.4	1
Treat Patients	7	8	8	12	Driver	0.4	1
Treat Patients	8	9	8	10	Doctor	0.8	1
Returns Home	16	19	1	2	Service	0.4	1
Returns Home	15	20	1	1	Driver	0.4	1
Returns Home	16	19	1	2	Doctor	0.8	1
Stay Home	17	21	10	10	Service	1	1
Stay Home	16	21	10	10	Driver	1	1
Stay Home	17	21	10	10	Doctor	1	1
Attend Event	12	14	2	4	Service	0.3	0.9
Attend Event	12	14	2	4	Driver	0.3	0.6
Attend Event	12	14	2	3	Doctor	0.3	0.7
Stay Home	0	0	12	13	Unemployed	1	1
Stay Hospital	0	0	24	24	Hospitalized	1	1
Stay Home	0	0	7	8	Student	1	1

Go to Work	7	8	1	1	Student	0.4	1
Work	8	9	6	7	Student	0.4	1
Returns Home	14	16	1	1	Student	0.4	1
Stay Home	15	17	10	10	Student	1	1
Attend Event	12	14	2	4	Student	0.4	0.9
Go to Work	12	13	1	1	Unemployed	0.3	0.8
Attend Event	13	14	2	4	Unemployed	0.35	0.9
Returns Home	15	18	1	1	Unemployed	0.3	0.8
Stay Home	16	17	10	10	Unemployed	1	1
Stay Home	0	0	24	24	No Outing Allowed	1	1

Table 3: The lower and upper bounds of duration, probability of occurrence, starting and ending times for different tasks performed by an agent in Ford county.

Name	Value
action_occurring_threshold	0.6
action_affecting_threshold	0.6
action_infect_threshold	0.7
infection_threshold	0.65

Table 4: Values of different thresholds for Ford county.

## 2. Supplementary Tables for New York City, USA:

Name	Value
min_age	1
max_age	81
min_name_length	3
max_name_length	7
min_family_size	1
max_family_size	6

n_workgroup	600
n_transport	2500
transport_seat_limit	60
n_events	100
n_persons	10000
n_infected_init	1
awareness_start	7
quarantine_start	27
quarantined_person_ratio	0.5

Table 5: Part 1 of location-specific data for New York City including total population, initial cases, average family size, life expectancy, lock-down declaration etc. The values have been scaled to accommodate for a population of 10000 from 8.3 million.

Name	Minimum age	Maximum age	Percentage	Total number (Per 10000 population)
Student	4	25	0.22	2200
Service	18	62	0.741	7410
Doctor	25	70	0.019	190
Unemployed	10	81	0.02	200

Table 6: Part 2 of location-specific data for New York City including percentage of the total population belonging to different professions.

Name	Value
action_occurring_threshold	0.55
action_affecting_threshold	0.55
action_infect_threshold	0.45
infection_threshold	0.55

Table 7: Values of different thresholds for New York City.

<b>Task</b>	<b>Minimum start time</b>	<b>Maximum start time</b>	<b>Minimum duration</b>	<b>Maximum duration</b>	<b>Profession</b>	<b>Minimum probability</b>	<b>Maximum probability</b>
Stay Home	0	0	7	8	Service	1	1
Stay Home	0	0	6	7	Driver	1	1
Stay Home	0	0	7	8	Doctor	1	1
Go to Work	7	8	1	2	Service	0.4	1
Go to Work	6	7	1	1	Driver	0.4	1
Go to Work	7	8	1	2	Doctor	0.8	1
Work	8	10	8	9	Service	0.4	1
Treat Patients	7	8	8	12	Driver	0.4	1
Treat Patients	8	9	8	10	Doctor	0.8	1
Returns Home	16	19	1	2	Service	0.4	1
Returns Home	15	20	1	1	Driver	0.4	1
Returns Home	16	19	1	2	Doctor	0.8	1
Stay Home	17	21	10	10	Service	1	1
Stay Home	16	21	10	10	Driver	1	1
Stay Home	17	21	10	10	Doctor	1	1
Attend Event	12	14	2	4	Service	0.3	0.9
Attend Event	12	14	2	4	Driver	0.3	0.6
Attend Event	12	14	2	3	Doctor	0.3	0.7
Stay Home	0	0	12	13	Unemployed	1	1
Stay Hospital	0	0	24	24	Hospitalized	1	1
Stay Home	0	0	7	8	Student	1	1
Go to Work	7	8	1	1	Student	0.4	1
Work	8	9	6	7	Student	0.4	1

Returns Home	14	16	1	1	Student	0.4	1
Stay Home	15	17	10	10	Student	1	1
Attend Event	12	14	2	4	Student	0.4	0.9
Go to Work	12	13	1	1	Unemploy ed	0.3	0.55
Attend Event	13	14	2	4	Unemploy ed	0.35	0.6
Returns Home	15	18	1	1	Unemploy ed	0.3	0.55
Stay Home	16	17	10	10	Unemploy ed	1	1
Stay Home	0	0	24	24	No Outing Allowed	1	1

Table 8: The lower and upper bounds of duration, probability of occurrence, starting and ending times for different tasks performed by an agent in New York City.

