Methods/Results

Methods

We present a spatial explicit stochastic agent based model that recreates the day to day dynamics in a typical nursery home during the COVID pandemic in the United States. We use an hourly time step resolution and we ran the model for 150 days or until the facility has been disease free for more than 7 days.

Based on a phone interview done during summer 2020 with a nursery home, we collected data from the day to day activities during the COVID 19 pandemic. We incorporate the data from this interview with a literature review to parametrize our model.

Population

Population structure

We used the floor plans and satellite imagery to recreate the spatial structure of a typical nursery home in the US (figure 1). The nursery home consist on 58 bedrooms designated for the residents, recreation areas (such as dining room, and activities rooms), and rooms for staff use. There are two type of agents represented in our model, staff and residents. There are 3 residents per room (total 174) and 170 staff divided into 3 different turns (morning, afternoon, night). The decision on the population distribution was based on information obtained from an interview with a nursery home in California.

Figure 1: Nursery home floor plans

Population dynamics

In our simulation, an agent can interact with other agents based on its location. Given the current guidelines of recommendations for long term care facilities, there are no visitations and the residents spend most of the day in their rooms, so the resident agents in our simulation can only interact with their roommates and the staff. The staff agents can be one of three different types: Certified nurse (CN), Registered Nurses (RN) or Licensed practical nurse (LPN). Our model allows to specify the proportion of each type and work schedule for the staff agents. Depending on the type, the staff agents will have different number of contacts with the residents. The contact rates for each staff type were parametrized based on the average number of resident contacts in a regular day (REFERENCE: Table shared via email??). The staff agents are assigned to one of 3 different work schedules (morning, afternoon or night) and they spend 8 hours inside the nursery home and the rest of the time outside in the community. We only follow the agents inside the nursery home and when the agents are outside we assume that they all have the same probability of contacting other people. The contact rates and the staff schedule distribution used in our model are presented in table from supplementary materials.

Table 1: Distribution of the Staff agent characteristics

Variable	Distribution
Work Schedule	$Multinom \sim (X_{morning} = 0.4, X_{Afternoon} = 0.4, X_{Night} = 0.2)$
Staff type	$Multinom \sim (X_{CN} = 0.6, X_{RN} = 0.15, X_{LPN} = 0.15)$
CN contacts per hour	$Multinom \sim (X_0 = 0.7, X_1 = 0.3)$
RN contacts per hour	$Multinom \sim (X_0 = 0.25, X_1 = 0.75)$
LPN contacts per hour	$Multinom \sim (X_0 = 0.15, X_2 = 0.2, X_3 = 0.25, X_4 = 0.2, X_5 = 0.2)$

Disease dynamics:

The transmission between agents inside the facility will depend on two parts, which are the probability that a person will shed the virus and the probability that another person will get the virus.This transmission rates represent the probability that given that two individuals are in the same room for 1 hour are going to shed or infect with the virus depending on their disease state. We decided on model the transmission this way to represent scenarios where the infected and susceptible could have different combination of interventions (i.e. only infected received the intervention, only susceptible received the intervention, both received the intervention, etc..). The parametrization of the transmission parameters was based on observed outbreaks in nursery homes in California.

The introduction from the community to the facility depends on a parameter *Introduction_p* that represents the chance that one of the staff members will get infected from the disease at the community.

All the agents start as susceptible and after 1 day there is a resident introduced with the disease. Then we follow up for 150 days or until the disease has been absent for more than 14 simulation days. Once the transmission between a infectious agent to a susceptible agent has been successful, the susceptible agent becomes exposed and based on a distribution for the latent period λ, the agent becomes infectious after λ number of days, which can be either symptomatic and asymptomatic. The agent can infect other agents only when its in the Infectious state, then they remain infectious during 15 days and they transition to recovered. The agents can transition to infectious to hospitalized at any moment based on the hospitalization rate. When the agents has been recovered they acquire infection immunity, which lasts for 120 days.

Figure 2: Disease states

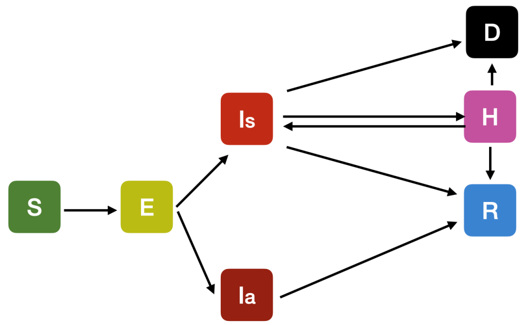

Table 2: Disease parameters. [a]Explored for sensitivity analysis and scenario modeling, [b]truncated distribution between a boundary of reasonable values, [c]fitted to a distribution

