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COVID-19 public transit precautions: Trade-offs between risk reduction and costs

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ABSTRACT

Public transit has received scrutiny as a vector for spreading COVID-19 with much of the literature finding correlations between transit ridership and COVID-19 rates by assessing the role that transportation plays as a vector for human mobility in COVID-19 spread. However, most studies do not directly measure the risk of contracting COVID-19 inside the public transit vehicle. We fill a gap in the literature by comparing the risk and social costs across several modes of transportation. We develop a framework to estimate the spread of COVID-19 on transit using the bus system in Pittsburgh. We find that some trips have demand that exceed their COVID-19 passenger limit, where the driver must decide between: (1) leaving a passenger without a ride or (2) allowing them on the bus and increasing COVID-19 risk. We consider five alternatives for alleviating overcapacity: allow crowding, additional buses, longer buses as substitutes, Transportation Network Company (TNC) rides, or Autonomous Vehicles (AVs) for passed-by passengers. We use transit ridership and COVID-19 data from the spring of 2020 by combining transportation data and an epidemiological model of COVID-19 stochastically in a Monte Carlo Analysis. Our results show that 4% of county cases were contracted on the bus or from a bus rider, and a disproportionate amount (52%) were from overcapacity trips. The risk of contracting COVID-19 on the bus was low but worth mitigating. A cost–benefit analysis reveals that dispatching AVs or longer buses yield the lowest societal costs of $45 and $46 million, respectively compared to allowing crowding ($59 million).

1. Introduction

The COVID-19 pandemic's level of global disruption to economic, environmental, and social aspects of society, over a relatively short period, is on par with the 1918 influenza pandemic and the world wars (Ceylan et al., 2020). While the occurrence of global pandemics seems infrequent, there have been other near misses in recent years (Mckay, 2021; Knowable Magazine, 2020) meaning future pandemics are a possibility (Knowable Magazine, 2020). Transportation sector decisions play a role in mitigating the negative effects of the current pandemic and future disruptive events. In particular, decisions made by local transit agencies play a huge role in the spread of infectious diseases, such as COVID-19, on buses. While different transit modes each play their role in the spread of COVID-19, we focus our analysis on buses as this form of transportation makes up the largest share of US public transit rides (46%) (Anon, 2019).[1]

In 2018, 11% of commuters in the US relied on public transportation and 36% of public transit commuters (2.8 million people) in the US

were essential workers (Transit Center, 2020b), disproportionately people of color and low-income individuals are essential workers (Transit Center, 2020a). Essential workers, such as grocers, healthcare employees, and public servants must continue working in-person during the strictest lock-downs (Governor Tom Wolf, 2020). Overall, public transit demand plummeted (80% decrease) in the early weeks of the pandemic across the US (Liu et al., 2020), but in areas with high essential worker and vulnerable populations, transit demand decreased less (Hu et al., 2021; Liu et al., 2020). Several papers show that high-income passengers were more easily able to shift away from public transit during the pandemic (Carrión et al., 2021; Hu et al., 2021; Liu et al., 2020; Wilbur et al., 2021) because of access to alternative modes of transportation and ability to work remotely. This indicates that low-income and minority essential workers rode the bus at higher rates during the pandemic (Liu et al., 2020; Transit Center, 2020a) potentially placing themselves at a higher risk of contracting COVID-19. This disparity highlights a need for transit agencies to customize their operations as

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[1] TNC: Transportation Network Company, AV: Autonomous Vehicle

these populations tend to lack health insurance coverage and/or have pre-existing health conditions that put them as higher risk of serious illness or death. In response to the pandemic, many public transit agencies (Chicago (Chicago Transit Authority, 2020), Oakland (Alameda County, 2020), Pittsburgh (Pittsburgh Regional Transit, 2020)) have set per vehicle passenger capacity limits to increase the physical distance between passengers and promote public safety, but this policy presents another equity issue.

Buses that have reached their reduced COVID-19 capacity limit can either pass by a commuter, potentially leaving them without a ride, or pick them up and break physical-distancing protocol, putting them at higher risk for contracting COVID-19. We evaluate the trade-offs between COVID-19 risk-reduction and costs for various policy alternatives to deal with transit pandemic crowding. To address this unmet demand versus crowding problem, transit agencies could promote physical distancing while meeting demand through alternatives such as, dispatching more buses, dispatching longer 60-ft articulated buses as a substitute on overcapacity routes, dispatching transportation network companies (TNCs), or in the future, dispatching single-passenger autonomous vehicles (AVs). Through our analysis, we investigate the degree to which each alternative could have reduced the spread of COVID-19 on public transit systems, and compare the additional costs, emissions, and marginal congestion to allowing crowding on the bus. We assess the role AVs and TNCs might play in rare events like the COVID-19 pandemic as a complement to public transit and the role different policy alternatives might play in reducing the spread of COVID-19.

