Mobility in Post-Pandemic under Social Distancing Guidelines: Congestion, Emission and Transit Contact Network

Center for Transportation, Environment, and Community Health
Final Report

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16. Abstract

COVID-19 has raised new challenges for transportation in the post-pandemic era. The social distancing requirement, with the aim of reducing contact risk in public transit, could exacerbate traffic congestion and emissions. We proposed a simulation tool to evaluate the trade-offs between traffic congestion, emissions, and policies impacting travel behavior to mitigate the spread of COVID-19 including social distancing and working from home. Open-source agent-based simulation models were used to evaluate the transportation system usage for the case study of New York City. A Post Processing Software for Air Quality (PPS-AQ) estimation was used to evaluate the air quality impacts. Finally, system-wide contact exposure on the subway was estimated from the traffic simulation output. The social distancing requirement in public transit was found to be effective in reducing contact exposure, but it had negative congestion and emission impacts on Manhattan and neighborhoods at transit and commercial hubs. While telework can reduce congestion and emissions citywide, in Manhattan the negative impacts were higher due to behavioral inertia and social distancing. The findings suggested that contact exposure to COVID-19 on subways is relatively low, especially if social distancing practices are followed. The proposed integrated traffic simulation models and air quality estimation model can help policymakers evaluate the impact of policies on traffic congestion and emissions as well as identifying hot spots, both temporally and spatially.

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1. INTRODUCTION

COVID-19 has proliferated around the world since the start of 2020 and cost lives and damaged economies like never before. Highly dense metropolitan areas are the most vulnerable places for the spread of infectious diseases (Alirol et al., 2011; Bell et al., 2009). Even with a potential vaccine, there is a serious public concern about the risk of epidemic spread in urban areas that impacts planning for cities. Such plans encompass traffic congestion and vehicle emissions, which are major issues in large metropolitan areas. Vehicle exhaust emissions are major contributors to greenhouse gas (GHG) emissions (US EPA, 2019) and cause negative health issues (Barone-Adesi et al., 2015; Batterman et al., 2014; Beelen et al., 2009; Slama et al., 2007). In a post-pandemic era, it is not clear what the trade-offs are between traffic congestion, emissions, and policies impacting travel behavior to mitigate the spread of COVID-19 including social distancing and working from home.

New York State set recovery plans in multiple phases (NY, 2020), where Phase 1 reopened only construction, agriculture, limited retail, manufacturing, and wholesale trade, while Phase 4 reopened most businesses and activities. As New York City (NYC) entered Phase 4 reopening from July 20, 2020, however, it became more evident that driving volume might increase post-COVID. With reopening the economy, traffic congestion returned to urban areas at varying rates. By late summer, vehicle miles traveled (VMT) was not only back to pre-COVID levels but in some areas the number of trips was more than 25% greater than pre-COVID levels (Streetlight, 2020). Vehicular traffic volumes at major New York City (NYC) crossings had bounced back to only 10% below pre-pandemic levels by the week of August 17 (Gao et al., 2020a). Meanwhile, transit trips were up from their 90% reduction during early April, but still down by 59% in October compared to 2019 (MTA Transit Data, 2020). The revenue loss due to transit ridership reduction and its subsequent series of effects are big issues in the post-COVID economic reopening. Without enough federal aid, the MTA may consider significant service reductions and lay-offs of operating staff, transit riders may face service cuts and decline of the quality of service due to the financial loss (MTA plan, 2020).

Social distancing as required by the Centers for Disease Control and Prevention (CDC) and other health authorities presents a new challenge not only for the transit system but also for the entire transport system in post-pandemic economic reopening. As driving volumes increase in the reopening, higher vehicle mode shares will exacerbate congestion and vehicle emissions. Consequently, this will negatively affect public health and climate change as long as this phase persists. There has been no strong empirical evidence that transit systems have been superspreaders for COVID-19 when social distancing practices are followed (Sam Schwartz, 2020; Sy et al., 2020; Tirachini and Cats, 2020). But previous studies do warn of the potential risks of outbreaks through public transit systems, especially if social distancing practices are not followed (Sam Schwartz, 2020).

With the added complexity of social distancing requirements, conventional traffic management policies may backfire on public health and hasten the spread of COVID-19. For example, congestion pricing shifts solo drivers to shared rides or public transit, which increase potential exposure when social distancing is not followed. However, Hu et al. (2020) and Wang et al. (2020) show that if even a fraction of people shift from transit to car mode, it will gridlock the streets and impact traffic congestion and emissions disproportionately. One recent report shows that pollution and low air quality may cause a higher risk of the pandemic spreading, presenting a 15% increase of death in regions with higher air pollution (Conticini et al., 2020). Congestion and emissions already have direct impacts on people's health, economic growth. and social equity, and social distancing further complicates the understanding of these impacts. Therefore, understanding the trade-offs between confining the spread of COVID-19 and traffic congestion and emissions and environmental impacts remains a critical policy objective to prepare communities to plan for the post-pandemic transportation system in the near future.

We propose to explore this research question using NYC as a case study. NYC entered Phase 4 reopening on July 20, 2020, but there is uncertainty about people's mode preference changes, and it is likely that many people may continue to work from home before vaccines are distributed throughout the population. Therefore, a traffic demand model is needed that is sensitive to individuals' mode choices and preferences to work from home while capturing traffic congestion and emission effects at a citywide level. To accomplish this, we employ agent-based travel simulation models built in MATSim (see Chow et al., 2020; Horni et al., 2016) combined with a Post Processing Software for Air Quality (PPS-AQ) estimation to evaluate the transportation system in terms of traffic congestion, emissions, and social proximity in public transit that can provide insights for transport policies in the post-pandemic era.

Agent-based simulation models are effective in capturing the interactions between agents and transportation systems to output the equilibrated simulation results at the agent level. A synthetic population was developed for the 8M+ population in NYC (Chow et al., 2020; He et al., 2020a) that includes employment in North American Industry Classification System (NAICS) industries. Based on the synthetic population along with calibrated transit schedules, a multi-agent simulation model, MATSim-NYC (Chow et al., 2020; He et al., 2020b) was developed for NYC. To

simulate traffic conditions during the COVID period, the MATSim-NYC model was recalibrated using ridership and work-from-home data during the COVID-19 period to update the mode choice utility functions for the synthetic population (Wang et al., 2020), resulting in a model called MATSim-NYC-COVID. The calibrated simulation model is used to test the network performance measures, including traffic congestion, emissions, and contact risk in transit to derive policy guidelines for cities.

The unique contributions of this study are threefold: (1) we analyze the spatial and temporal impact of COVID-19 on network performance for NYC in the post-pandemic era; (2) we evaluate the trade-offs between traffic congestion, emissions, and contact exposure in public transit; and (3) we provide insights into policies that can benefit the transportation system without sacrificing public health in post-pandemic era.

The rest of the paper is structured as follows. In section 2 we discuss the impact of COVID-19 on transportation and summarize the scenarios that will be evaluated in this paper. In section 3, we introduce the traffic simulation models, emissions estimation model, and contact exposure estimation in transit. Section 4 presents the results and discussions. Section 5 presents the conclusion and discusses future work.

2. REVIEW OF THE IMPACT OF COVID-19 ON TRANSPORTATION AND POTENTIAL SCENARIOS

2.1 Impact of COVID-19 on traveler's mode preference

COVID-19 is changing people's travel behavior, with people shifting their mode preferences from shared use modes (e.g., public transit, shared taxis, carpooling) to more personal modes (auto, bikeshare, walking). After the outbreak of COVID-19, health authorities published guidelines urging people to avoid large crowds and contact with others (CDC 2020c; DfT, 2020). However, these are features of transit systems at normal times. Facing this infectious disease, people may try to reduce their risk by taking precautionary actions (Sadique, 2007). Many people avoided taking public transit as it is difficult to maintain social distance and avoid contact with others. After the severe acute respiratory syndrome (SARS) epidemic in 2003, a survey found that 75% of responders reported avoiding public transit in response to the perceived threat of the epidemic (Sadique, 2007). In NYC, subway data from the Metropolitan Transportation Authority (MTA) shows that transit ridership dropped by 90% during April 2020, the height of the first wave of the COVID-19 outbreak in 2020 (Gao et al., 2020b). The estimated impacts of COVID-19 on mode choices during the shutdown is shown in **Figure 1 (**Wang et al., 2020). Compared to the pre-COVID period, the mode share of transit decreased about 19%, while the mode share of cars increased about 6% in the COVID period.

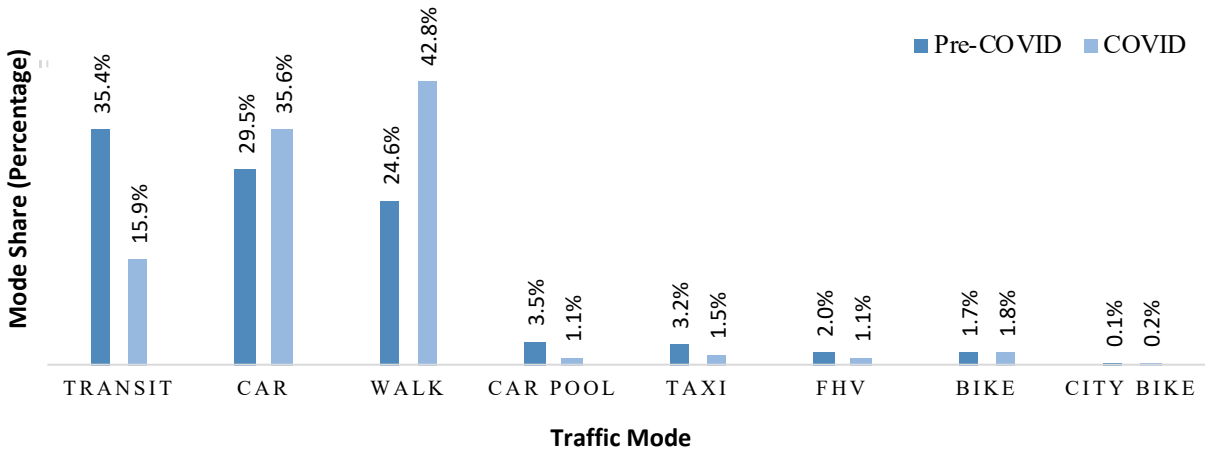


Figure 1. Comparison of mode share in the pre-COVID model and the COVID model (source: Wang et al., 2020).

COVID-19 has caused changes in traffic patterns due to social distancing practices, but what is unknown is how long these changes will last, and whether these patterns will return to the pre-COVID behavior. As such, it is difficult to predict the long-run effects on the transit system. On the one hand, transit ridership may slowly return to pre-COVID levels in the future. On the other hand, people's travel behavior may be changed by a longstanding fear of transit. As the community reopens, the changed behavior may exhibit inertia (Cherchi et al., 2014; Chorus and

Dellaert, 2009; Srinivasan and Mahmassani, 2000), where travelers continue to behave in a stay-at-home manner due to residual caution.

With more data revealed during the recent reopening, we are seeing a shift to an outright "new normal" for transportation. In many cities, transit ridership has rebounded during reopening, but is still lower than before the pandemic. Subway ridership from multiple cities in China shows that 85% of pre-COVID ridership levels has been restored six months after full reopening. Where a second wave occurred, only 65% of ridership was restored compared to pre-COVID levels (Gao et al., 2020a). Ridership on the Tokyo Metro dropped by 60% in April 2020 during the lockdown period and reached 63% of normal levels by August after reopening (Sam Schwartz, 2020). Ridership on the Paris metro system dropped to just 5% of pre-pandemic rates by April 2020 and by late June 2020 recovered to 55% of pre-pandemic rates (Sam Schwartz, 2020). Transit ridership remains far below pre-COVID levels, but car traffic has roared back. Even with more people working from home after the outbreak of COVID-19, INRIX has reported that VMT across the United States surpassed 100% of normalized VMT in July 2020 (Markezich, 2020). In NYC, after the Phase 4 reopening beginning in July 2020, transit ridership was restored to 41% of normal by October 2020, but VMT was restored to 104% of pre-COVID levels (Streetlight, 2020).

