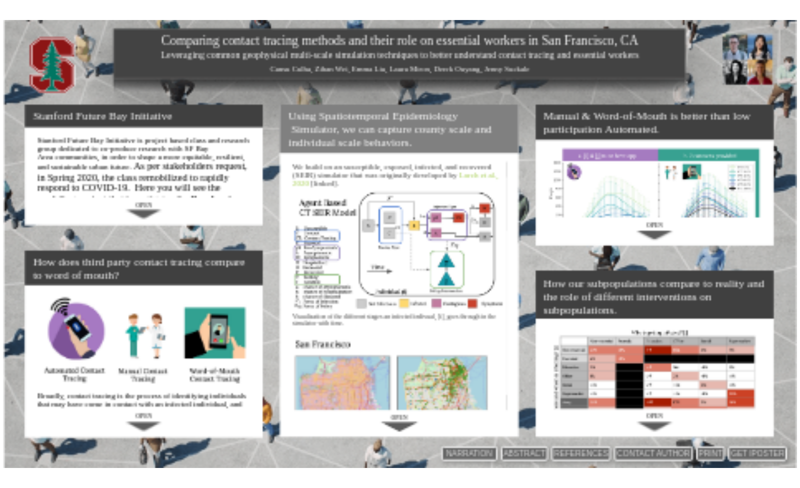
# Comparing contact tracing methods and their role on essential workers in San Francisco, CA



Leveraging common geophysical multi-scale simulation techniques to better understand contact tracing and essential workers

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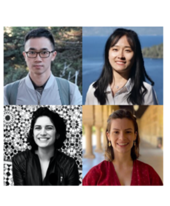

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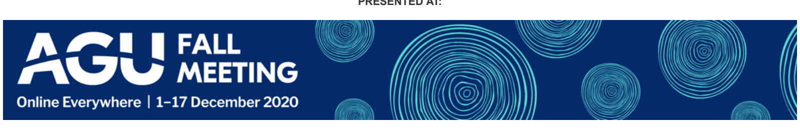
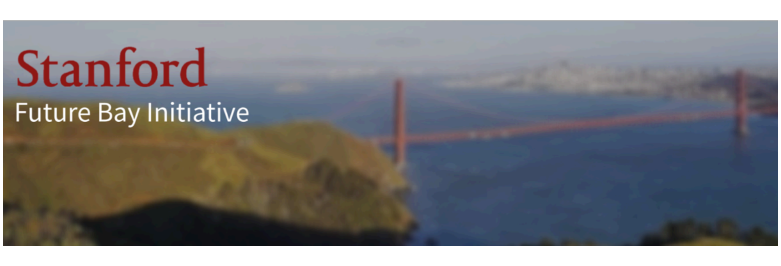



## STANFORD FUTURE BAY INITIATIVE

Stanford Future Bay Initiative is project based class and research group dedicated to co-produce research with SF Bay Area communities, in order to shape a more equitable, resilient, and sustainable urban future. As per stakeholders request, in Spring 2020, the class remobilized to rapidly respond to COVID-19. Here you will see the modeling project that investigates the Bay Area's response to COVID-19.




## HOW DOES THIRD PARTY CONTACT TRACING COMPARE TO WORD OF MOUTH?

Automated Contact Tracing | Manual Contact Tracing | Word-of-Mouth Contact Tracing

Broadly, contact tracing is the process of identifying individuals that may have come in contact with an infected individual, and warning them of the possible infection.

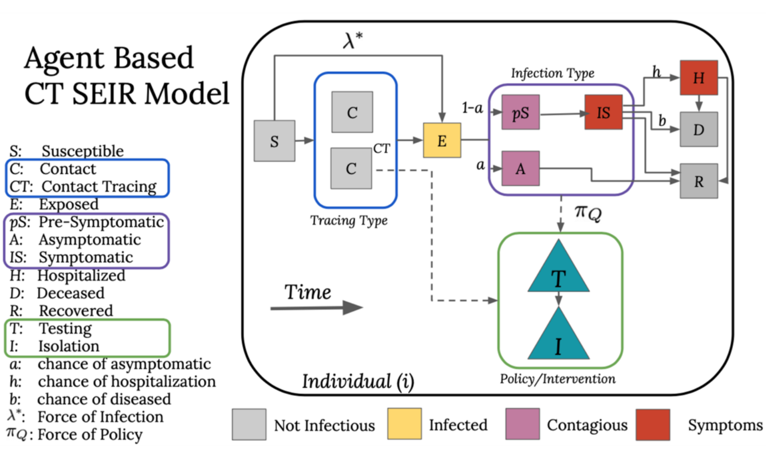
***"Word-of-mouth"*** contact tracing is when an infected person informs their internal social network, in which they have been in contact with, that they have the virus.