2. Literature review

2.1. Public transit and spread of COVID-19

Several researchers have investigated the role of transit in the spread of COVID-19. To date, most of the COVID-19 transportation literature assesses the role of human mobility in spreading COVID-19 because of the secondary and tertiary interactions once passengers have reached their destination (Christidis and Christodoulou, 2020; Zheng et al., 2020; Carrión et al., 2021; Lu et al., 2021; McLaren, 2020). Table 1 shows the breakdown in type of analysis for several papers that assess the role that public transit plays in the spread and incidence of COVID-19. Specifically, Christidis and Christodoulou look at the correlation of passenger flights out of Wuhan vs. the spread of COVID-19 cases globally to assess the correlation between air travel and COVID-19 spread in the early stages of the pandemic (Christidis and Christodoulou, 2020). Zheng, et al. (2020) regresses COVID-19 case counts and transit trip frequency (airports, trains, buses) (Zheng et al., 2020). Carrión, et al. (2021) use Bayesian Weighted Quantile Sums regression of zip-code level COVID-19 cases vs. geographical information on essential workers and transit use to assess the correlation between COVID-19 case prevalence and transit usage for the NYC Subway (Carrión et al., 2021). Lu, et al. (2021) use geographical weighted regression and deep neural network for several transportation modes to assess the correlation of COVID-19 cases in a geographical region in China and the frequency and turnover of various transportation used (Lu et al., 2021). Mclaren (2020) shows the correlation between COVID-19 deaths and public transit dependence for commuting at the county-level in the US (McLaren, 2020). Siewwuttanagul and Jittrapirom (2023) show a correlation between ridership decrease and increase in COVID-19 case counts and restrictions in Bangkok on multiple modes of transportation, Finally, Nouvellet, et al. (2021) use general mobility trends (Google and Apple Mobility data) to assess the correlation between human movement in a city and COVID-19 incidence (Nouvellet et al., 2021). These studies all look at the correlation of various transportation metrics with the prevalence of COVID-19 incidence in regions or cities. However, these studies do not assess the risk of spreading COVID-19 in the vehicle itself nor do they quantify the resulting economic benefits and costs of

different policy alternatives. Even if no COVID-19 spread occurred on public transit, transit would be correlated with the spread of COVID-19 by facilitating human mobility and further interactions. These papers show the role that human mobility play in COVID-19 incidence, but do not isolate the risk of contracting COVID-19 while physically on public transit vehicles.

A few papers assess risk within the transportation vehicle in a simulation; however, these papers do not compare alternatives modes and dispatch options for reducing risk. McGowan, et al. (2022) simulate a high resolution model of risk on a single bus. They use a commercial Navier–Stokes flow solver, RavenCFD, to model the flow of air through the bus under varying conditions to assess the risk on contracting COVID-19 on a single bus (McGowan et al., 2022). However, this paper does not compare alternative modes or assess the trade-offs of risk on the bus with other metrics. Finally, Luo et al. (2022) develop a simulation framework to investigate the trade-offs between COVID-19 risk and mobility using a network flow and SEIR model to maximize transit flow and minimize COVID-19 cases modeled using a meta-population model for the NYC subway (Luo et al., 2022). This paper assess the trade-offs of mobility and the spread of COVID-19. However, it only considers transit re-routing as a means to reduce passenger crowding but does not directly assess alternative modes of transit (AVs, TNCs, buses) or other reduction methods (e.g., mask efficiency). Additionally, it does not quantify the economic and social costs of the trade-offs considered. Kamga, et al. (2021) is a comprehensive literature review of COVID-19 transportation policies including system changes like dispatching additional vehicles or public private partnerships with TNC companies and passenger-level policies (e.g., mask mandates and passenger limits). Sanquinetti et al. (2021) is also a comprehensive literature review of COVID-19 risk mitigation strategies for various modes of shared and pooled transportation, but does not directly simulate COVID-19 infections on a transportation system (Sanquinetti et al., 2021). Both literature reviews outline the policy and mitigation options that transportation network operators can choose, rather than model or quantify the benefits or trade-offs of the policies with dispatch costs.