2.2 Impact of CDC guidelines on transit capacity

Health authorities across the world have prepared guidelines for people to safely use public transit and prevent the spread of COVID-19. For instance, for employees who commute to work using public transportation or ride-sharing, the CDC suggested that employers should "offer employees incentives to use forms of transportation that minimize close contact with others (e.g., biking, walking, driving or riding by car either alone or with household members)" (CDC, 2020b). For people who need to use public transportation, the CDC suggested they "avoid touching the surface, practice social distancing, and practice hand hygiene" (CDC, 2020c). Ultimately, social distancing guidelines require people to stay at least 6 feet (2 meters) from other people.

To ensure social distancing, some cities have reduced vehicle capacity for public transit during the shutdown and reopening periods. For example, the Metropolitan Transit Authority of Harris County (METRO), Texas, reduced seating by 50% by tagging seats as unavailable during the shutdown and the current reopening. When buses reach capacity, digital signs advise individuals to wait for the next bus (Houston Metro, 2020). New Jersey Transit Corporation (NJ TRANSIT) was ordered to cut capacity to 50% until July 15, 2020, when the state entered reopening stage 2, after which full-capacity operations have resumed (NJ TRANSIT, 2020). In NYC, there was no transit capacity restriction during shutdown and reopening, although new markings and signage with directional cues have been used to help maintain social distancing and overnight subway closures from 1 a.m. to 5 a.m. to disinfect stations and trains were instituted (MTA Service, 2020). Maintaining the social distancing required by CDC guidelines should impose an effective reduction on transit capacity. However, it is unclear how such a policy will impact transit ridership and the contact risk that commuters will face on their daily commutes.

Although there is no strong empirical evidence that transit systems have been superspreaders for COVID-19 (Sam Schwartz, 2020; Sy et al., 2020; Tirachini and Cats, 2020), high population density may increase the risk of spreading infectious disease (Salathé et al., 2010; Yang et al., 2007). Understanding the daily travel patterns of transit passengers to identify hotspots is important for studying virus spreading, especially for large cities like NYC. Previous researchers have studied social interaction and disease spreading using "contact networks" (Bóta et al., 2017; Litvinova et al., 2019; Salathé et al., 2010). A contact network is a network structure used to represent the potential physical encounters between individuals. Mo et al. (2020) used smart card data to model disease spread in transit in the case of COVID-19. However, it is expensive and time intensive to collect such real data for each individual. Furthermore, there are issues of privacy, as explained in the literature (Funk et al. 2010; Nassir et al. 2012). Therefore, a model that can capture individual space-time trajectories is needed to compute measures of proximity like contact networks to evaluate the impact of social distancing policy.

2.3 The rise of telework and staggered work hours

Telework is one of the most popular traffic demand management strategies for reducing commuting trips. As a public health measure designed to stem the spread of COVID-19, teleworking increased abruptly after the outbreak of COVID-19. Before the COVID-19 outbreak, there was a clear difference between the number of people who could telework and the number who did so. The impacts of telework on travel behavior, traffic congestion, and emissions have been widely studied in previous research (Asgari and Jin, 2017; Choo et al., 2005; Helminen and Ristimäki, 2007; Shabanpour et al., 2018). The COVID-19 pandemic has since forced many companies' employees to work from home on a large scale, behavior which may continue once the pandemic subsides (Kramer & Kramer, 2020). A number of companies have switched to work-from-home (WFH) policies during the pandemic including

Amazon, Facebook, Salesforce, Siemens, Microsoft, Twitter, and Aetna (Courtney, 2020). As the spread of the COVID-19 continues to slow in Spring 2021, many companies have announced plans to reopen offices, for example, Google announced a hybrid return to work plan that including both remote and in office options (Kelly, 2021). The study by Dingel and Neiman (2020) estimated that 37% of jobs in the United States could be performed entirely at home. Sostero et al. (2020) estimated that the teleworkable rate ranges between 33% and 44% in five European Union member states. Higher teleworking rates could in turn reduce traffic congestion and negative transport externalities, such as greenhouse gas emissions. For transit, if a fraction of transit riders shifts to working remotely, a de-densified transit could be achieved.

Besides telework, health authorities are encouraging employers to provide flexible work hours that can shift some commuting traffic to off-peak periods. This flexibility in work schedules is also called staggered work hours (SWHs). The SWHs strategy allows employees to adjust their commuting time away from peak periods, which can help lower the number of vehicles on the road during peak times. The COVID-19 guidance for businesses published by the New York City Department of Health and Mental Hygiene (NYC Health) suggests employers "Create staggered work hours and make work schedules flexible. For example, instead of all staff reporting 9 a.m. to 5 p.m., consider changing some work hours to 10 a.m. to 6 p.m. or 8 a.m. to 4 p.m." (NYC Health, 2020). For transit, SWHs can help reduce population density during peak hours, a change that can increase safety while the pandemic exists.

These trends raise questions as to how telework and flexible work hours might impact traffic performance and transit safety. Is the benefit evenly distributed throughout the city? To address this question, we need a travel demand model that is sensitive to the industries that commuters are employed by to compute the proportion of people that will work from home in the post-pandemic era.

2.4 Scenarios

We identify factors that may have affected or will affect the transportation system as shown in **Figure 2**, and design scenarios with the aim of simultaneously protecting public health from COVID-19 and alleviating traffic congestion and emissions. The four key factors that are studied include: travelers' mode preference changes due to the pandemic, social distancing guidelines and transit operations, the rise of remote work, and flexible work schedules.

A total of 12 scenarios are designed to address the research questions discussed earlier. Because there is uncertainty about the amount of inertia in travel mode choices during reopening (without a vaccine), we run two sets of scenarios that assume pre-COVID mode choice and COVID mode choice. The impact on ridership of reduced transit operational capacity to maintain social distancing is also unclear. As such, separate scenarios are modeled for 100% capacity and 50% capacity operations. Finally, three sets of post-pandemic strategies are evaluated: no change (100% commuting without telework and SWHs), partial commuting with telework assumed, and 100% commuting with SWHs. The scenarios listed in **Table 1** are designed to investigate the transportation system in the post-pandemic era.

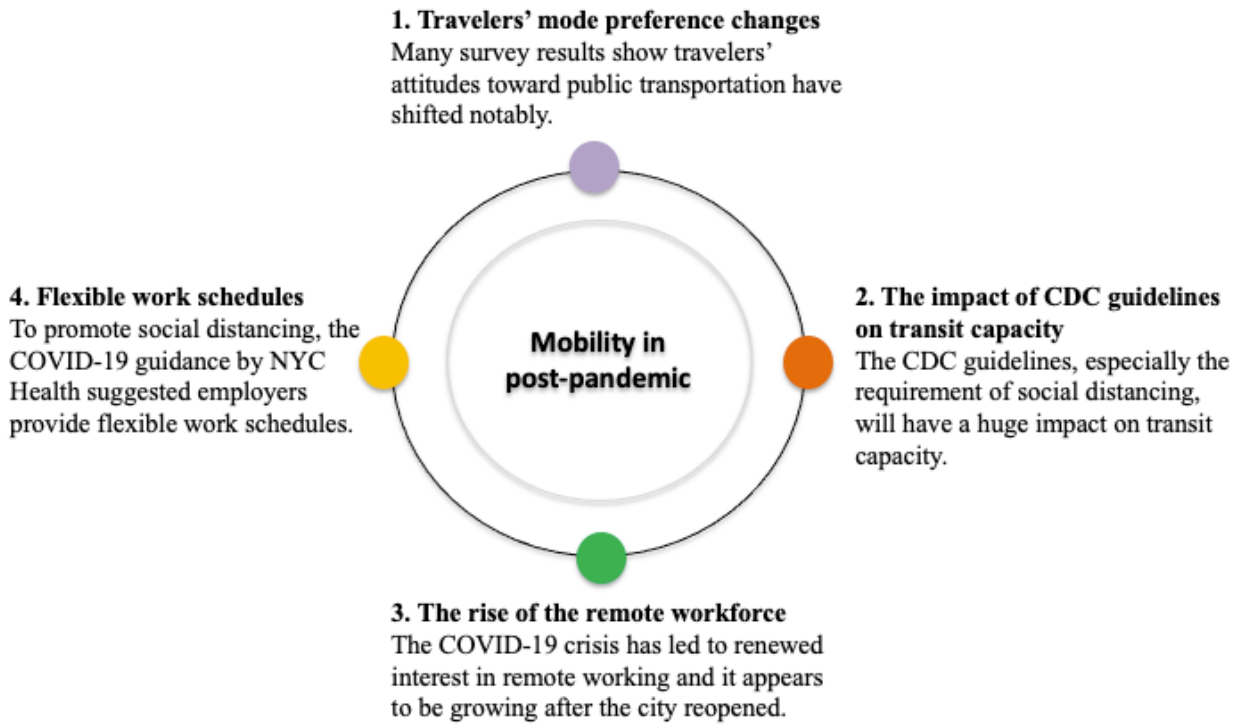


Figure 2. The impact of COVID-19 on transportation systems.

Table 1 Scenarios to investigate the changes in the transportation system in the post-pandemic reopening

Scenarios	Mode preference	Transit Capacity	Commuting
s0 (Base scenario)	pre-COVID level	100% capacity	No change (100% commuting)
s1 (PreCOVID-100-Telework)	pre-COVID level	100% capacity	Telework
s2 (PreCOVID-100-SWHs)	pre-COVID level	100% capacity	Staggered work hours
s3 (PreCOVID-50-No)	pre-COVID level	50% capacity	No change
s4 (PreCOVID-50-Telework)	pre-COVID level	50% capacity	Telework
s5 (PreCOVID-50-SWHs)	pre-COVID level	50% capacity	Staggered work hours
s6 (COVID-100-No)	COVID level	100% capacity	No change
s7 (COVID-100-Telework)	COVID level	100% capacity	Telework
s8 (COVID-100-SWHs)	COVID level	100% capacity	Staggered work hours
s9 (COVID-50-No)	COVID level	50% capacity	No change
s10 (COVID-50-Telework)	COVID level	50% capacity	Telework
s11 (COVID-50-SWHs)	COVID level	50% capacity	Staggered work hours

3. METHODOLOGY

3.1 The agent-based traffic simulation models

An agent-based transportation simulation framework—MATSim—is used to simulate large-scale transport on a per-agent timestep-based level (Horni et al., 2016). MATSim optimizes the daily plans for each agent by iteratively running the three main components in MATSim: execution, re-planning, and scoring (Balmer, 2007; Horni et al., 2016). The objective of MATSim is to optimize the daily plans for each agent by iteratively running the three