Name	Value	Reference
Latent period (λ)	$Lognormal(7,3)$	(He et al. 2020)[b,c]
Shedding probability	0.45	[a]
Infection probability	0.45	[a]
Introduction probability	0.5	[a]
Asymptomatic probability	0.25	[a]
Infection duration	15 *days*	
Hospitalization rate	0.11	

Interventions

We explore 3 different COVID-19 control strategies and the combination of them. Each of the interventions have an impact in the transmission of the disease, interventions such as the use of PPE and vaccination reduces the probability of transmission affecting directly the *Shedding* and *Infection probability*, while the isolation affects the transmission indirectly stopping the agent to interact with other agents. The equation 1 shows the effect of *PPE effect* and *Vaccine effect* on the transmission probability, where $odds_\omega$ represent the global transmission probability for all agents, OR_π represent the odds ratio for the *PPE effect*, X_π represent the presence or absence of PPE, ORv is the *Vaccine effect*, and X_υ. This probability is computed for all agents at each step so we can have different probabilities of transmission based on the interventions each individual received.

$$p_T = \frac{e^{\ln(odds_\omega)+\ln(OR_\pi X_\pi)+\ln(OR_\upsilon X_\upsilon)}}{1+e^{\ln(odds_\omega)+\ln(OR_\pi X_\pi)+\ln(OR_\upsilon X_\upsilon)}}$$

For the implementation of the vaccination, we specified by the proportion of residents and staff vaccinated, and a fixed interval between the first and second dose of 21 days. After the first dose, the agents will only obtain a 60% of the total immunity protection assumed to be conferred by the vaccine, then on the second dose the agents will have 100% of the assumed effect. Then the vaccination immunity will have a decay of 120 days and the individual will no longer have the vaccination immunity protective effect.

Since there is still some uncertainty in the effect of the use of PPE and the vaccine for older population, we started with values that are within the range of reported values and then varied these values for the sensitivity analysis and scenario modeling.

Testing and isolation

Other models have explored this more in detail, in our model we wanted to simplify and used this detection probability parameter to represent the chance that an individual that is tested for the disease will be correctly identified regardless which test is used.

Once a individual has been detected positive is isolated. There are special isolation rooms for the residents and in the case of the staff they are sent home. Once the individual is tested negative they return to the facility.

Interventions parameters:

Table 3: Interventions parameters. [a]Explored for sensitivity analysis and scenario modeling, [b]truncated distribution between a boundary of reasonable values, [c]fitted to a distribution

Name	Value	Reference
Proportion of staff using PPE	0.9	[a]
Proportion of residents using PPE	0.75	[a]
PPE Effect (OR_{π})	0.34089	(Chu et al. 2020)[a]
Test detection probability	80%	[a]
Proportion of Staff tested	90%	[a]
Proportion of Residents tested	33.3	[a]
Frequency of testing	Weekly	[a]
Vaccine effect (OR_{v})	0.0493	(Pfizer-BioNTech 2020)[a]
Vaccine immunity duration	120 *days*	[a]

Sensitivity analysis

We performed sensitivity analysis on selected parameters to show the influence of these parameters on the outcomes. We present the disease outcomes from our model summarized using plots and median and 95% confidence intervals for the days until the facility became disease free, infection rate, cumulative number of infected staff and residents and cumulative number of hospitalizations.

Table 4: Parameters used for sensitivity analysis

Scenario	Target parameter	Value used
Low transmission	Shedding and infection probability	0.4
High transmission	Shedding and infection probability	0.4
Low Introduction Probability	Introduction probability	0.01
High Introduction Probability	Introduction probability	0.15
Low Detection Probability	Detection probability	0.75
High Detection Probability	Detection probability	0.90
High effect PPE	PPE effect	0.0493
Low effect PPE	PPE effect	0.3408
Every 5 days	Testing frequency	every 5 days
Every 3 days	Testing frequency	every 3 days

Effect of vaccination

To effect of the vaccine on reducing the transmission we parametrized the model according to the current vaccine effect reported by the trials from the Moderna and Pfizer vaccine (Baden et al. 2020; Polack et al. 2020). Since there is still some uncertainty about the effect of the vaccine in population >65 years, we defined 3 scenarios that explore the possible outcomes under 3 different assumptions:

- Equal effect: The vaccine has the same effect both populations (>65 years and >65 years).

- Pfizer: The vaccine is less effective on populations >65 years parametrized according to the reported by (Baden et al. 2020).
- Moderna: The vaccine is less effective on populations >65 years parametrized according to the reported by (Polack et al. 2020).