Fig. 1 shows the dimensions and methods that each paper in addresses. Multiple papers use econometric methods to show the correlation of COVID-19 cases and deaths with public transit ridership, dependency, frequency and turnover (Christidis and Christodoulou, 2020; Zheng et al., 2020; Carrión et al., 2021; Lu et al., 2021; McLaren, 2020). However, these papers do not assess the risk mitigation of crowding reduction and they do not compare routing changes or alternative modes of transit and the trade-offs of transit alternatives. Kamga et al. (2021) reviews transit policies and touches on the potential policy paths for COVID-19 mitigation on transit, but does not compare or quantify the risks of each policy or routing option. McGowan, et al. (2022) models COVID-19 spread on a bus using an airflow model, but does not compare alternative modes of transit or assess the trade-offs of mobility and risk for various mitigation strategies. Luo, et al. (2022) combines a model of COVID-19 spread with a network flow analysis to optimize the trade-off between mobility and COVID-19 risk. Luo, et al. (2022) only assess changing the flow of the transit network to limit passenger crowding and does not consider alternative modes of transit and mask efficiency as a policy option.

This paper makes a contribution to the literature by developing a method to estimate the risk of contracting COVID-19 on the transit vehicle (in the early stages of the pandemic) and assess the societal costs and benefits of different policy alternatives for COVID-19 mitigation. Specifically, we integrate bus ridership and COVID-19 infection data into an epidemiological framework to stochastically model the risk of catching COVID-19 on public buses. Then we assess how implementing traditional and novel policy alternatives (e.g., dispatching longer buses, TNCs, AVs, and mask efficiency) could have impacted the risk of contracting COVID-19 on transit. In addition, we estimate the associated economic trade-offs of policy alternatives from changes in transit agency operational costs, emissions costs, and the value of

Table 1
Examples of papers directly assessing the role of public transportation in the spread of COVID-19.

| Author Year	Mode of transit Location	Interactions on transit	Infections in the community	Infections in the vehicle	Alternative modes	Crowding reduction	Assesses trade-offs	Changes in routing	Methods
Luo, et al. (2022)	Subway New York City, US	yes	yes (susceptibility)	yes	no	yes	yes	yes	Optimization using a SEIR model & network flow analysis
McLaren (2020)	multiple US	no	yes	no	no	no	no	no no	County-level regression
Lu, et al. (2021)	flights, trains, buses China	yes (rider density)	yes	no	no	no	no	no	Geographical weighted regression & deep neural network
Zheng, et al. (2020)	flights, trains, buses China	no	yes	no	no	no	no	no	Regression of trip frequency and cases
Carrión, et al. (2021)	Subway New York City, US	no	yes	no	no	no	no	no	Bayesian weighted quantile sums regression
Chistidis and Chistodoulou (2020)	flights China/Global	no	yes	ratio of infected	no	no	qualitative	no	Spread of COVID-19 using flight data
Nouvellet et al. (2021)	general mobility 52 countries	no	yes	no	no	no	no	no	regression of mobility and COVID-19 deaths
Siewwuttanagul and Jittrapirom (2021)	bus, metro, boat Bangkok, Thailand	no	yes	no	yes	yes	no	yes	regression of ridership and COVID-19 cases and policies
Kamga, et al. (2021)	several US and Canada	yes (literature review)	no	no	yes (TNC)	yes	qualitative	yes	literature review of transit policies
Sanquinetti, et al. (2021)	several US and Canada	yes (literature review)	no	not directly modeled	yes (TNC)	yes	no	no	literature review of risk mitigation mitigation
McGowan, et al. (2022)	bus single bus	no	no	yes	no	no	no	no	Air flow & passenger model of a bus
This Study (2022)	bus Pittsburgh, US	yes	yes (first degree)	yes	yes (AV, TNC)	yes	yes	yes	Monte Carlo simulation
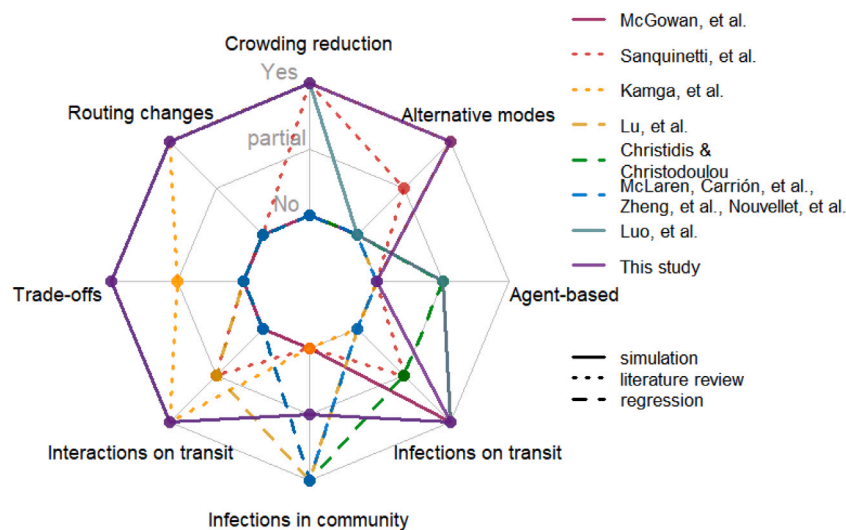
Fig. 1. Gaps in the literature across papers assessing COVID-19 risk on public transit. Dashed lines represent papers that used regressions-based methods, solid lines represent simulations, and the dotted line represents a literature review.