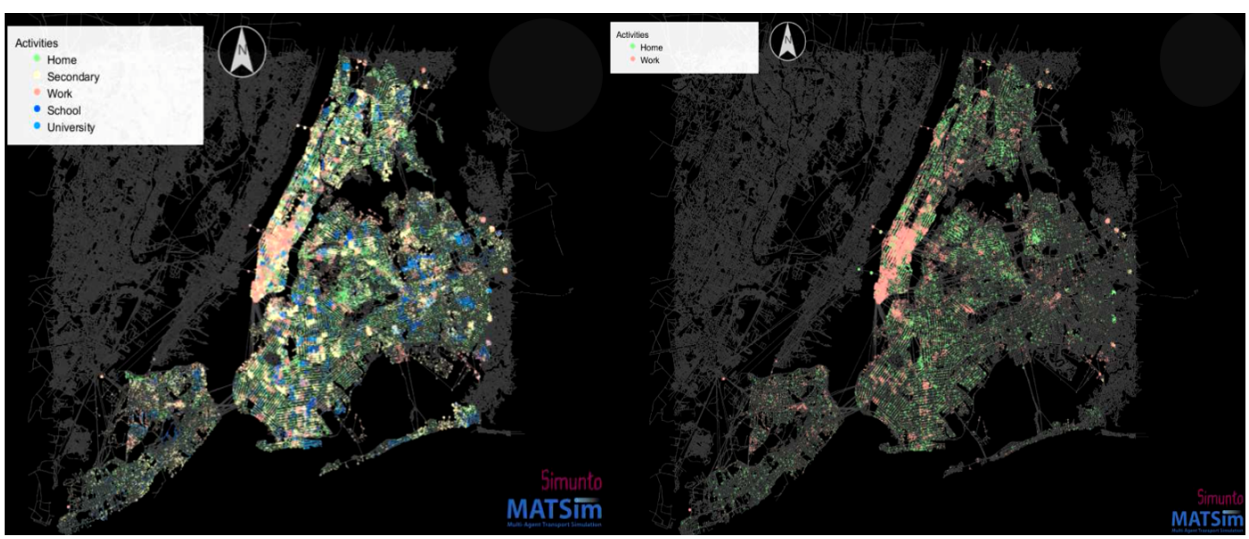
components. In the execution module, all agents choose one plan and execute their chosen plan. The scoring module uses a utility function to evaluate the performance of each agent's plan in the execution module. The re-planning module adjusts the plan elements (e.g., departure time, traffic mode) according to the planned score and adapts plans to traffic conditions.

Agent-based simulation models are effective in capturing the interactions between agents and the transportation system to output the equilibrated simulation results at the agent level. A synthetic population of NYC was created that incorporates the demographic information and travel patterns of 8.24 million people for the base year of 2016 (He et al., 2020a). We extracted people's travel agendas from 2010/2011 Regional Household Travel Survey (RHTS), which was conducted by NYMTC, includes 18,965 households with 143,925 linked trips. We assign these travel agendas minus travel mode information to individuals in the synthetic population according to their home locations and work or school enrollment status. We also sample from the travel survey agendas to replicate agendas for the synthetic population. The result synthetic population includes personal attributes like age, gender, school enrollment status, work status, and work industry, and household attributes like income group, household size, and number of cars owned. The built synthetic population is validated and fit well with the real data: an average 4% difference in the distribution of the employment industry proportions compared to 2016 Longitudinal Employer-Household Dynamics (LEHD), and 3% to 9% difference compared to different attributes in the NYMTC 2040 SED Forecasts. A summary is provided with details of the synthetic population available in He et al. (2020a).

MATSim-NYC (**Figure 3**(a)) was developed for NYC at normal conditions (pre-COVID) based on the synthetic population along with transit schedules from General Transit Feed Specification (GTFS) data (Chow et al., 2020; He et al., 2020b). The agent-based simulation tool is used for this study for four reasons:

1) Work-from-home rates are modeled differently by industry of employment, which can be captured with a synthetic population (He et al., 2020a).
2) MATSim-NYC, the underlying model, is the only citywide travel demand modeling tool that includes emergent mobility modes like Citi Bike and Uber/Lyft (He et al., 2020a).
3) MATSim captures time-of-day sensitivities, which are essential for evaluating dynamic transportation systems like public transit with differing schedules or staggered work hours.
4) The multi-agent simulation can track individual trajectories over time, which makes it possible to compute interactions between travelers for potential COVID-19 exposure analysis.

For the mode choice of the synthetic population, a tour-based nested logit model was estimated for Manhattan and non-Manhattan population segments. Since MATSim's mode utility functions are assumed to follow a flat multinomial logit (MNL) structure as opposed to nested structures, the estimated mode choice model was converted into an equivalent trip-based MNL structure. The validation of the model was conducted using the 2017 Citywide Mobility Survey provided by the New York City Department of Transportation (NYCDOT) and shown to be a good fit (He et al., 2020a).



(a) (b)

Figure 3. Illustration of the simulation for (a) the pre-COVID model and (b) the COVID model.

For the network topology, first the base topology was converted into a network in MATSim from Open Street Map (OSM) and then a transit network generated from GTFS data is added (the transit schedule for all scenarios is generated from GTFS data on Monday August 3, 2020). The road network is shown in **Figure 4** (left), while the green layer in **Figure 4** (right) shows the transit network. For computational efficiency, MATSim models in other cities like Zurich (Balmer et al., 2008) typically use a population scaled to 10%, because of the size of NYC, the population in the simulation is scaled to 4% of the real population (~320K agents) with calibration of the road and transit networks. Since a 4% scaled population is used, the model results will need to increase by a factor of 25 to match the full population size.

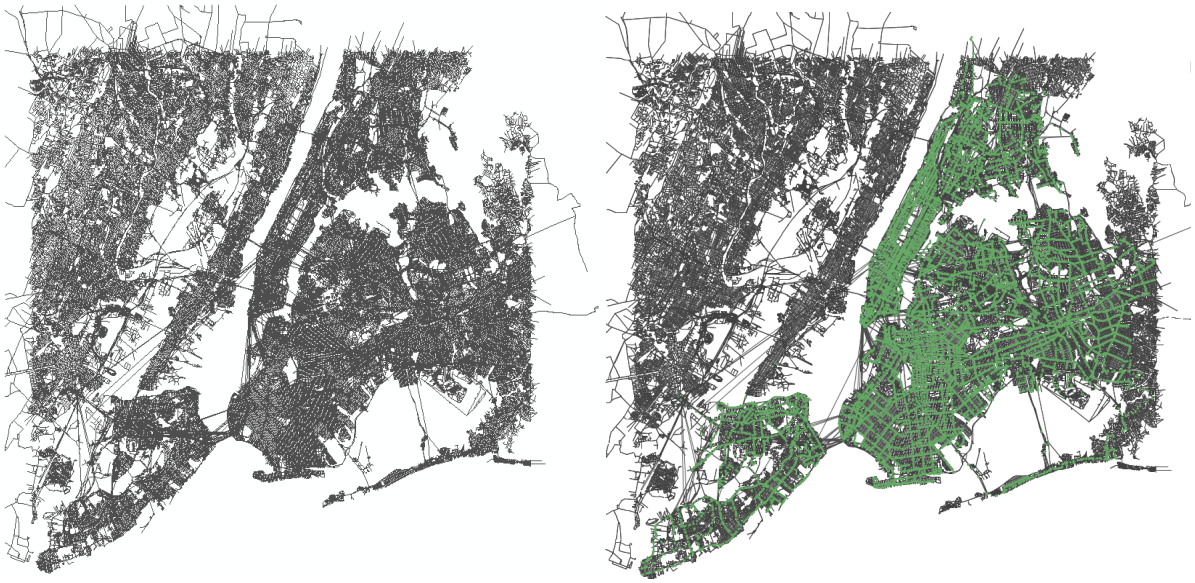


Figure 4. Input road network (left) and transit network (right) of NYC.

MATSim-NYC was calibrated to 2016 conditions (Chow et al., 2020; He et al., 2020a; He et al., 2020b). The road network is calibrated use 2016 bridges/tunnels volumes data (NYCDOT, 2016) and INRIX (https://inrix.com/) speed data from NYCDOT. The average relative difference between the simulated link speed and the INRIX data is 7.2% on freeways and 17.1% on arterials. A screenline was defined along the East River that consists of Queensboro Bridge, Williamsburg Bridge, Queens Midtown Tunnel, Hugh Carey Tunnel, Manhattan Bridge, and Brooklyn Bridge. The average difference between the total daily simulated volumes and real volumes is only + 1.8% (compared to 2.4% with the NYBPM 2010 model). The validation of the MATSim-NYC trip assignment was conducted by comparing the outputs to two data sets: ten stations from the 2016 Average Weekday Subway Ridership data and fifteen traffic locations from the 2014-2018 Traffic Volume Counts data. The difference in daily ridership among the ten stations is 8%, while the median difference in the traffic volumes among the traffic sites is 29% (Chow et al., 2020).

To study the changes in travel behavior due to COVID-19, the synthetic population's mode choice model and MATSim-NYC's network were recalibrated by Wang et al. (2020) using ridership and work from home data during the COVID-19 stay-at-home period (March to May 2020) to update the mode choice utility functions for the synthetic population. The population's agenda was modified to have work-from-home rates to fit to data from Dingel and Neiman (2020) and GTFS from that period. The recalibrated model (which is called the MATSim-NYC-COVID model in **Figure 3**(b)) captures the effect of COVID-19 on shifts in mode preferences from users during the stay-at-home period (Wang et al., 2020). Using this recalibrated model, we can compare the post-pandemic reopening scenarios where the population is assumed to continue to exhibit either the same mode preferences or some degree of change in their mode preferences.

As NYC entered Phase 4 reopening from July 20, 2020, we evaluated the performance of the MATSIM-NYC-COVID model during the post-pandemic era in Wang et al. (2020) using VMT data from Streetlight (Streetlight, 2020), daily transit ridership data from the MTA (MTA Transit Data, 2020), and Citi Bike trip ratios from Citi Bike system data (Citi Bike, 2020). The transit schedule was updated to Monday August 3, 2020 from GTFS data. Assuming people's mode preferences during the crisis are maintained, the trip ratio was predicted for all traffic

modes assuming all the commuting traffic returns. The predicted VMT restoration from the simulation model is 137%, while the observed average daily VMT in October 2020 was restored to 104% of pre-COVID levels. The observed average daily transit ridership in October 2020 was restored to 41% of pre-COVID level and the predicted transit trip restoration was 77%. The observed average Citi Bike ridership in September 2020 was restored to 101% compared to 2019, and the predicted Citi Bike trip ratio was 110%. It should be noted that some industries that were planned to be fully reopened in Phase 4 did not do so (e.g., universities, indoor dining, etc.). Therefore, predicted VMT and transit ridership are higher than the observed data. In addition, the overestimation of the trip ratio in Wang et al., (2020) might have arisen because the reopening scenarios failed to capture telework populations, which we address in this study by incorporating a telework ratio in the scenario analysis.

To evaluate the impact of telework during reopening, the WFH rate was calculated based on a real-time survey conducted by Fluent Pulse (Fluent Pulse, 2020). Their results showed that "if given the option, 59% of Americans currently working from home would continue to do so once restrictions are lifted and offices reopen." According to the classification of teleworkable employment for different industries by Dingel and Neiman (2020), the WFH rate during the COVID-19 shutdown was estimated as 44% for NYC by Wang et al. (2020). We assume during reopening that 59% of people continue to WFH based on findings from the survey by Fluent Pulse (Fluent Pulse, 2020). **Table 2** shows the estimated WFH rates during COVID-19 based on the classification in Dingel and Neiman (2020) and the estimated WFH rates in the post-COVID reopening corresponding to the survey results.

To test the impact of staggered work hours, we simply assume 50% of people change their departure times to one hour earlier and the remaining 50% of people change their departure time to one hour later. The assumptions for staggered work hours and telework can be customized in the future when more data is revealed.