Table 5: Vaccine effect scenarios

Scenario	$OR_{V,S}$	$OR_{V,R}$	Reference
Equal effect	0.0493	0.0493	(Baden et al. 2020)
Pfizer	0.0434	0.0619	(Baden et al. 2020)
Moderna	0.0441	0.1357	(Polack et al. 2020)

Vaccine distribution

Scenario modeling

To illustrate the applications of our model we wanted to answer the question "How should the resources should be distributed under two different levels of community transmission?". We defined as a low community transmission where the probability of introduction is 1% and high community transmission where the probability of introduction is 5%. Then we used the worst case scenario for the effect of the vaccine on the two age groups and looked at the disease outcomes including infection rate and time to duration of the outbreak.

Results

Baseline scenario

The baseline scenario follows the current interventions implemented in a typical nursery home. The parameters for the population dynamics, disease transmission and interventions effect used for the baseline scenario are the ones presented on the tables 1, 2, and 3 respectively. Testing is performed once a week to all the staff and one resident per room. Once that the resident is detected positive is sent to a isolation room, and in the case that one of the staff members test positive, it will be send home. Both the staff and residents are required to use PPE.

The baseline scenarios is meant to represent the possible outcomes for an average nursery home under the current conditions in the US. Our baseline scenario shows a wide range of disease impact ranging from 7-56 days to disease control, and an infection rate ranging between 0.01 to 0.56.

Sensitivty analisis

The influence of different parameters in our model outcomes are presented in the table 6.

Table 6: Results from the sensitivity analysis using the median and 95% confidence intervals

Scenario	Days to eradication	Infection rate	Total Infected	Infected residents	Infected staff	Hospitalizations
Baseline	28 (7,56)	0.34 (0.01,0.56)	117 (3,192.6)	72 (0.4,125.2)	44 (2.6,76.6)	29 (0.2,55.4)

Scenario	Days to eradication	Infection rate	Total Infected	Infected residents	Infected staff	Hospitalizations
Low transmission	28 (7,59.2)	0.17 (0.01,0.38)	58 (2.2,130.8)	30 (0,88.4)	26 (2,55.2)	11 (1,34)
High transmission	21 (10,42)	0.5 (0.08,0.65)	172 (27.4,224.6)	102 (16.2,137.8)	66 (11.2,88.6)	32 (3.4,62.8)
Low Introduction Probability	16 (9,40.6)	0.08 (0,0.48)	27 (0,166.2)	13 (0,109.4)	14 (0,59.4)	8 (0.2,44.2)
High Introduction Probability	28 (14,49)	0.35 (0.05,0.55)	120 (18.8,188.4)	71 (8.2,118.2)	48 (10.6,73.6)	24 (4,47.4)
Low Detection Probability	28 (9.6,57.8)	0.42 (0.04,0.58)	145 (14.8,199.2)	91 (7.6,124.4)	56 (7.2,77.2)	25 (3,48)
High Detection Probability	21 (7,46.8)	0.24 (0.01,0.44)	81 (2.2,150.6)	45 (0,92.2)	26 (2.2,58.4)	7 (0.2,29.4)
High effect PPE	16 (7,53.2)	0.03 (0,0.26)	11 (1,88.2)	2 (0,55.4)	9 (1,35.4)	1 (0,21.4)
Low effect PPE	21 (14,28)	0.83 (0.6,1.03)	285 (207.4,354.6)	177 (124.6,221.4)	111 (87.6,140)	48 (20.4,71.4)
Every 5 days	20 (5,78.2)	0.19 (0.01,0.42)	65 (2,144)	39 (0,87.2)	29 (1.2,59.2)	14 (0.2,31.8)
Every 3 days	0 (0,6)	0 (0,0.01)	0 (0,2)	0 (0,0)	0 (0,1)	0 (0,0)
Same vaccine effect	14 (7,35)	0.02 (0,0.13)	6 (0.2,46)	1 (0,25.4)	5 (0.2,21.8)	1 (0,7.4)
Pfizer	14 (7,32)	0.02 (0,0.12)	6 (0.2,41.8)	1 (0,24.6)	5 (0.2,17.2)	1 (0,9.6)
Moderna	14 (7,33.6)	0.02 (0,0.15)	6 (0,50.6)	1 (0,26)	5 (0,22.2)	1 (0,6.8)
Resident priority	9 (7,26.6)	0.01 (0,0.08)	4 (0,27)	1 (0,13.6)	3 (0,15.6)	1 (0,6.2)
Staff priority	21 (7,34.8)	0.03 (0,0.18)	9 (1.2,60.4)	3 (0,44.2)	5 (1.2,21.4)	1 (0,9.6)

Scenario modeling

References

Baden, Lindsey R., Hana M. El Sahly, Brandon Essink, Karen Kotloff, Sharon Frey, Rick Novak, David Diemert, et al. 2020. "Efficacy and Safety of the mRNA-1273 SARS-CoV-2 Vaccine." *New England Journal of Medicine*, December, NEJMoa2035389. https://doi.org/10.1056/NEJMoa2035389.