a statistical life saved. This framework can be used by transportation agencies (e.g., Transit Authorities) to assess the economic and social costs of implementing policy alternatives and their impact on the risk of spreading an infectious disease within a public transit vehicle.

2.2. Autonomous vehicles and transportation equity

AVs have the potential to fill the transportation needs of vulnerable groups that otherwise lack consistent transportation options. Several papers have explored what role AVs will play in improving equity and accessibility of transportation in pre-pandemic conditions (Cohn et al., 2019; Meyer et al., 2017; Fagnant and Kockelman, 2015; Patterson, 2020; Harper et al., 2016). For example, Cohn et al. (2019) assessed how integrating AVs into transit systems could affect job accessibility for minority and low-income populations (Cohn et al., 2019), Patterson (2021) highlights integrating AVs into public transportation plans as a key strategy to reduce transportation gaps in Black communities (Patterson, 2020), and Harper et al. (2016) estimated the upper-bound increase in travel demand from AVs for people with travel-restrictive medical conditions (Harper et al., 2016). We make a contribution to

the AV and transit equity literature by assessing the role AVs could play to reduce bus crowding during COVID-19 to help reduce risk disparities. We define transit equity during the pandemic as all passengers receiving access to transit commensurate with demand; transit service equity results in COVID-19 risk equality (passengers on the bus face a similar risk of contracting COVID-19). Transit Equality would be providing the same level of service despite differing ability to switch away from public transportation during a pandemic. Equitable policies lead to equal risk outcomes by providing levels of service that reflect different levels of demand.

3. Case study

3.1. System bounds

Our case study is COVID-19 risk analysis of the bus system for Allegheny County, PA (home to Pittsburgh) with a population of 1.2 million residents. The Pittsburgh Regional Transit in Allegheny County encompasses both urban and rural regions, extending out from Pittsburgh. See Appendix E for further demographic details on essential riders and transit commuters in the county. In Allegheny County buses represent 86% of public transit rides (Pittsburgh Regional Transit, 2019). In February 2020, the port authority had a total of 4.4 million passengers; early in the COVID-19 pandemic (April 2020) total ridership dropped to 900,000 passengers (80% decrease).

3.2. Data sources

We source bus ridership data for April through September 2020 from the Pittsburgh Regional Transit. The data collected contains the passenger load and time at each bus stop of each of the 76,000 trips in the time-frame we model. This gives us occupancy and length of bus ride for each trip. We use bus load data to calculate overcapacity ridership during the COVID-19 pandemic and to find the peak load of each bus trip. In the early months of the pandemic, Pittsburgh Regional Transit enacted passenger limits on their buses; overcapacity is defined as the peak passenger load of a trip that surpasses the COVID-19 social distancing capacity. Pittsburgh Regional Transit bus ridership data can be sourced via a request from the agency. Automatic passenger counters equipped on all Pittsburgh Regional Transit buses provide the location, time, and load of each bus at each stop along with information on the size of the bus (Pi et al., 2018). Pi discusses the functionality, accuracy, and reliability of the automatic passenger counters that operate at each door to scan when a passenger enters and exits the bus giving the current bus load (Pi et al., 2018). Additionally, Pi discusses validation practices, such as flagging instances where passenger load measurements are infeasible (e.g., negative) (Pi et al., 2018).