Table 2 Estimated WFH rates during COVID-19 and post-COVID

ID	Industry	Estimated WFH rates for COVID-19 shutdown	Estimated WFH rates for post-COVID reopening
1	Not working	1	0.59
2	Agriculture, forestry, fishing and hunting, and mining	0.92	0.54
3	Construction	0.81	0.48
4	Manufacturing	0.78	0.46
5	Wholesale trade	0.48	0.28
6	Retail trade	0.86	0.51
7	Transportation and warehousing and utilities	0.72	0.42
8	Information	0.28	0.17
9	Finance and insurance, and real estate and rental and leasing	0.41	0.24
11	Professional, scientific, and technical services	0.2	0.12
12	Management of companies and enterprises	0.21	0.12
13	Administrative and support and waste management and remediation services	0.69	0.41
14	Educational services and health care and social assistance	0.46	0.27
15	Arts, entertainment, and recreation and accommodation and food services	0.83	0.49
16	Other services, except public administration	0.69	0.41
17	Public administration	0.59	0.35

3.2 Emissions and energy simulation

The PPS-AQ developed by Cornell University is used to estimate the air quality impacts of reopening scenarios. PPS-AQ integrates the outputs from the traffic simulator with the emission rates from the US Environmental Protection Agency (US EPA) Motor Vehicle Emission Simulator (MOVES), as shown in **Figure 5 (**Baghestani et al., 2020). PPS-AQ first adjusts the vehicle miles traveled and speed on each roadway segment based on the observed data for the base condition and according to seasonal and monthly variations. To estimate carbon dioxide

equivalent (CO_2eq) and particulate matter with diameters that are 2.5 micrometers and smaller ($PM_{2.5}$) emissions rates in grams/mile, we tailored US EPA MOVES with local data including source type population, inspection-maintenance programs, fleet age distribution, average speed distribution, fuel characteristics, and meteorology data. MOVES also has the ability to estimate emissions rates based on road types including rural restricted, rural unrestricted, urban restricted, and urban unrestricted. The emissions rates are estimated for 16 speed bins from 2.5 to 75 miles per hour at 5 mph increments. PPS-AQ calculates the emissions by multiplying traffic volume on the roadway segments with the emissions rates matched for roadway type and average travel speed for every hour during a daily period. Finally, to calculate the total emissions inventory, the PPS-AQ aggregates the emissions on roadway segments for the entire roadway network.

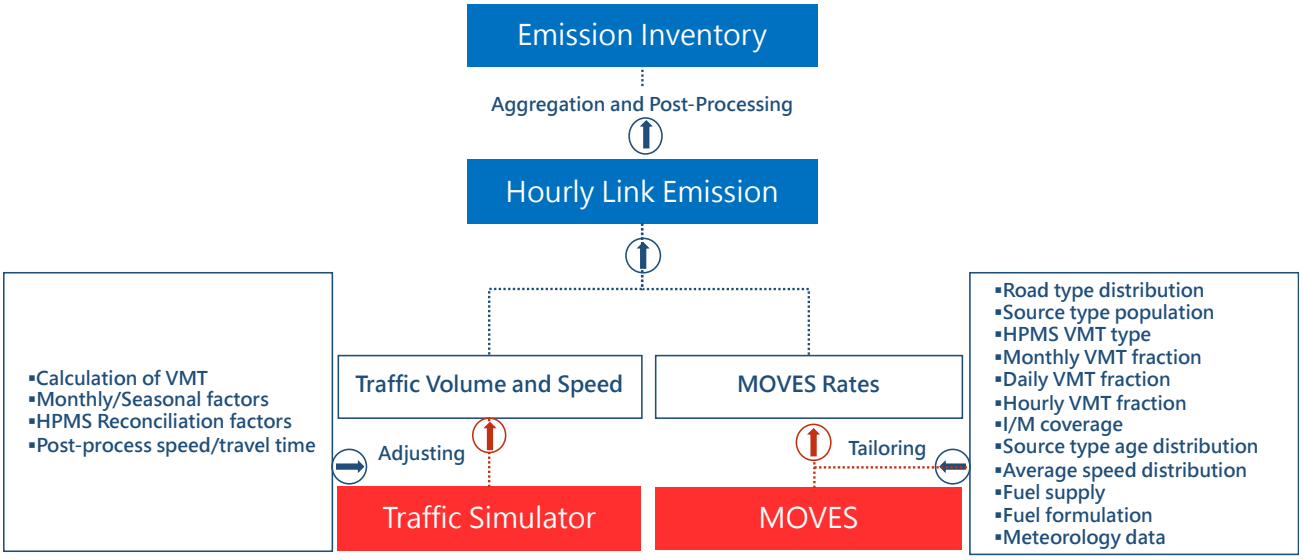


Figure 5. Integrated emissions modeling framework.

3.3 Quantifying contact exposure in transit

One of the advantages of using a multi-agent simulation is that individual space-time trajectories can be simulated, which allows us to compute measures of proximity such as contact networks. The contact network structure is used to quantify the number of contacts made by the movement of individuals using transit (Bóta et al., 2017). The output from MATSim includes the activity and travel path for each agent. Transit trips can be extracted with a detailed commuting pattern at both temporal and spatial levels. The contact network can be used to calculate the number of contacts in the transit system as well as to identify hot spot locations that need to be closely monitored for the control of disease spreading.

We define the contact network as a graph $G(V, E)$, which is a set of nodes (V) together with a set of edges (E). The nodes in the contact network refer to passengers and the link between them is the edge if two passengers were traveling on the same vehicle at the same time. This network is undirected since the relationship is mutual. The edge of the network includes three labels: *contact start* indicates the start time of the contact between two passengers, *contact duration* indicates the length of the contact and *vehicle id* indicates in which vehicle the contact takes place. The "vehicle" here refers to specific car within a train. Since MATSim only provides the number of people enter/exit of a subway train, but there are no contact for people in different vehicles, so we will divide the total number of contacts by the number of vehicles per train. A typical subway train consists of 8 to 10 vehicles, here we assume each train has 10 vehicles.

The original network can be divided into several subgraphs based on the edge labels. We assume passengers are only considered in the contact network if their contact duration is longer than a certain amount of time. According to public health guidance from the CDC, individuals who have had close contact (< 6 feet) for longer than 15 minutes with an infected person should stay at home and self-monitor for COVID-19 symptoms (CDC, 2020c). We define the measure of the number of contacts with duration (t_d) longer than 15min as **individual contact exposures** to COVID-19, which is used only as a measure of magnitude without consideration of probability or risk (see Jenelius et al., 2006). System-wide contact exposure is the aggregation of individual contact exposure.

From the MATSim output, we can obtain the travel path of each individual passenger, so we have the information for each passenger i including all transit vehicles on which passenger i traveled, and the boarding time and duration for all involved vehicles. Then we can obtain the corresponding contact network for the transit system by counting the pairs of contact exposure between each individual (the number of edges between each pair of nodes with label $t_d > 15\ min$). The sum of those pairs is the system contact exposure. We are not modeling the risk or probability of disease spread. A higher contact exposure means there is a higher pool of potential contacts from which disease spread may occur. The main objectives here are to evaluate the impact of social distancing requirements and to identify transit routes with higher numbers of contacts made.

The contact network is represented as G_{--}. Since the entire subway contact network for NYC is very large and hard to visualize, the G_{15} contact network at 9–10 a.m. on a typical day, including 681 nodes and 1,753 links (based on the 4% sample population), is illustrated as an example in **Figure 6** (results are aggregated over the hour). The nodes represent individual agents (passengers) and the edges/links connect passengers that are in the same vehicle at the same time. The size of the node represents the number of contacts he/she has, the larger the node, the higher the number of contacts. The color of the edge indicates the contact duration, the darker the color, the longer the contact duration.

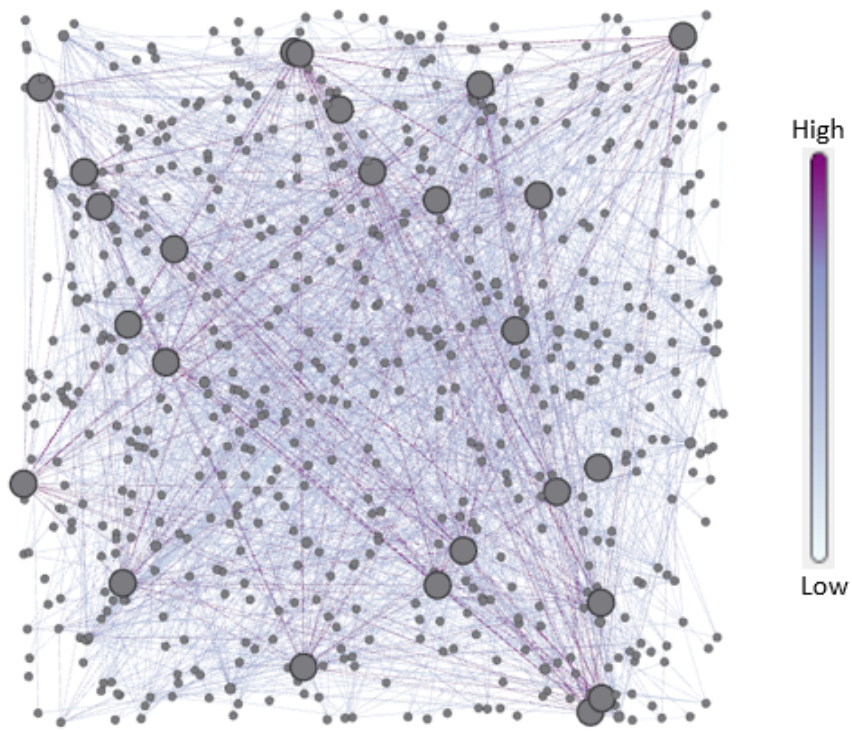


Figure 6. Contact network at 9–10am for a typical day in the NYC Subway (G_{15} contact network).

4. RESULTS AND DISCUSSION

The increased use of private cars may continue well after the COVID period until vaccines are distributed through the population, especially if the perceived risk of public transit remains high. This will undoubtedly affect traffic congestion and emissions in the post-pandemic era. In this section, we will analyze traffic congestion, emissions, and contact exposure in transit under different reopening scenarios. It should be note that the results reply on the scenario settings and assumptions we mentioned in previous discussions, a subsection of limitations will be presented in the end of this section. The most recent transit schedule at the time of writing (GTFS on August 3, 2020) is applied for all scenarios. The simulation model for each scenario was run for 100 iterations (shown to be sufficient to reach demand convergence for MATSim-NYC in Chow et al. (2020) and the computation time for each scenario was, on average, about 14 hours using an Intel Xeon 2.1 GHz with 64 GB RAM.