Chu, Derek K., Elie A. Akl, Stephanie Duda, Karla Solo, Sally Yaacoub, Holger J. Schünemann, Amena El-harakeh, et al. 2020. "Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: a systematic review and meta-analysis." *The Lancet* 395 (10242): 1973–87. https://doi.org/10.1016/S0140-6736(20)31142-9.

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Pfizer-BioNTech. 2020. "Vaccines and Related Biological Products Advisory Committee Meeting December 10, 2020." Pfizer-BioNTech.

Figure 3: Baseline scenario

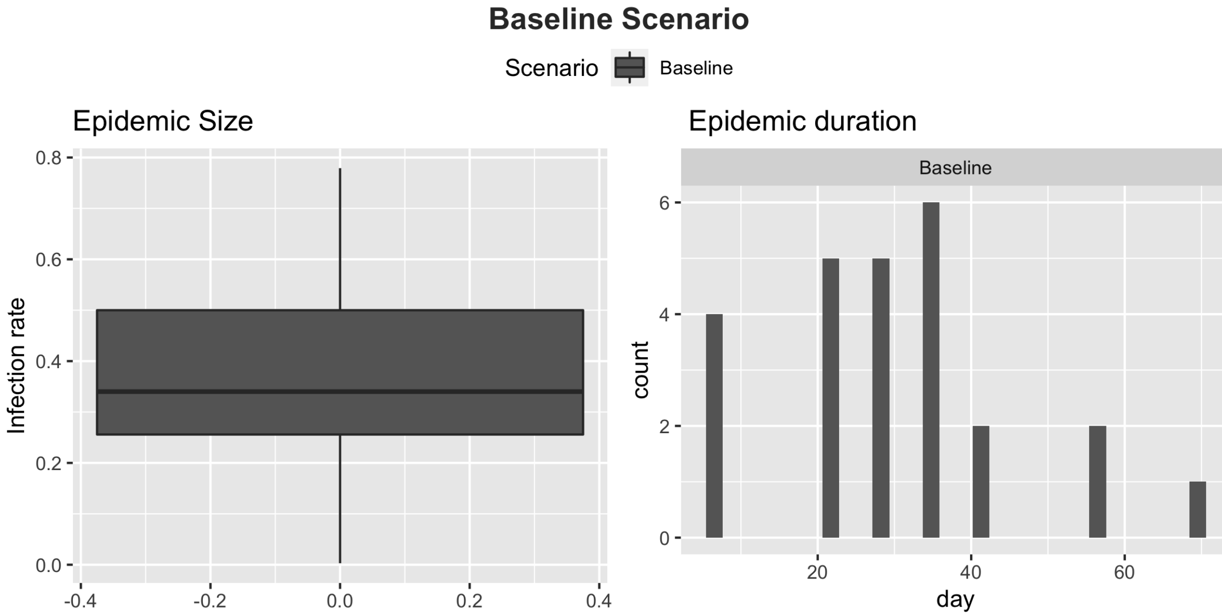


Figure 4: Sensitivity analysis on the transmission parameter