Transit App is a route-finding app used for all types of transportation (Transit App, 2020). Transit App records bus demand 'sessions' from the app opening and mapping a bus route inside the Allegheny County bounds. Transit App provides demand during the pandemic for all of Allegheny County per hour per date as a percentage of demand in 2018. The Transit App demand has been normalized to account for changes in app-user numbers in the city. The transit app data also compares dates from 2020 to 2018 by taking the day of the week in 2020 that date falls on and then averaging that with the three nearest to that day of the week in 2018. For example, if March 15th is a Sunday in 2020, Transit App will average Sunday, March 11th 2018, Sunday, March 18th 2018, and Sunday, March 25th 2018, so that it does not compare a Sunday in one year to a Tuesday in another year. The demand data is used to model high-demand scenarios for COVID-19 bus ridership in the sensitivity analysis.

The Make My Trip Count Survey, which was conducted by the Green Building Alliance in 2015, recorded the total commute length of bus commuters in Allegheny county (n = 15,492) and is used to create a probability distribution of commute lengths to model the distance that

each AV or TNC would need to go. This is used instead of total bus trip length because most passengers do not ride the full length of a bus trip and many riders make transfers, thus their total commute is not represented by the bus trip distance. For this reason, we use survey data from the Make My Trip Count Survey to give a more accurate reflection of total trip distance for modeling TNC and AV rides.

The 2014–2018 American Community Survey is used to find the per capita income and percent of residents that are an ethnic minority in each census tract in Allegheny County. A census tract is a community-level geographical designation by the US census. Integrated Public Use Microdata Series Transportation Survey aggregated from the 2018 American Community Survey. This data provides demographic, age, and career data for bus commuters from 2018. This provides a representation of the demographics of bus commuters in Allegheny County by career.

3.3. Data limitations

Here we present the data limitations of our analysis. There is inherent uncertainty about the level of unmet demand in the public transportation system. Our analysis uses bus trackers which only measure if a person gets on or off the bus, but not if a person is passed by the bus. We overcome this limitation using Transit App data to approximate the upper bound of unmet demand. Transit App shows the level of desired bus demand by recording when a passenger opens the app and maps a route, but it does not provide information on if the app user actually gets on the bus. This Transit App reflects overall bus demand (including latent and unmet demand), whereas bus ridership alone reflects met bus demand. We acknowledge that transit riders may open the app before they would like to take a bus, which is one limitation of this method. Another limitation is the inability to track the individual riders, which stems from the bus ridership data being load-based (as opposed to agent-based). In our dataset at each bus stop the change in passenger load is recorded (passengers on/off), but passengers are not tracked from their origin to their destination. This induces uncertainty in the length of COVID-19 exposure time on the bus.

4. Methods

In this section, we detail our methods for evaluating the costs of deploying COVID-19 mitigation alternatives for a public bus public system, including extra buses, longer buses, TNCs, and AVs. We start by defining unmet demand within the bus system and outlining the Monte Carlo model used. After that, we detail our methods for quantifying costs, benefits, externalities, and changes in COVID-19 risk for each option. Finally, we consider the range of uncertainty inherent to the risks and externalities with a Monte Carlo Analysis.

We use an existing model of COVID-19 spread in a well-mixed room combined with tested and validated constants in our model. We combine this model with real world transportation data of bus load for each trip over a five-month period in Allegheny county. Our approach is novel because it takes an existing and validated model of COVID-19 and pairs it with public transportation data in a simulation that captures the uncertainty, models 76,000 real trips (rather than one hypothetical bus trip), and captures uncertainty through the use of a Monte Carlo simulation. By combining real passenger load data with the simulated spread of COVID-19 for each trip, we can model and estimate the spread of COVID-19 and test the sensitivity to inputs that cannot be directly measured.

4.1. Overcapacity on the bus

Public transit in Allegheny County has limited passenger capacity on buses to promote physical distancing between commuters during the pandemic, (10 passengers for 35-ft buses, 15 passengers for 40-ft buses, and 25 passengers for 60-ft buses). The method for measuring crowding on the bus is defined in Eq. (1). The total number of overcapacity passengers (O) is the sum of overcapacity (O_i) per trip (i) for all trips (I). If the peak passenger load of a trip (L_i) is greater than the capacity (C_i), the overcapacity is the difference between the load and capacity. If the peak load is less than or equal to the capacity, the overcapacity (O_i) is zero (See Appendix A for the full list of variables).