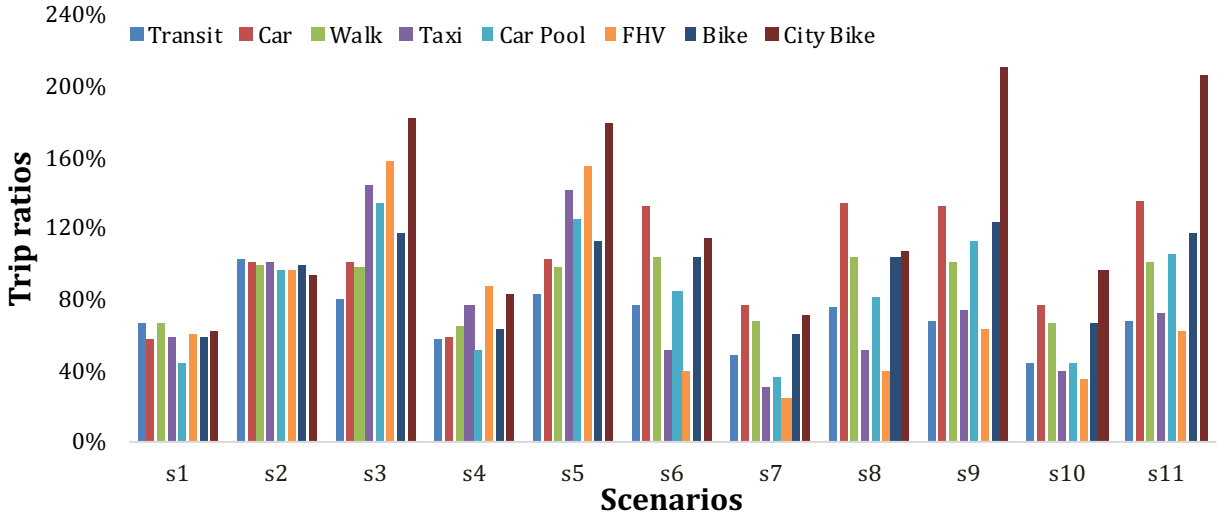
4.1 Trip ratio, mode share, and VMT comparisons

The estimated trip ratio and mode share in different scenarios are shown in **Figure 7**, while **Figure 8** shows the estimated VMT in each scenario. Firstly, the change of mode preferences has large impacts on traffic. If the mode preferences held during the crisis are maintained during reopening due to behavioral inertia (Scenario 6), the result shows that 77% of transit trips, 132% of car trips and 128% VMT will transpire compared to the base scenario. Meanwhile, telework (Scenario 7) reduced the number of trips compared to Scenario 6, with car trips reduced from 132% to 77% and VMT decreased from 128% to 78% (note that observed VMT in October 2020 was 104% of the pre-COVID baseline). The SWHs (Scenario 8) only shifts trip demand in peak hours to other times, so the trip ratio, mode share, and VMT do not change much compared to the unchanged commuting pattern (100% commuting without telework and SWHs).

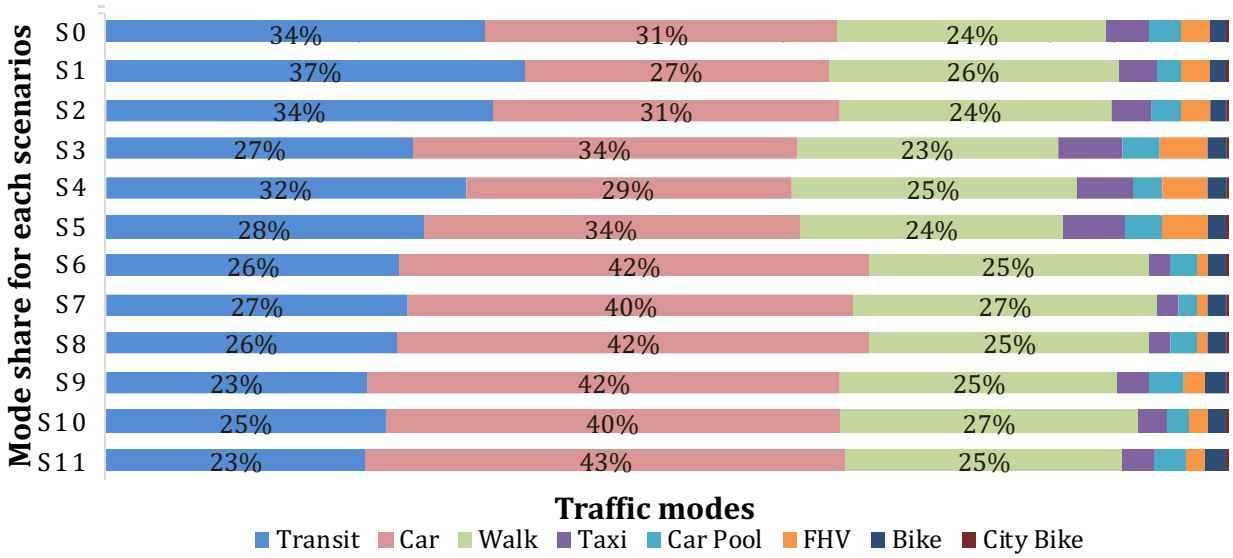
With more people back to using transit, transit capacity restrictions could be applied to ensure social distancing in transit. In our estimation, with a 50% transit capacity restriction in Scenario 9 compared to Scenario 6, transit ridership decreased from 77% to 68%, while car trips only increased by one percentage point (132% to 133%). Although NYC has not implemented explicit transit capacity restrictions (like closing off seats) after reopening, data from the MTA shows transit ridership was restored to only 41% of pre-COVID levels by October. This suggests that transit users are self-enforcing social distancing (and, in effect, transit capacity) even more than the 50% restriction analyzed in Scenario 9. Although NYC is in Phase 4 reopening, some industries have not fully reopened (e.g., universities, indoor dining, etc.).

In summary, recent data that shows 41% of transit ridership, 101% of Citi Bike trips, and 104% of VMT compared to the pre-COVID period (Citi Bike, 2020; MTA Transit Data, 2020; Streetlight, 2020). The observed data shows some mixture between Scenarios 10 and 11, indicating: (1) COVID-19 mode preferences remain in effect during reopening, (2) commuters' self-enforced social distancing is effectively imposing a transit capacity reduction, and (3) telework is reducing the number of trips.

Figure 7(b) shows the change of mode share in each scenario. With changed mode preference in Scenario 6, the mode share of transit may decrease from 34% to 26% compared to the pre-COVID period. By adding transit capacity restrictions, the mode share of transit further decreases to 23% in Scenario 9. While the mode share of cars increases from 31% to 42% due to the changed mode preference, the mode share of cars does not change by adding transit capacity restrictions. It does not change because transit capacity restrictions would shift most users to non-car modes, e.g., taxis, shared mobility, bikes and Citi Bike (Figure 7(a)). Interestingly, we found the mode share of transit and walking increased while the car mode share decreased in scenarios with telework compared to the unchanged commuting scenario (without telework and SWHs). This indicates that teleworkable populations are more car-based commuters, while non-teleworkable populations are more transit-based commuters, which agrees with the findings from Irlacher and Koch (2020).



(a) Trip ratio compared to the base scenario (s0)



(b) Mode share in each scenario

Figure 7. The trip ratio and mode share comparison between different scenarios.

The trip ratio, mode share, and VMT comparisons above show the negative impact of changed mode preference and the ability to telework by reducing trip demand (**Figure 8**). But these results are averaged citywide and do not reflect spatial-temporal effects. For example, we found transit capacity restrictions do not shift many users to personal cars, but it may have higher impact in regions where transit is the dominant traffic mode (e.g., Manhattan). This might bring a flood of new cars to those regions and cause adverse congestion and emissions effects.

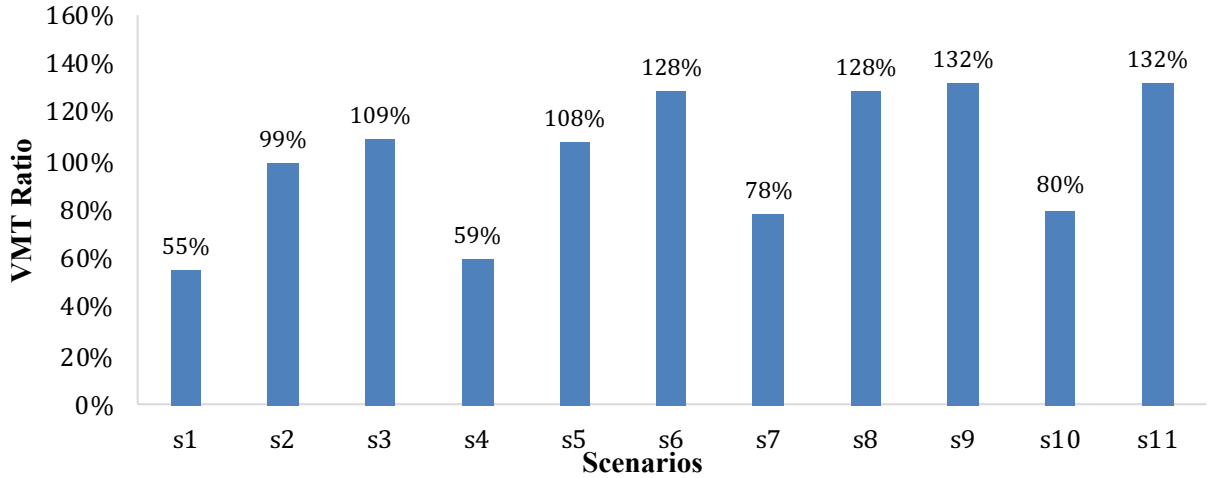


Figure 8. The estimated VMT in each scenario.

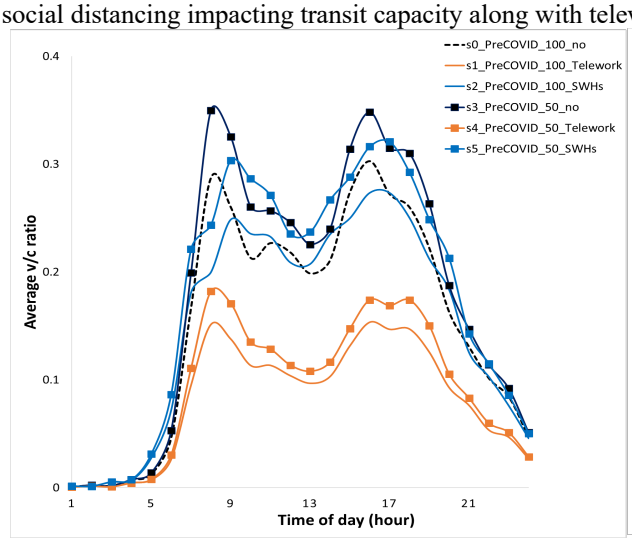
4.2 Spatial and temporal scenario analysis: congestion, emissions, and contact exposure in transit

4.2.1 Temporal analysis

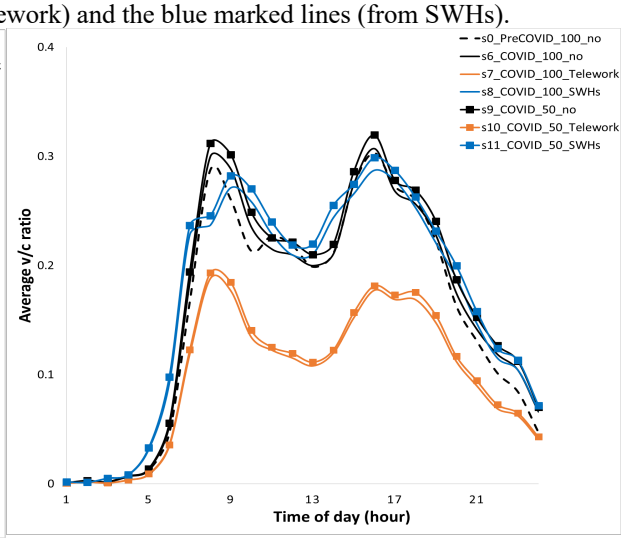
To scrutinize the changes in urban transportation networks due to COVID-19, the temporal distribution of the congestion index, GHG emissions, and subway contact exposure are compared in **Figure 9**. The congestion is represented by the volume-to-capacity ratio (V/C), which measures the level of congestion on a roadway by dividing

traffic volume by the roadway capacity. To better represent the results, we grouped the scenarios into two categories. The left column shows the results for scenarios 1–5 (s1–s5) compared to the base scenario (Scenario 0), assuming that in s1–s5 people's mode preference is same as the pre-pandemic mode preference. The right column shows results for s6–s11 compared to s0, where s6–s11 assume mode preferences in reopening are the same as during the COVID-19 shutdown due to behavior inertia. Under different categories, we use different colors to represent commuting strategies, and markers to represent a 50% transit capacity restriction. The orange lines represent scenarios with telework, the blue lines are scenarios with SWHs, and black lines are scenarios without any changes in commuting.