***"Manual"*** contact tracing is when an infected person reveals their social network to a trained hospital employee.

***"Automated"*** contact tracing relies on cellphone applications to record the contacts made by an individual. The approach relies on both the infected [i] and contacted [j] people need to have the application downloaded and functioning.

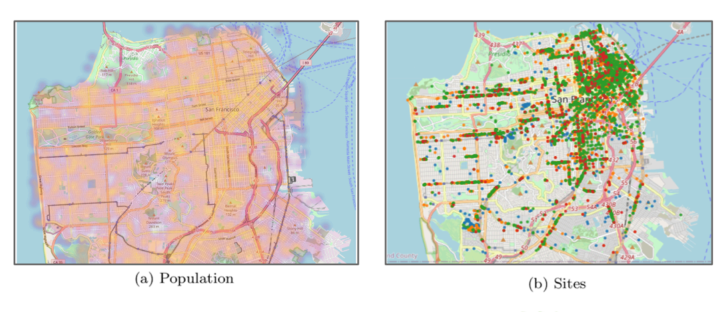
## USING SPATIOTEMPORAL EPIDEMIOLOGY SIMULATOR, WE CAN CAPTURE COUNTY SCALE AND INDIVIDUAL SCALE BEHAVIORS.

We build on an susceptible, exposed, infected, and recovered (SEIR) simulator that was originally developed by Lorch et al., 2020 [linked].




Visualization of the different stages an infected indivual, [i], goes through in the simulator with time.

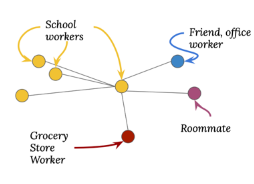
### San Francisco



(a) Population (b) Sites

OpenStreetMap

In Fig. a, orange indicates higher population density. Fig. b shows location types where schools and research institutes are blue, social places are orange, bus stops are green, workplaces are red, and supermarkets are purple.




Our biggest contribution to the simulator is adding essential workers and a social network to the population. Essential workers work at the site locations indicated above. Left figure shows who an individual might be in contact with in our simulation. We simulate grocery store, restaurant, school, and office space employees.

| | Education | Office | Social | Supermarket |
|---|---|---|---|---|
| 0-4 | 5 | 0 | 0 | 0 |
| 4-14 | 5 | 0 | 0 | 0 |
| 15-19 | 5 | 0 | 3.6 | 0.22 |
| 20-24 | 1.48 | 3.52 | 3.6 | 0.21 |
| 25-44 | 0 | 5 | 3.6 | 0.27 |
| 45-59 | 0 | 5 | 3.6 | 0.36 |
| 60-79 | 0 | 0 | 3.6 | 0.35 |
| $\geq 80$ | 0 | 0 | 3.6 | 0.35 |
| Supermarket Employee | 0 | 0 | 3.6 | 5 |
| Restaurant Employee | 0 | 0 | 5 | 0.27 |

**Table 1.** Mobility Rate

| | Education | Office | Social | Supermarket |
|---|---|---|---|---|
| Regular Agent | 5 | 5 | 0.64 | 0.4 |
| Supermarket Employee | 0 | 0 | 0.64 | 5 |
| Restaurant Employee | 0 | 0 | 5 | 0.4 |

**Table 2.** Duration of Each Visit (h)

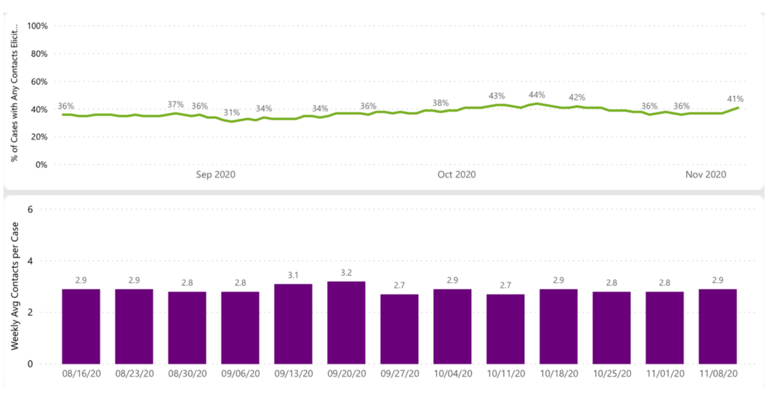
We assume each agent can randomly visit 1 school, 1 office, 10 restaurants, and 2 supermarkets.

### Contact Tracing

We implement different contact tracing in the simulation as follows:
(1) ***automated contact tracing*** requires both person [i] and [j] to be compliant to tracking

(2) ***manual*** and ***word-of-mouth*** contact tracing both only require person [i] to be complaint to testing. The person [j] they contact is random in our simulations. The simulation does not directly differentiate between the two types of contact tracing, but we suggest that word-of-mouth has a higher participation.