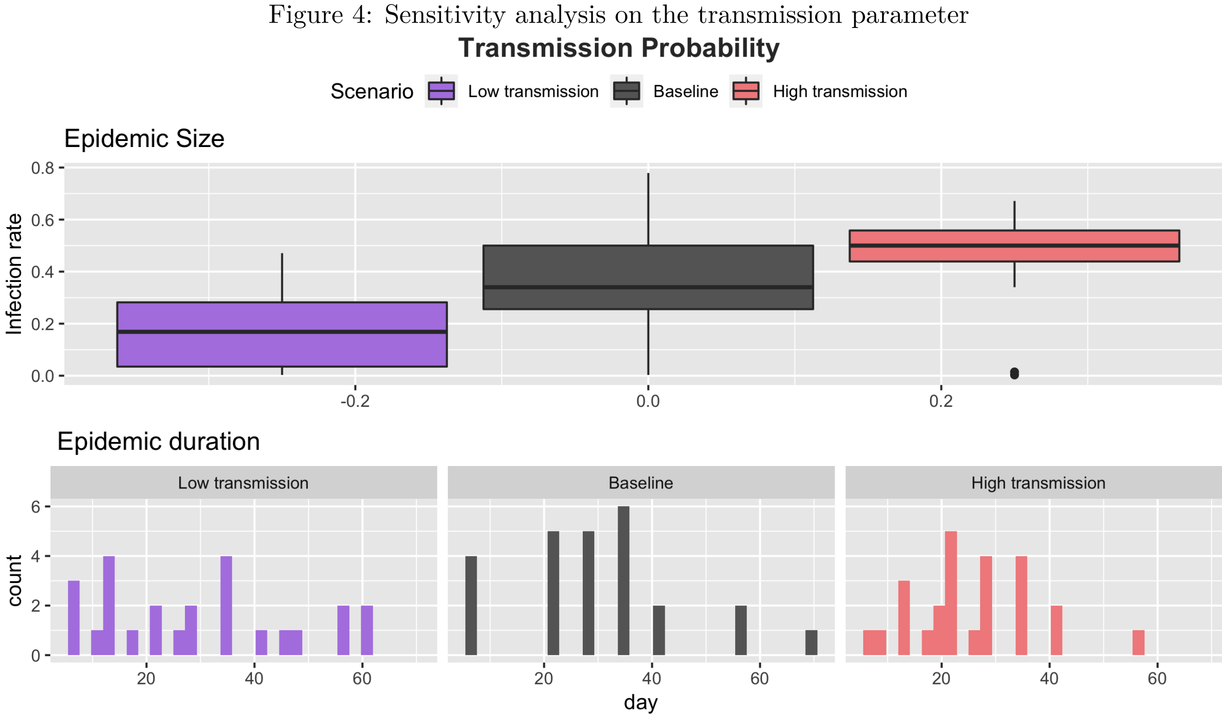


Figure 5: Sensitivity analysis on the introduction probability

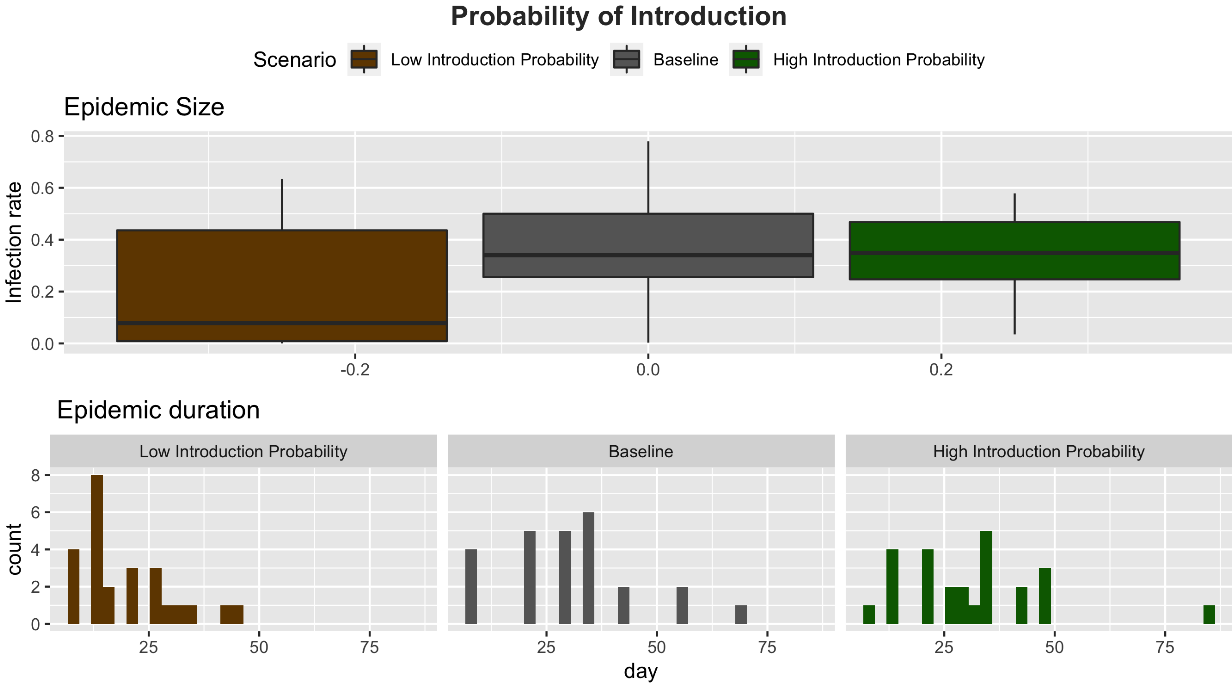


Figure 6: Sensitivity analysis on the probability of detection

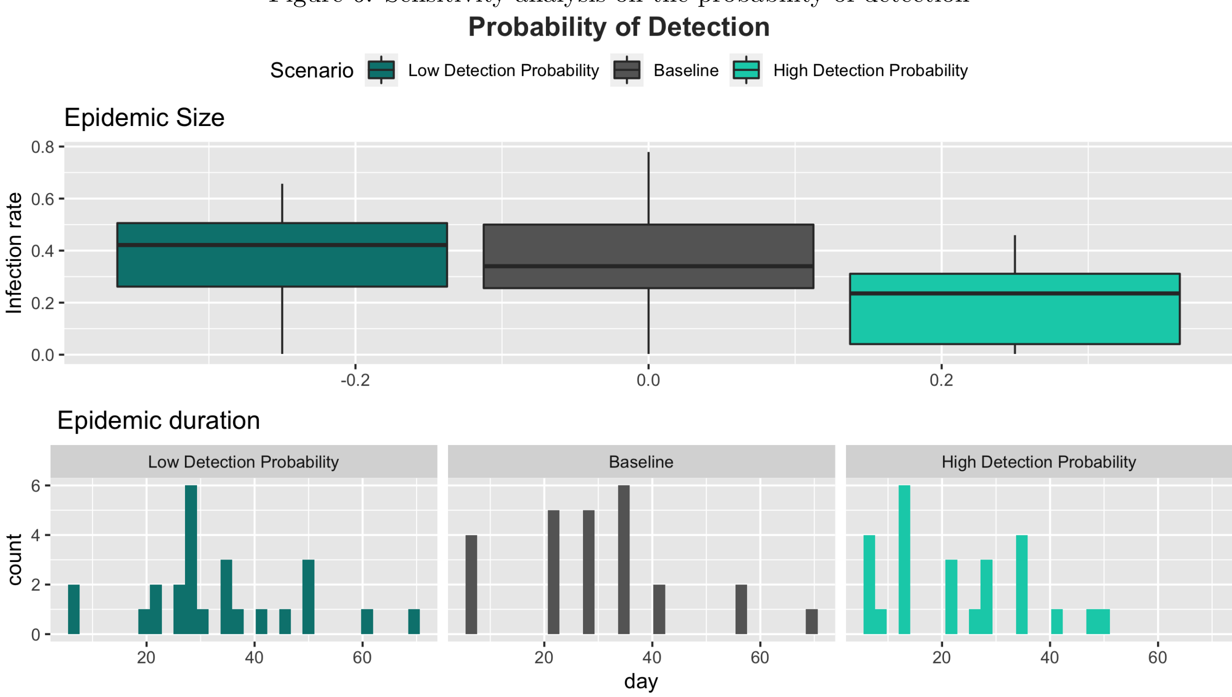


Figure 7: Sensitivity analysis on the effect of the PPE