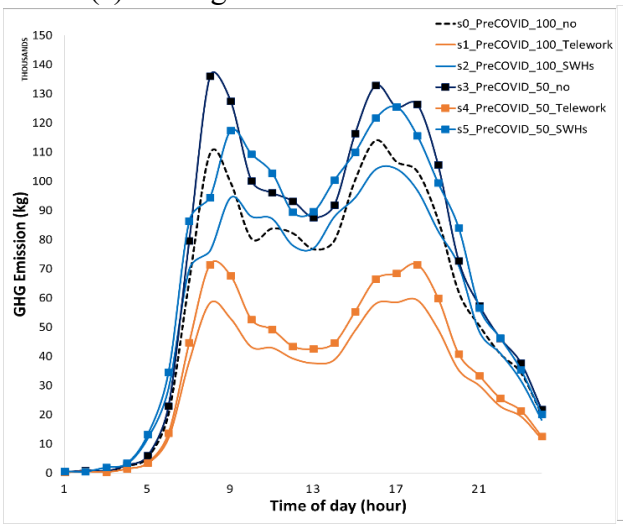
The orange lines are lower than other lines in **Figure 9**, which shows that telework settings explains the significant decrease in traffic congestion and emissions as well as contact exposure in transit. The blue lines show how SWHs can shift traffic in peak hours to relieve traffic congestion and emissions as well as to reduce social contacts in transit during peak hours. The findings from transit capacity restriction scenarios, however, are controversial. While these scenarios reduce contact exposure in transit, they increase overall congestion and emissions (with a higher increase from the morning peak to the evening peak). The results suggest that the current 41% transit ridership and 104% of VMT by October 2020, and 101% of Citi Bike trips by September 2020, compared to the pre-COVID period are captured by the magnitude between the orange marked lines (self-enforced social distancing impacting transit capacity along with telework) and the blue marked lines (from SWHs).



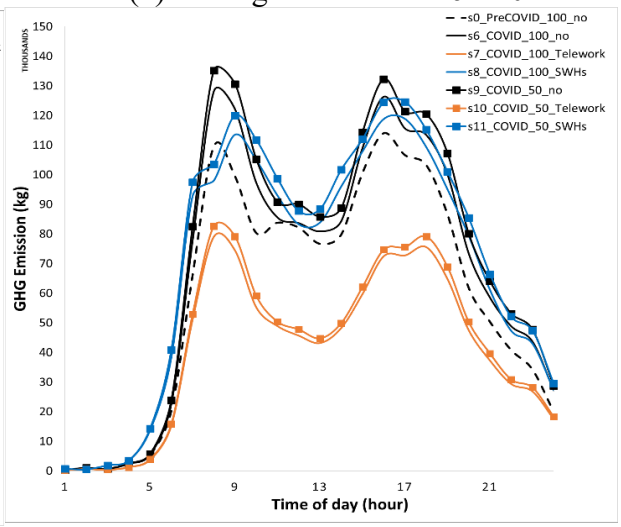
(a) Average v/c ratio in s1–s5



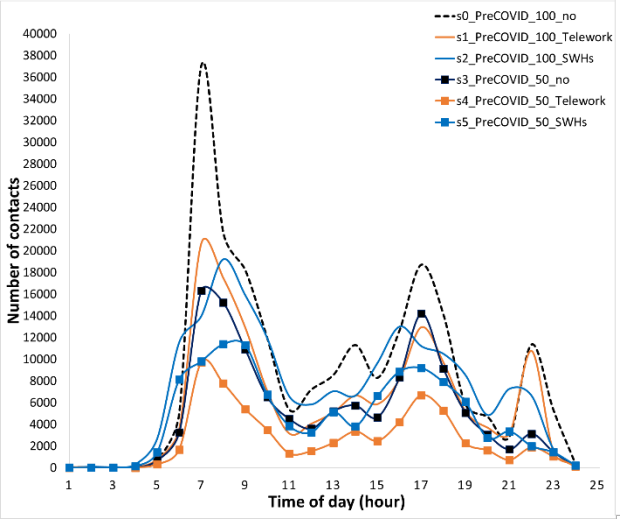
(b) Average v/c ratio in s6–s10



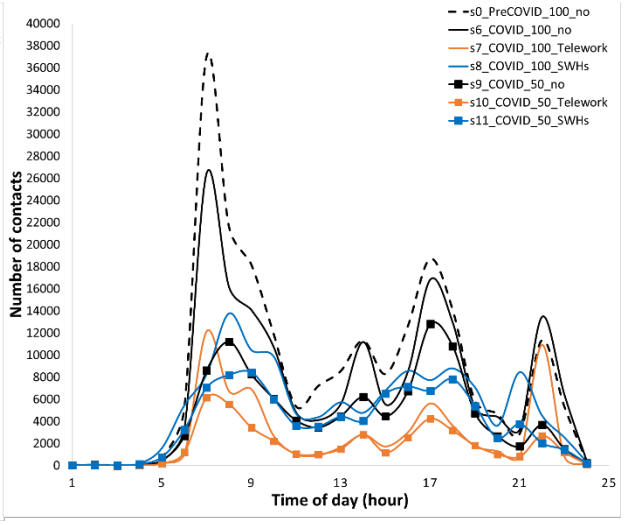
(c) GHG emission in s1–s5



(d) GHG emission in s6–s10



(e) Subway contact exposure in s1–s5



(f) Subway contact exposure in s6–s10

Figure 9. Temporal distribution of link volume, GHG emission, and subway contact exposure.

4.2.2 Spatial analysis

The effects can also be disproportionally distributed in the spatial domain. We evaluate the spatial impacts of different policies on citywide traffic congestion, emissions, and transit contact exposure in this section.

4.2.2.1 Traffic congestion

The congestion hot spots can be identified at a spatial level to identify corridors or neighborhoods where the traffic congestion is most severe. The map in **Figure 10** shows the top 1% of congested road links by volume-to-capacity (v/c) ratio during the morning peak in the base scenario (highlighted in red). The area south of 60th street in Manhattan is often referred to as the central business district (CBD) with the greatest concentration of economic activity. The Manhattan CBD area shows severe congestion compared to other neighborhoods in the city. The congestion also extends to transit and commercial hubs, such as downtown Brooklyn and the South Bronx. In addition to those busy commercial and transportation hubs, some congested corridors can be identified on the map in Brooklyn and Queens, such as Broadway and Northern Boulevard in Queens, and Flatbush Ave. and 4th Ave. in Brooklyn. A citywide congested corridors project by New York City Department of Transportation (NYCDOT) identified congested corridors that are similar to these results.

Figure 10. The top 1% congested links by v/c ratio at 8–9 a.m. in the base scenario.

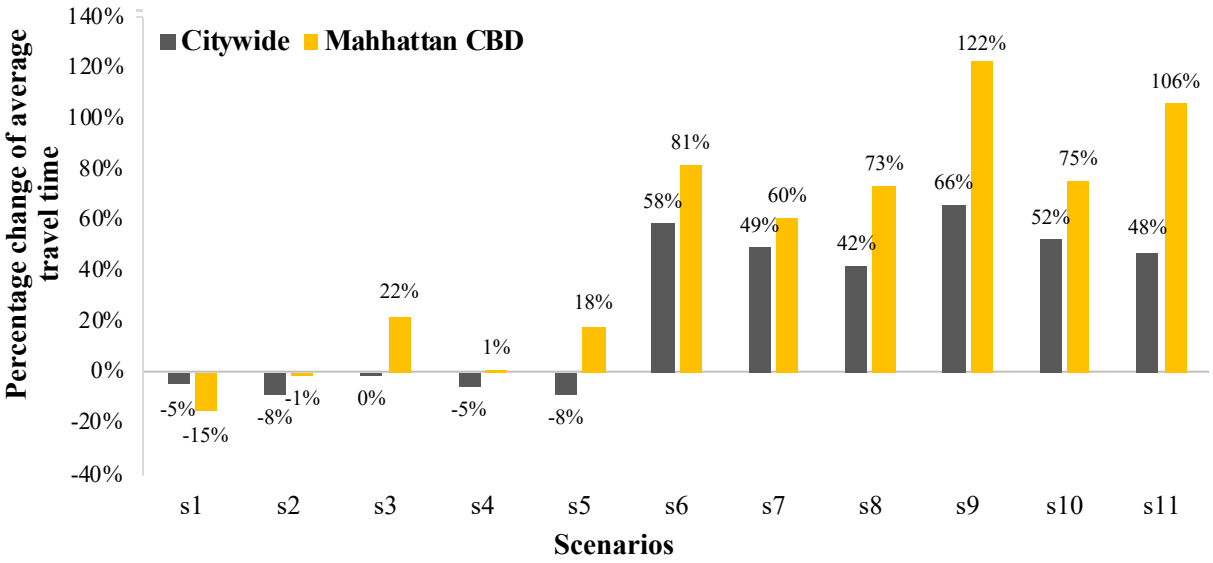


Figure 11. Percentage change of average travel time per car trip Citywide and in the Manhattan CBD.

The most straightforward impact of traffic congestion is travel time. Travel times increase when more people switch from transit or carpool to single-occupancy vehicles. We compare the percentage change of average travel time per car trip citywide and in Manhattan separately, based on their home location, in each scenario in **Figure 11**. In s6 to s11, the average travel time increases about 42% to 66% citywide, while higher increases are

found in Manhattan, from 60% to around 122%. By comparing scenarios with or without transit capacity restriction (s3 and s0, s9 and s6), we find that capacity restrictions have a huge impact on travel times in Manhattan but a much smaller impact citywide.

Figure 7 shows that transit capacity restrictions do not have a big impact on trip ratio and the mode share of cars citywide, but Manhattan is different. Manhattan has dense transit stations and a heavy traffic volume, so transit capacity restrictions have a higher impact on Manhattan. Both telework and staggered work hours reduce travel time citywide as well as in Manhattan.

Assuming each hour is valued at $18.58, the 2018 national median hourly wage as reported by the Bureau of Labor Statistics, we can qualify the increase/decrease of travel time in dollars per day. By comparing s6 to s0, the travel time cost increases by $96.58 million citywide and $18.08 million in Manhattan per day due to the impact of COVID on behavior change. By adding transit capacity reductions by social distancing requirements (from s6 to s9), travel time costs further increase by $10.06 million citywide and $6.89 million in Manhattan per day. With telework implemented in s10 compared to s9, $93.2 million in travel time costs can be saved per day citywide and $10.65 million can be saved in Manhattan. With SWHs in s11 compared to s9, the travel time costs saved per day are $19.97 million citywide and $1.63 million in Manhattan. Individual travelers can benefit more from telework. For example, an agent from the synthetic population who drives from home (on Staten Island) to work (in Midtown Manhattan) takes 54 min. in s6, but it increases to 1h 35min. with transit capacity restrictions in s9 (a 111% increase compared to the base scenario). But if they can telework, the travel time becomes 0 min., which saves $28–$59 round trip per day for this traveler.

In summary, behavioral inertia makes the already congested road network even worse, and this impact is magnified in Manhattan. Adding transit capacity restrictions due to social distancing, causes damaging side effects on traffic congestion. When combined with other polices like telework and staggered work hours, the side effects can be effectively reduced.