(3) while San Francisco does not provide details on what percent of positively tested individuals, [i], provide contacts, Santa Clara County does. Below we see that roughly 40% of positively tested individuals on average provide 2.5 contacts.




The green plot shows the percent of individuals who are providing contact information. The purple histogram shows the number of contacts that are provided. Click on image to learn more.

### Simulator and current set up limitations...

1. we do not simulate realistic worker type density and distributions, but the site type density and distribution are realistic. 5% of the population is in each essential worker type
2. we do not simulate school, grocery store, house party, social site, and office dynamics, such as class rooms and checkout lines
3. we do not simulate a lock down

## MANUAL & WORD-OF-MOUTH IS BETTER THAN LOW PARTICIPATION AUTOMATED.

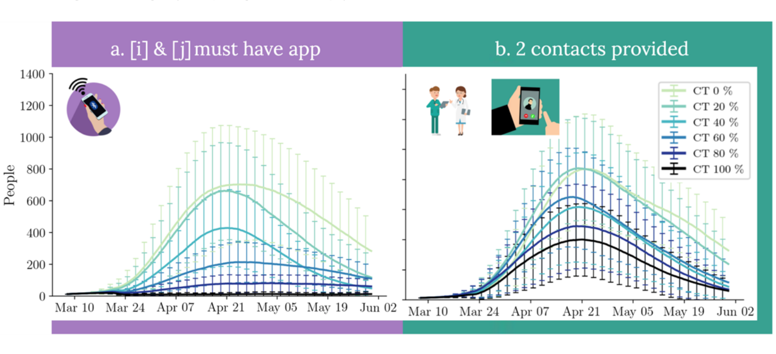



Figure a shows the number of infected individuals over time when different automated compliance rates are tested. Increasing the compliance rate decreases the spread of the virus. Figure b shows manual and word of mounth contact tracing at different compliance percents, where 2 people are contacted. We reach manual CT saturation around 5 people, because on average, individuals have fewer than 5 contacts within their social network (friends+coworkers). Household members of infected individuals are sheltered too. Variance is based on 40 random initializations.

### Discussion

1. In Switzerland, 20% of the population has the contact tracing app downloaded [link]. According to our simulations, if 20% of the population in SF had contact tracing, on average contact tracing would decrease the number of infections.
2. In Santa Clara County, roughly 40% of the population opts-in to manual contact tracing and provides roughly 2.5 contacts [link]. According to our simulations in SF, Manual contact tracing is potentially performing better than having 20% of the population using automated contact tracing.
3. *The percent of individuals who opt-in to Word-of-Mouth contact tracing is likely higher than Manual contact tracing.*

## SUBPOPULATION RESULTS, INTERVENTION TECHNIQUES AND COMPARISON TO OBSERVATIONAL DATA.

Who is getting infected? [i]

Where and whom is infecting? [j]

| | Non-essential | Essential | Education | Office | Social | Supermarket |
|---|---|---|---|---|---|---|
| Non-essential | 22% | 18% | 51% | 15% | 3% | 3% |
| Essential | 4% | 13% | | | | |
| Education | 3% | | 14% | 0% | <1% | 0% |
| Office | 1% | | <1% | 2% | <1% | <1% |
| Social | <1% | | <1% | <1% | 2% | <1% |
| Supermarket | <1% | | <1% | <1% | <1% | 30% |
| Away | 26% | | 66% | 17% | 5% | 34% |
| At-home | 9% | | 5% | 13% | 15% | 9% |

Our simulation results at the sub-population level. This allows us to compare our simulation results to studies of real populations. Reminder: essential workers are education, office, social, and supermarket workers.

Who is getting infected [i] and what contact tracing is deployed?

Where and whom is infecting? [j]

| | No contact tracing | | Automated, 20% | | Manual, 40% | | Word of Mouth, 100% | |
|---|---|---|---|---|---|---|---|---|
| | Non-essential | Essential | Non-essential | Essential | Non-essential | Essential | Non-essential | Essential |
| Non-essential | 22% | 18% | 17% | 15% | 15% | 13% | 10% | 10% |
| Essential | 4% | 13% | 4% | 8% | 3% | 8% | 2% | 4% |
| Total | 26% | 31% | 21% | 23% | 18% | 21% | 12% | 14% |

In our simulation...

1. most education workers are getting infected by non-essential workers (students in this case) or other education workers at school. Most students are not getting infected by education workers.
2. most non-essential individuals are infected by non-essential individuals
3. most essential workers are infected by essential workers
4. virus spreads most away from home, because we do not implement a lock-down
5. while automated contact tracing shows a greater relative decrease in infections for essential workers than non-essential individuals, Manual and Word-of-Mouth contact tracing decrease the total number of infected individuals all across.