### 3. Supplementary Tables for Physiological Data

Action	Min time gap	Max time gap	Min prob affect	Max prob affect	task	Min prob	Max prob	Min effect other s	Max effect others	Min effect self	Max effect self
Sneeze	40	50	0.1	0.7	Work	0.1	0.605	0.1	0.705	0	0
Contaminate Thing	50	55	0.1	0.7	Work	0.1	0.605	0.1	0.705	0	0
Physical Contact	20	30	0.1	0.7	Work	0.1	0.605	0.1	0.705	0	0
Sneeze	40	50	0.1	0.7	Attend Event	0.1	0.65	0.1	0.8	0	0
Contaminate Thing	20	30	0.1	0.8	Attend Event	0.1	0.8	0.1	0.8	0	0
Physical Contact	20	30	0.2	0.8	Attend Event	0.2	0.8	0.3	0.8	0	0
Sneeze	40	50	0.1	0.7	Go to Work	0.1	0.7	0.1	0.705	0	0
Contaminate Thing	20	30	0.1	0.7	Go to Work	0.1	0.7	0.1	0.705	0	0

Physical Contact	20	30	0.1	0.7	Go to Work	0.1	0.7	0.1	0.705	0	0
Sneeze	40	50	0.1	0.7	Returns Home	0.1	0.7	0.1	0.705	0	0
Contaminate Thing	20	30	0.1	0.7	Returns Home	0.1	0.7	0.1	0.705	0	0
Physical Contact	20	30	0.1	0.7	Returns Home	0.1	0.7	0.1	0.705	0	0
Sneeze	40	50	0.1	0.7	Stay Hospital	0.1	0.7	0.1	0.705	0	0
Contaminate Thing	50	55	0.1	0.8	Stay Hospital	0.1	0.8	0.1	0.705	0	0
Physical Contact	20	30	0.1	0.8	Stay Hospital	0.1	0.8	0.1	0.705	0	0
Physical Contact	20	30	0.1	0.8	Treat Patients	0.1	0.8	0.1	0.705	0	0
Sleep	1000	1000	0	0	Stay Home	1	1	0	0	0	0
Wash Hands	30	40	0.5	1	Work	0.1	0.7	0	0	-0.75	-0.1
Wash Hands	30	40	0.5	1	Stay Home	0.2	0.7	0	0	-0.75	-0.1
Wash Hands	30	40	0.4	1	Attend Event	0.1	0.7	0	0	-0.75	-0.1
Wash Hands	20	40	0.4	1	Treat Patients	0.2	0.7	0	0	-0.75	-0.1
Contaminate Thing	50	55	0.1	0.7	Treat Patients	0.1	0.605	0.1	0.705	0	0
Sneeze	40	50	0.1	0.7	Treat Patients	0.1	0.605	0.1	0.705	0	0

Table 9: Lower and upper bounds of time interval between actions, probability of occurrence, effects on oneself and others etc. Here, min, max and prob refer to minimum, maximum and probability respectively.

#### 4. Scaled-down version of New York City

For conducting our experiments in the case of New York City, we have chosen to run the simulations for 10,000 people. This involves scaling the location-specific input parameters for the smaller population. Table 6 shows that the proportion of people engaged in different professions are supplied as percentages to the model. However, some parameters are adjusted for the population of size = 10000. This can be understood from Table 10.

Name of Parameter	Total population of NYC	Scaled-down version of NYC
Population size	8,399,000	10,000
Number of events (approx)	84,000	100
Number of groups (approx)	504,000	600
Number of vehicles (approx)	2,000,000	2,500

Table 10: Scaling of parameters for New York City for a population of 10000.

Data pertaining to Table 10 has been collected from various sources.<sup>1,2,3,4</sup> Moreover, we have considered each working group to contain 10-12 people approximately. In the case of the gatherings, we have considered approximately 100 people or less to be present.

To compare the daily values of effective reproduction number ( $R_t$ ) of our scaled-down ABM model with an SIR model, we calculate the  $R_t$  values for each day using the following formula:

$$R_t(x) = \frac{\sum_{i \in I(x)} d_i^{out}}{|I(x)|}$$

Here,  $R_t(x)$  denotes the  $R_t$  value on day  $x$ .  $I(x)$  is the set of persons infected on day  $x$ .  $d_i^{out}$  is the number of secondary infections caused by person  $i$ . Venkatramanan *et al.* provided a formula for calculating the weekly values of  $R_t$  that has been adopted for determining daily values in the above equation.<sup>5</sup> To remove noise generated by randomness of each day, the  $R_t$  curve was smoothened.