4.2.2.2 Greenhouse gas and $PM_{2.5}$ emissions

The percentage change in total daily GHG emissions is shown in **Figure 12**. Similar to the finding in the traffic congestion analysis, the change of mode preference due to the pandemic increases GHG emissions over the entire study area. Without any intervention and only because of changes in mode preference, in Scenario 6, the total daily GHG emissions increase by 4.4 million tons (+14%) compared to the base scenario (Scenario 0). Transit capacity restrictions exacerbates the emissions increase. Under s9, transit capacity restrictions increase GHG emissions by 6.84 million tons, a 21% increase compared to the base scenario. Telework reduces GHG emissions in s10 by 8 million tons (28%) citywide, although Manhattan still sees a rise (20%). The staggered work hours scenario reduces traffic congestion and emissions at peak hours but does not show a significant daily emissions reduction because it only shifts travel demand to off-peak hours (compare s2 to s0 and s8 to s6). This can also be seen in **Figure 9**, where the SWHs scenarios only suppress the peak values.

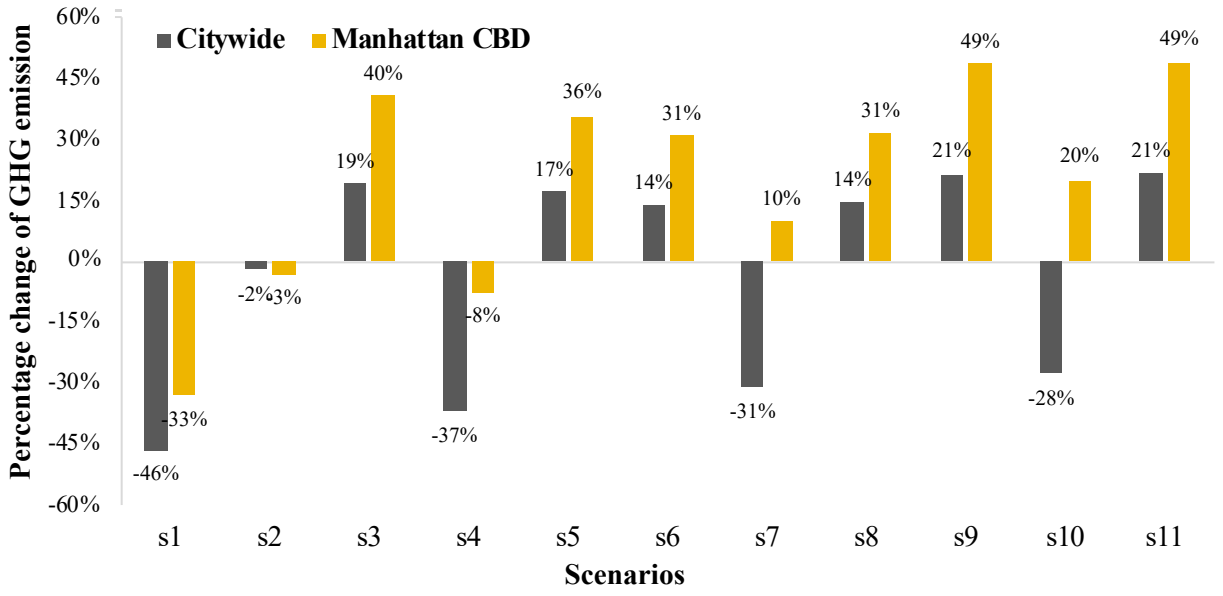


Figure 12. Percentage change of total daily GHG emissions inventory in each scenario compared to the base scenario.

We evaluate the impacts of transit capacity restrictions and telework on $PM_{2.5}$ emissions and changes in the spatial pattern of the emissions, due to health concerns about exposure to such emissions (Requia et al., 2018). To analyze the impacts at a disaggregate neighborhood level, the percentage change of $PM_{2.5}$ is compared to the base scenario by Neighborhood Tabulation Area (NTA) zone citywide (s3, s4, s9, and s10 in **Figure 13**). Manhattan is the borough hardest hit by transit capacity restrictions in s3 and s9. Similarly, high increases in $PM_{2.5}$ can be seen for other neighborhoods at transit and commercial hubs (e.g., downtown Brooklyn). Telework is one of the key strategies to curb these negative impacts; s4 and s10 show visible reductions in $PM_{2.5}$ for different neighborhoods in **Figure 13**. This finding highlights the spatial heterogeneity of the trade-offs: with telework and social distancing in transit in place, there are significant $PM_{2.5}$ emissions savings for some communities (some of Queens, most of Brooklyn, and all of Staten Island) but not so for others (Manhattan, Bronx).

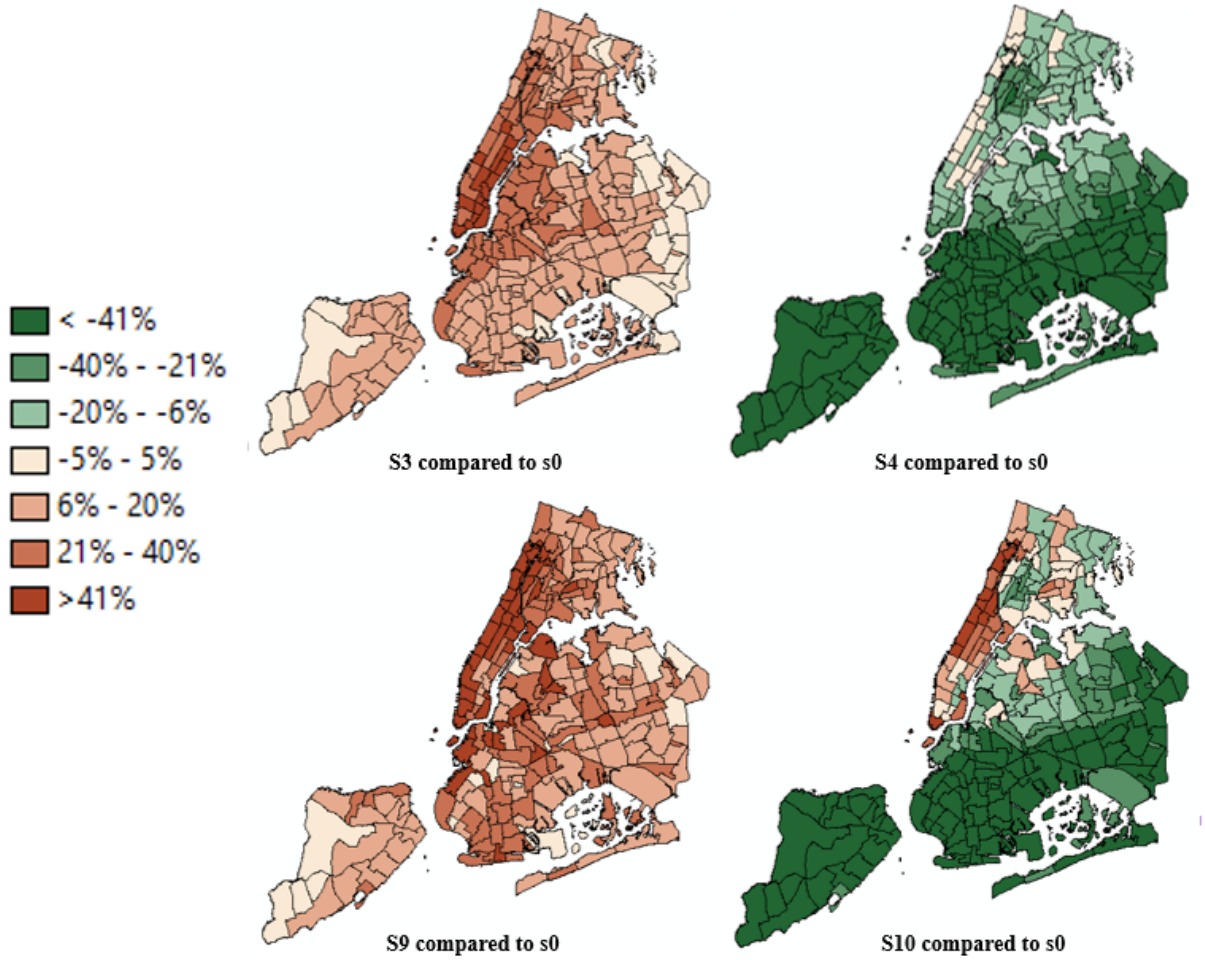


Figure 13. Percentage change of total $PM_{2.5}$ emission inventory per area with/without transit capacity restrictions and transit capacity restrictions combined with telework (24 hours).

As to the areas most impacted by transit capacity restrictions in s3 and s9, the top two impacted neighborhoods are found to be the same in both scenarios and both are located in Manhattan: Stuyvesant Town-Cooper Village (NTA code: MN50) and Battery Park City-Lower Manhattan (NTA code: MN25). Table 3 shows the percentage change of total $PM_{2.5}$ compared to the base scenario in those two neighborhoods. If the mode preference is assumed to be the same as during the pre-COVID period, total $PM_{2.5}$ increases 62% in MN50 and 61% in MN25 due to transit capacity restrictions. Telework in s4 lowers emissions compared to the base scenario. In s9, however, the

total $PM_{2.5}$ increases by as much as 235% in MN50 and 140% in MN25. Telework in s10 reduces (relative to s9) $PM_{2.5}$ emissions to 129% in MN50 and 42% in MN25.

4.2.2.3 COVID contact exposure in the subway network

The simulation model can identify transit trips with higher contact exposure. **Figure 14** shows the number of passengers of the subway trip with the highest contact exposure in the base scenario: the southbound A line departing at 6:13 a.m. The x-axis shows the station stops of this route; it is clear that passenger density is disproportionally distributed in different locations, where the Manhattan CBD and downtown Brooklyn have higher passenger volume.

Table 3 Percentage change of total $PM_{2.5}$ compared to the base scenario

Scenarios	MN50: Stuyvesant Town-Cooper Village	MN25: Battery Park City-Lower Manhattan
s3 (PreCOVID-50-No)	62 percent	61 percent
s4 (PreCOVID-50-Telework)	-9 percent	-26 percent
s9 (COVID-50-No)	235 percent	140 percent
s10 (COVID-50-Telework)	129 percent	42 percent

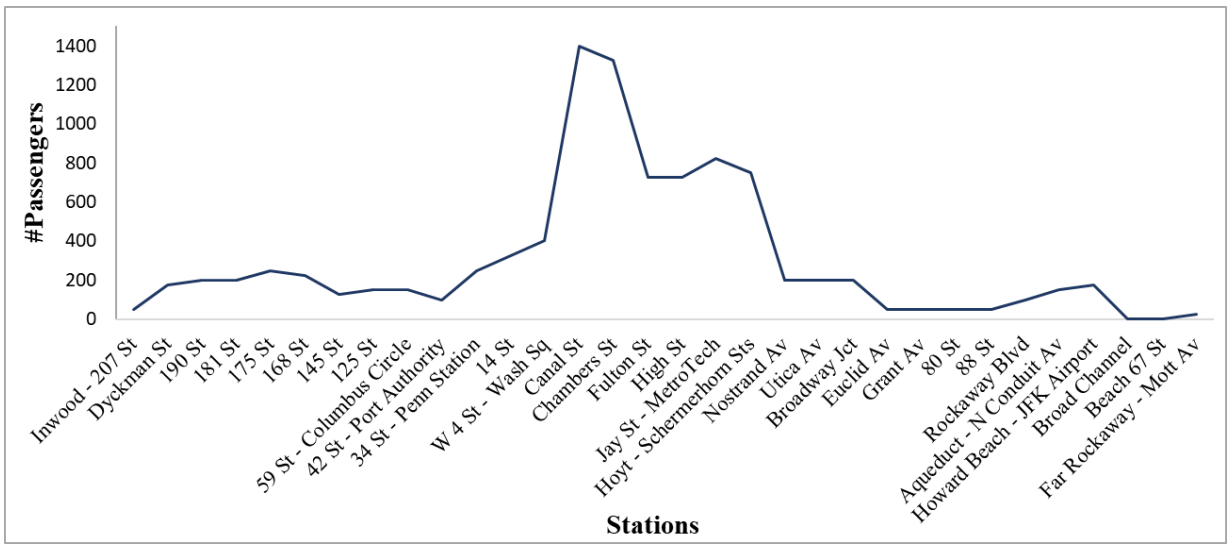


Figure 14. Number of passengers on a southbound A line trip, which has the highest contact exposure among all subway trips in the base scenario.