### Comparing subpopulation study

Although most of the real case data is at the county or large population scale, there have been studies conducted at grocery stores, call center offices, and house holds to understand the spread of the virus. In the town of Liaocheng, the likelyhood of getting infected at a grocery store was two orders of maginute higher if you were a grocery store employee than if you were a shopper in February 2020. This is consistent with our observations of our simulation people.

We compare our results to infections at schools. Studies show young students do not spread the virus to many other young students or staff (education workers table above). While we do not look at young students spreading the virus amongst one another, our results show that all students can spread the virus to education workers. Lorden et al. suggest that since children can still contract the virus, the higher preventative measures in schools as compared to the rest of the community are the reason for the lack of school outbreaks. This is consistent with our results, because we simulate transmission to be at the same rate at all locations and show that outbreaks do happen at schools. Additionally, children appear to have a significantly lower chance of getting infected. We do not simulate a higher resistivity of the virus in children, but show that students infected by education workers at schools make up only 3% of the non-essential infections. While this is a low percentage, it is the highest category of essential workers to non-essential infections. Our results suggest that there would be outbreaks in schools; however, real world observations show that this is mainly happening in colleges and universities. This contrast between different age populations and different styles of schooling (for example, many college/university students might have higher transmission rates because students live together and enjoy social gatherings together) highlight the preventative measures in K-12 schools that decrease transmission and the resistance of young children to the virus, both of which are not simulated here.

Our simulator provides a platform to compare our results at the subpopulation scale to real observations.

## ABSTRACT

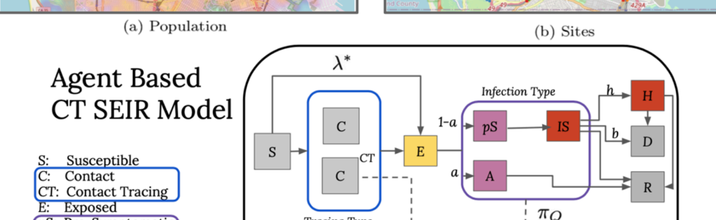
COVID-19 success stories from countries using contact tracing as an intervention tool for the pandemic have motivated US counties to pilot opt-in contact tracing applications. Contact tracing involves identifying individuals who came into physical contact with infected individuals. Recent studies show the effectiveness of contact tracing scales with the number of people using the applications. We hypothesize that the effectiveness of contact tracing also depends on the occupation of the user with a large-scale adoption in certain at risk occupations being particularly valuable for identifying emerging outbreaks.

We build on an agent-based epidemiological simulator that resolves spatiotemporal dynamics to model San Francisco, CA, USA. Census, OpenStreetMap, SafeGraph, and Bureau of Labor Statistics data inform the agent dynamics and site characteristics in our simulator. We test different agent occupations that create the contact network, e.g. educators, office workers, restaurant workers, and grocery workers. We use Bayesian Optimization to determine transmission rates in San Francisco, which we validate with transmission rate studies that were recently conducted for COVID-19 in restaurants, homes and grocery stores.

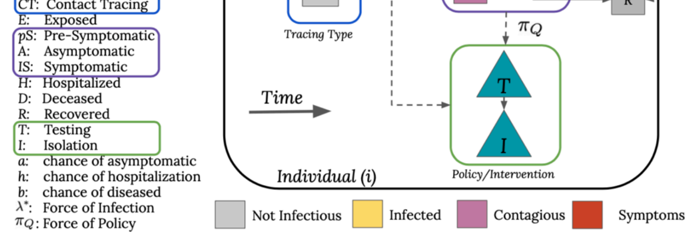
Our sensitivity analysis of different sights show that the practices that impact the transmission rate at schools have the greatest impact on the infection rate in San Francisco. The addition of occupation dynamics into our simulator increases the spreading rate of the virus, because each occupation has a different impact on the contact network of a city. We quantify the positive benefits of contact tracing adopted by at risk occupation workers on the community and distinguish the specific benefits on at risk occupation workers. We classify to which degree a certain occupation is at risk by quantifying the impact (a) the number of unique contacts and (b) the total number of contacts an individual has for any given work day on the virus spreading rate. We also attempt to constrain if, when, and for how long certain sites should be shut down once exposed to positive cases. Through our research, we are able to identify the occupations, like educators, that are at greatest risk.

We use common geophysical data analysis techniques to bring a different set of insights into COVID-19 and policy research.

San Francisco, CA, USA



(a) Population (b) Sites




## REFERENCES

Background image: https://sloanreview.mit.edu/article/your-dormant-social-network/
All cited material are hotlinked. Click on either word or image.