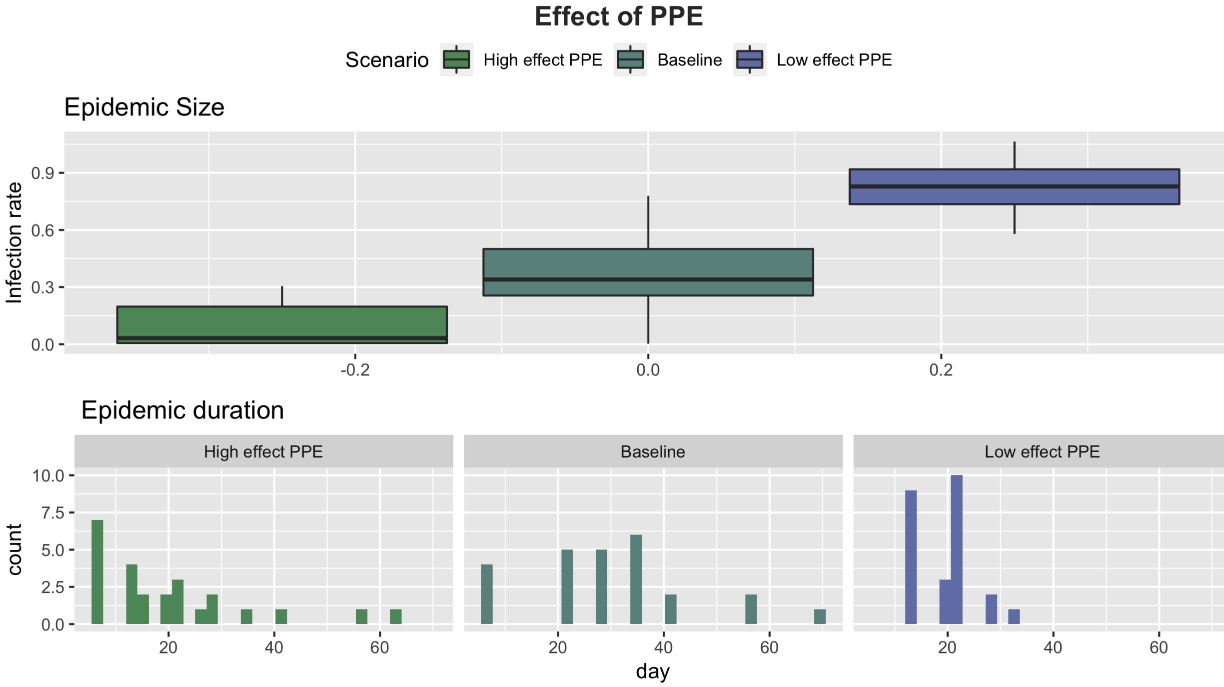


Figure 8: Sensitivity analysis on the testing frequency

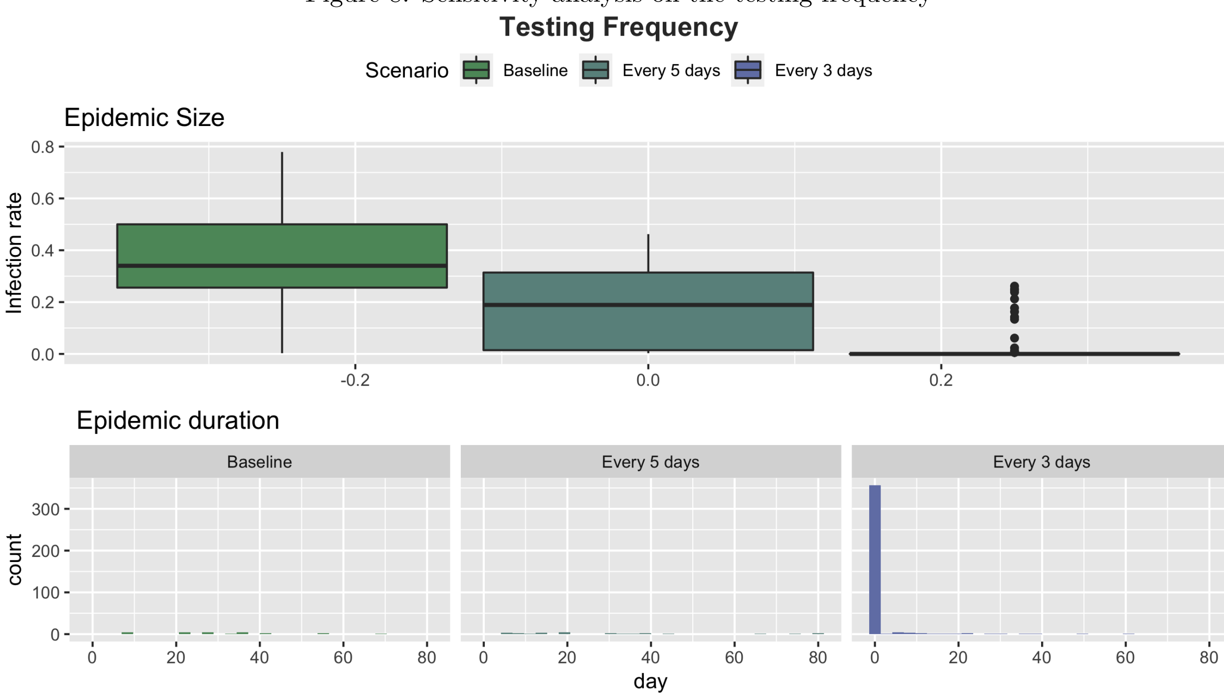


Figure 9: Sensitivity analysis on the effect of vaccination

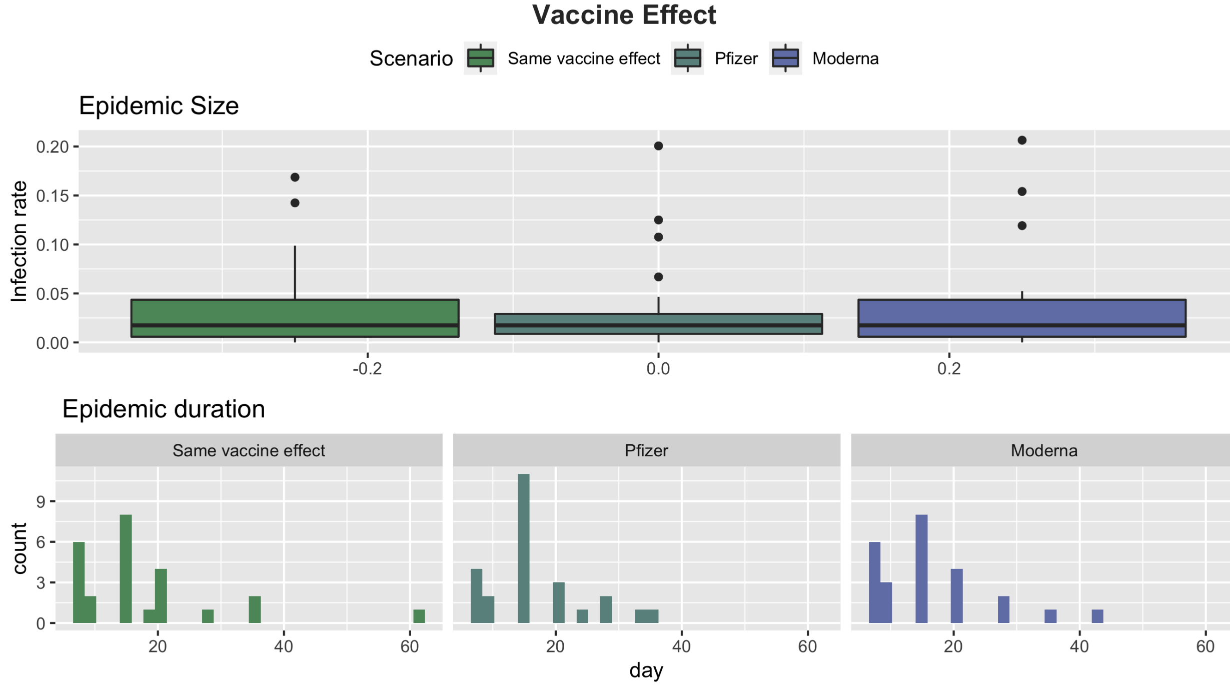
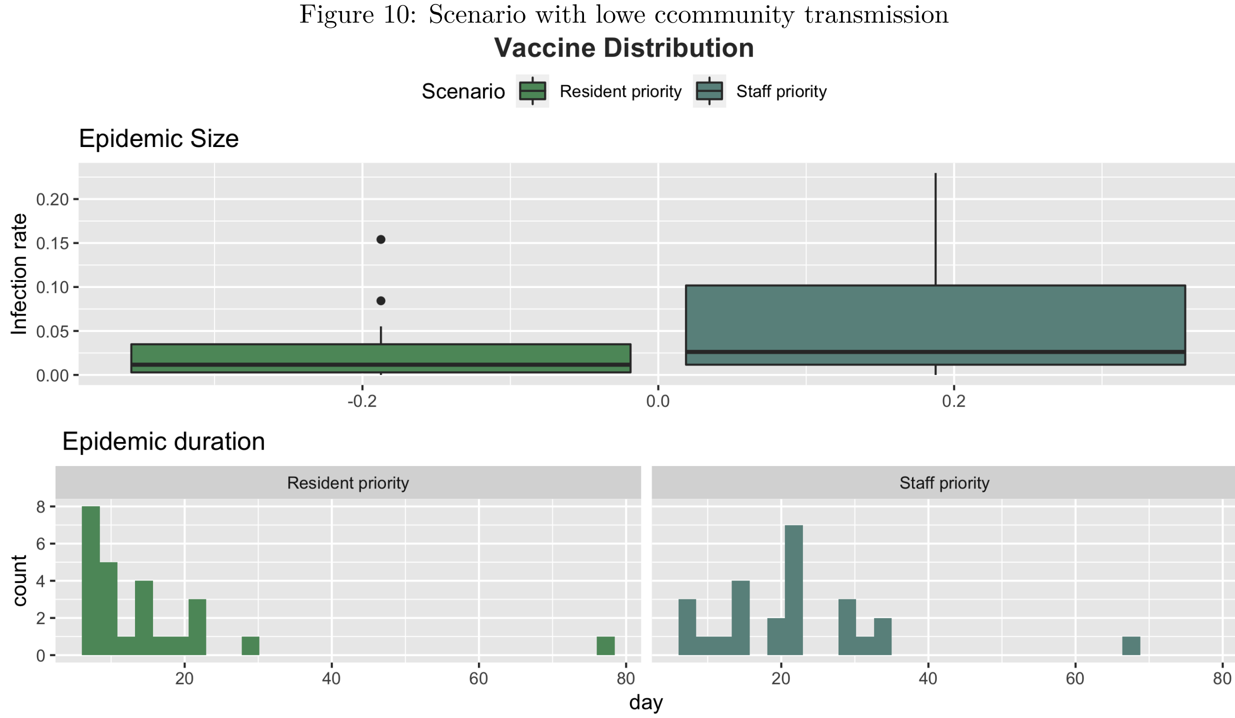


Figure 10: Scenario with lowe ccommunity transmission



Polack, Fernando P, Stephen J Thomas, Nicholas Kitchin, Judith Absalon, Alejandra Gurtman, Stephen Lockhart, John L Perez, et al. 2020. "Safety and Efficacy of the BNT162b2 mRNA Covid-19 Vaccine." *The New England Journal of Medicine*, 2603–15. https://doi.org/10.1056/NEJMoa2034577.