For each scenario, we computed the number of G_{15} (contact duration > 15min) contact exposures compared to the base scenario (**Table 4**). The changes in mode preference in Scenario 6 decrease contact exposure to 83.9% of that in the base scenario (Scenario 0). Under s9, transit capacity restrictions reduce contact exposure to 72.54% of that in the base scenario. Telework (s10) reduces contact exposure to 36.19% of the base scenario and SWHs (s11) reduces contact exposure to 69.8% of that in the base scenario. The percentage of contact exposure is computed by dividing the number of passengers with contact exposure ($t_d > 15\ min$) by the total ridership (**Table 4)**, which is around 3%. In other words, this means only three passengers per hundred have contact with others longer than 15 min. in the subway, to say nothing of the presence of masks, PPE, etc. We identified the subway trip with the highest contact exposure found in each scenario in **Table 4**, noting the direction and departure times. Subway lines 2, 5, and A top each scenario as they are all busy subway lines in NYC. Also, the departure times are mostly during peak hours.

Data from the MTA shows only 41% transit ridership was restored by October 2020 (this is closest to s10). When more people come back to transit, route-based or station-based transit strategies can be implemented, such as limiting the number of passengers entering at stations with higher passenger volume, or implementing other transit

capacity restrictions on certain routes and stations (such as lines 2, 5, and A at peak hours in Manhattan). Crowd density information in transit is important for passengers to avoid crowds, which would help make transit systems more attractive in the post-pandemic period.

Table 4 Contact exposure comparison and subway trips with the highest number of contact exposures

Scenarios	Number of contact exposures compared to s0	Percentage of contact exposures (divided by ridership)	Subway trips with the highest contact exposures (line, direction, departure time)
s0_PreCOVID_100_no	100.00 percent	3.14 percent	A, South, 6:13AM
s6_COVID_100_no	83.90 percent	3.20 percent	A, South, 6:13AM
s9_COVID_50_no	72.54 percent	3.08 percent	5, North, 08:05AM
s10_COVID_50_Telework	36.19 percent	2.37 percent	A, South, 6:18AM
s11_COVID_50_SWHs	69.80 percent	3.00 percent	2, South, 7:22AM

4.3 Discussion

COVID-19 affects travel behavior and consequently congestion and emissions from traffic. At some point, traffic emissions may be reduced due to increased remote working and business and school closures. Transit capacity restrictions due to social distancing enforcement increases traffic congestion and emissions while reducing contact exposure. More importantly, we find that not all areas are impacted equally by congestion and emissions increases. Areas such as Manhattan that rely heavily on public transit are hit hardest and see a spike in traffic congestion and emissions; even the effects of telework do not scale back these impacts to the base condition.

The trade-offs between traffic congestion, emissions, and subway contact exposure are summarized in Table 5 (estimated per day). The impact of COVID on behavior change (s0 -> s6) increases travel time costs by $96.58 million citywide and $18.08 in Manhattan, while GHG emissions increase by 26.54 million tons citywide and 1.31 million tons in Manhattan. With fewer people using transit in s6 due to behavior change, contact exposures decrease 40% compared to the base scenario. By adding transit capacity reductions due to social distancing (s6 -> s9), travel time costs further increase by $10.06 million citywide and $6.89 million in Manhattan, while GHG emissions increase by 2.37 million tons citywide and 0.76 million tons in Manhattan, but contact exposure reduces by 16%. In search of solutions, we studied alternative scenarios with telework and staggered work hours. By implementing telework (s9->s10), $93.2 million of travel time costs can be saved citywide and $10.65 million can be saved in Manhattan, while 15.23 million tons of GHG emissions can be saved citywide and 1.23 million tons can be saved in Manhattan. Telework can also benefit public health, with contact exposure decreased by 75% in s10 compared to s9. Staggered work hours (s9->s11) will save travel time costs of $19.97 million citywide and $1.63 million in Manhattan, while not having large effect on GHG emissions and contact exposure.

Table 5 Trade-offs between traffic congestion, emissions, and subway contact exposure

Scenarios	Total travel time costs (million dollar per day)	Total travel time costs (million dollar per day)	GHG emissions (million tons per day)	GHG emissions (million tons per day)	Subway contact exposure (percent change)
	Citywide	Manhattan	Citywide	Manhattan	

Mode preference change (s0 to s6)	+96.58	+18.08	+26.54	+1.31	-40 percent
With transit capacity reduction (s6 to s9)	+10.06	+6.89	+2.37	+0.76	-16 percent
Implementing telework (s9 to s10)	-93.20	-10.65	-15.23	-1.23	-75 percent
Implementing SWHs (s9 to s11)	-19.97	-1.63	-0.33	0.00	-3 percent

The already very popular telework strategy is found to be one of the most effective ways to reduce traffic congestion, emissions, and contact exposure in transit. When evaluating the impact of telework, we assumed 59% of Americans working from home during closure are continuing to do so during reopening (Fluent Pulse, 2020). **Table 5** shows that without telework and SWHs, the travel time costs can increase up to $106.64 million citywide, GHG emissions increase up to 28.91 million tons. While under this telework assumption, we see significant benefits from telework, which can save millions of dollars and hours for the city by saving travel time. The COVID-related telework situation is keep changing with the situation of COVID and the company's polices, but even fewer people telework than we assumed in the future reopening, telework can still save travel time cost up to $93.2 million citywide and GHG emission up to 15.23 million tons per day. Staggered work hours make a positive impact by reducing traffic congestion as well as contact exposure in transit at peak hours, but the strategy only shifts travel demand to off-peak hours, so it has very little impact on total trip demand and daily traffic emissions. Providing telework and staggered work hours are highly dependent on the type of work and will need support from employers.. Policymakers wishing to simultaneously improve traffic and control contact exposure on the transit system may consider further promoting telework and flexible work hours for commuters.

Having transit capacity restrictions is found to be effective in reducing contact exposure, but it has higher negative impacts on Manhattan and neighborhoods at transit and commercial hubs. When combined with telework, daily GHG emissions decrease by 28% citywide but increase by up to 20% in Manhattan compared to the base scenario. Neighborhoods near transit and commercial hubs also experience higher $PM_{2.5}$ emissions, which can directly impair people's health. The top two impacted neighborhoods are found to be Stuyvesant Town-Cooper Village (NTA code: MN50) and Battery Park City-Lower Manhattan (NTA code: MN25). Our findings suggest that policymakers should plan accordingly to accommodate those local effects, perhaps planning for bike lanes, considering the use of other forms of micromobility like e-scooters in those locations, and employing demand management strategies like congestion pricing.

We computed the percentage of contact exposure for the subway trips with highest exposure in **Table 4**, which is around 3%. This suggests the opportunities for transmitting COVID are fairly low, especially if social distancing practices are followed. Interestingly, subway lines 2, 5, and A running at peak hours are found to have the highest contact exposure. Route-based or station-based transit strategies can be implemented to ensure social distancing at those sites. The results rely on the input transit schedules, future analysis should always update to the latest transit settings or customized ones.

4.4 Limitations

We provide methodologies for using such tool to model COVID-19 related events, such as traveler's mode preference change, telework rate, flexible work hours, and their impact on transit usage, traffic congestion, emissions, and the way to use the existing tool to estimate the potential contact exposure in transit. To analyze these various scenarios, we made specific assumptions to help model each scenario. Nonetheless, how the real traffic would be like in the post-COVID is a more complex question and there are many uncertainties in the reopening process.

It should be note that the results and policy recommendations will be limited by the assumptions. The transit schedule in this study was set to be consistent with MTA GTFS data on Monday August 3, 2020. However, transit revenue loss and its subsequent series of effects are big issues in post-COVID reopening, which may result service reductions and lay-offs of operating staff, and transit riders may face service cuts and decline of the quality of service. Moreover, the COVID-related telework situation is also keep changing as the spread of the COVID-19

continues to slow in Spring 2021. In addition, a key assumption in this study is that the mode preference during the reopening phases mirrors what was observed during the pandemic period due to behavioral inertia. This assumption can be conservative and should be treated as worst-case scenarios for transit because people's attitude towards transit is also changing as the ease of COVID-19. There are other factors that are not discussed in this paper but are quite important that may change the travel pattern, such as the influence of people moving out of NYC during pandemic, whether downtown Manhattan will remain to the financial sector and potential impact of shopping behavior on retail industry. Therefore, the scenario results only reflect the scenario settings and assumptions used in this paper, more insights can be obtained with appropriate modification of the scenarios and assumptions. In summary, the individual level dynamic system allows MATSim and similar multiagent simulation models to study various scenarios of interest that can help evaluate and inform policy.

5. CONCLUSIONS

While NYC has entered Phase 4 of reopening from COVID-19, many new challenges for economic reopening remain unanswered. The simulation models proposed in this study are designed to evaluate the impact of COVID-19 on traffic systems, with special attention to the trade-off of transit density with traffic congestion and emissions. Since NYC entered Phase 4 reopening in July 2020, the health authorities have provided many guidelines for public transportation, ranging from work-from-home polices to staggered work hours for businesses (CDC, 2020c; NYC Health, 2020). Until this study, there has been no answer for how those polices can impact the transport system. The key contributions of this study include:

- A tool to evaluate trade-offs between traffic congestion, transit contact exposure, and traffic emissions (including GHG and $PM_{2.5}$ emissions) for different reopening policies.
- Quantifying the factors that explain the current observations of 41% transit ridership and 104% VMT in October 2020 and 101% Citi Bike trips in September 2020 in NYC compared to the pre-COVID period:
    - Lower transit ridership is explained by a combination of behavioral inertia, self-enforced social distancing (translating to effective transit capacity restrictions), and teleworking.
    - The 104% VMT is explained by a combination of behavioral inertia and self-enforced social distancing, offset by teleworking and staggered work hours.
- Telework reduces GHG and $PM_{2.5}$ emissions citywide, but in Manhattan they remain higher due to the magnitude of behavioral inertia and social distancing. These impacts can be mitigated with more traffic- and demand-management policies like congestion pricing in lower Manhattan combined with more offerings of bike lanes and micromobility solutions.
- COVID contact risk on subways is relatively low, with the greatest hot spots on certain lines: the 2, 5, A at peak hours.

The findings of this study concur with ongoing policies and operational strategies deployed by the city. As we have done in nowcasting the scenarios, we can continue to adjust our recommendations in real time alongside NYC's reopening ("Nowcasting" often used in economics that means the prediction of the present, the very near future, and the very recent past state of an economic indicator). In particular, we can use the outcome of this model to help monitor the degree to which people revert back over time (pre- and post-vaccine) to pre-COVID behavior, and the self-enforcement of social distancing on transit. This will also enable us to monitor the cumulative savings and costs in terms of traffic congestion and GHG emissions, both temporally and spatially. Further studies should look at other cities to compare impacts, perhaps even providing an assessment of local policies employed in different countries. The impact of revenue loss and its subsequent series of effects would be another future work, such as the impact analysis of service reductions. Moreover, the 4% sample population is used in the current model due to the large computation time, which need to be improved as a future work.

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