### **The methodology of SIR model:**

We have used the well-known SIR model,<sup>6</sup> which divides the total population into three different compartments, namely *Susceptible*, *Infectious* and *Removed*. We have assumed the total population to be *Susceptible* initially. The rate of change from *Susceptible* to *Infectious* is defined as *Transmission Rate* ( $\beta$ ). On the other hand, the rate of change from *Infectious* to *Removed* is termed as *Removal Rate* ( $\gamma$ ). *Removal Rate* is assumed to be constant over the period of time, while the *Transmission Rate* is assumed to be time-variant. We performed a grid search among the plausible values of *Removal Rate* and the value with maximum likelihood is used as *Removal Rate* henceforth. On the other hand, based on the work of Kurchaski *et al.*,<sup>7</sup> we have modeled transmission (i.e., *Transmission Rate*) as a stochastic random walk process. We have used Sequential Monte Carlo simulation (i.e., Particle Filter),<sup>8,9</sup> in order to find *Transmission Rate* with time, and consequently  $R_t$  as well. Sequential Monte Carlo simulation is run 100 times with bootstrap fits to deduce various confidence intervals of  $R_t$ . Our model is fitted with the number of daily confirmed cases. While fitting the model, we have tried to maximize the negative log-likelihood.



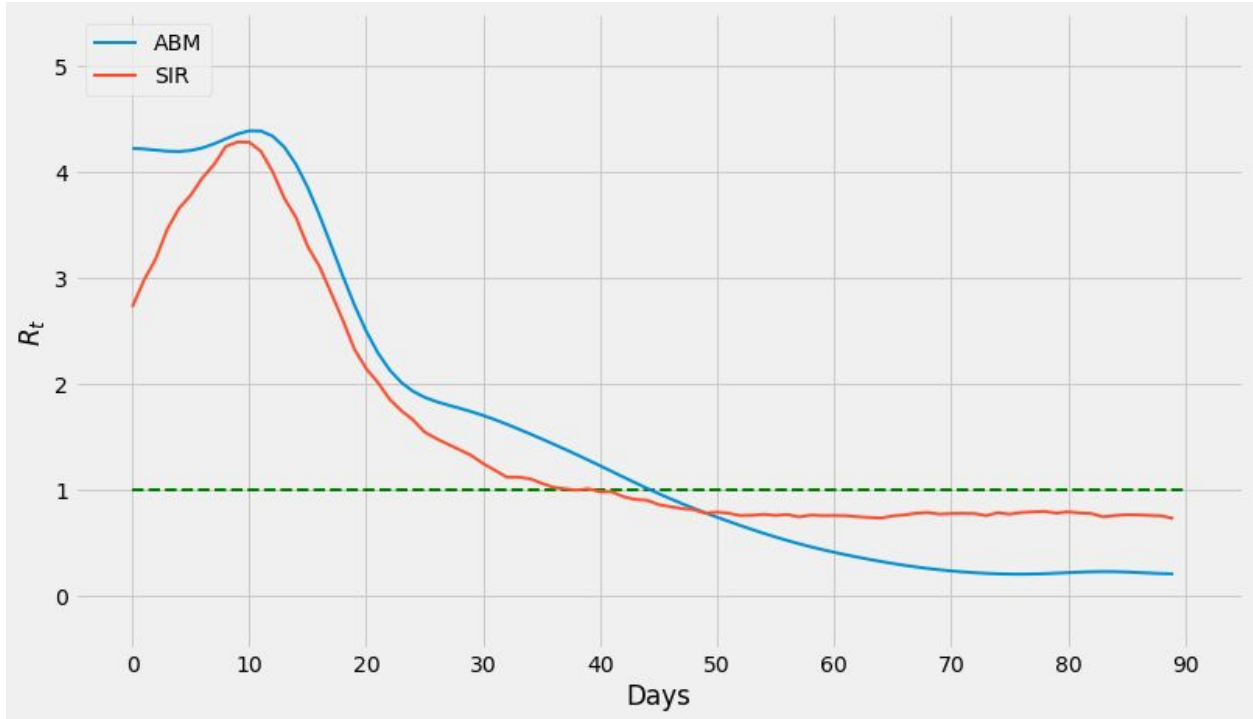


Figure 1:  $R_t$  curves by ABM model with the scaled-down population (blue) and SIR model with the full population (red) of NYC. The blue curve appears to be similar to the red curve with an RMSE value of 0.4626, although converging to zero sooner than the red curve because of the smaller size of the population.

Figure 1 shows that the  $R_t$  curves obtained in the ABM and SIR models are consistent, thus supporting the reasoning behind choosing to scale down the parameters of New York City.

The comparison between ABM and SIR models are shown to provide a preliminary validation of our scaled-down ABM model. These two models were run with different population sizes and because of that, the number of infections must be different. But given the characteristics of a certain population, the initial spread pattern in a scaled-down model should keep a resemblance with that of a full sized model. Both  $R_t$  curves should match during this period. At some point, the susceptible population becomes significantly lower in the scaled-down (ABM) model and it starts to make it difficult for the disease to spread. Then the spread starts to get contained in the scaled-down model due to less susceptible people left, and as a result, from that point, the ABM's  $R_t$  goes down before SIR's  $R_t$ .

## 5. References

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