$$O_i = \begin{cases} (L_i - C_i) & L_i > C_i \\ 0 & L_i \le C_i \end{cases} \quad (1)$$

$$O = \sum_{i=1}^{I} O_i \quad (2)$$

In the 'extra buses' alternative an additional bus is dispatched each time the bus reaches its capacity (C_i), so the total number of additional buses (Z_i) dispatched for a trip is the peak passenger load of the original trip (L_i) divided by the capacity of the bus and rounded down (represented mathematically by $\lfloor \rfloor$). The original bus plus the extra buses represent the total number of buses ($1 + Z_i$) for a given trip (i).

$$Z_i = \lfloor \frac{L_i}{C_i} \rfloor \quad (3)$$

Total unmet demand due to COVID-19 encompasses anyone who would have liked to take the bus but was not permitted to get on due to the bus being at capacity or the bus being more crowded than they were comfortable within the pandemic. Even if a bus is not at capacity, some commuters may choose to find a different mode of transportation due to the infection risk from the other commuters on the bus. Therefore our base unmet demand represents a conservative lower bound for unmet demand during the pandemic.

4.2. Monte Carlo

A Monte Carlo simulation is conducted to compare how the range of costs changes under varying TNC/AV trip lengths.[2] and the stochastic uncertainty of increased risk of contracting COVID-19 on the bus. The TNC/AV trip lengths and number of infections are used to calculate social costs. The total cost includes operating costs ($/km), marginal congestion, accident, & pollutant costs ($/km), the value of a statistical life from COVID-19 risk, and the social cost of vehicle emissions.

We run the Monte Carlo to simulate passengers sick on each bus trip (76,000 trips) for each dispatch alternative 1000 times (See Appendix B for Monte Carlo convergence details). Each simulation used the probability density function of commute trip lengths to assign a commute distance to each AV and TNC ride. The number of people with COVID-19 on each bus trip is assigned using Bernoulli Likelihood functions (Eq. (5)) and a random number generator in Python. We run an epidemiological model (Gkantonas et al., 2021; Oliveira et al., 2021a) to find the probability of the other passengers (and bus driver) getting sick and Bernoulli Likelihood functions and random number generators are again used to model how many passengers contracted COVID-19 on each trip given that trip's risk of infection.

In each run, we model five dispatch alternatives. In the first alternative, we assume crowding is allowed and we model the risk of contracting COVID-19 (Oliveira et al., 2021a) with all passengers on the same bus. In the second alternative, extra buses are dispatched for the overcapacity passengers.[3] In the third alternative, we model all

passengers on one bus and assume the vehicle size changes from the true vehicle size to a 60-ft articulated bus. In the fourth alternative, we assume all overcapacity passengers take a TNC with a driver. We model the risk of contracting COVID-19 on the at-capacity bus and the risk in the TNC with two individuals (driver and passenger). In the fifth alternative, we assume all overcapacity passengers take single-passenger AVs. We model the risk of contracting COVID-19 on the at-capacity bus and assume risk of zero for the single-passenger AV trips. We assign a commute distance using a probability density function of distances and a random number generator to each overcapacity passenger (Pittsburghers for Public Transit, 2015). The COVID-19 risk calculator assumes a well-mixed room (Gkantonas et al., 2021). To find the number of people that enter the bus sick we use a rate of sickness for that day within the county. Eq. (4) shows the percent of residents (ρ_d) with COVID-19 in the county on any given day (d) as the sum of the newly reported cases (σ_d) for the past 20 days divided by the total population of the county (β). This assumes residents are contagious for a mean of 20 days which accounts for the five days of pre-symptomatic contagiousness period and symptomatic period of illness of 10–20 days for the Alpha variant of spring 2020 following the onset of symptoms (Center for Disease Control, 2021b; Widders et al., 2020).

$$\rho_d = \frac{\sum_{(d=-20)}^{0} \sigma_d}{\beta} \quad (4)$$

Eq. (5) shows the Bernoulli likelihood function used to represent the discrete probability for how many sick passengers (α_i) would be on a bus trip (i) given the percent of the population currently sick each day (ρ_d) and the number of people on the bus ($N_{\phi,i}$). The ϕ represents the set of five alternatives modeled in the Monte Carlo: allow crowding, extra buses, longer buses, TNCs and AVs.

$$P(\alpha_i) = \binom{N_{\phi,i}}{\alpha_i} \rho_d^{\alpha_i} (1 - \rho_d)^{(N_{\phi,i} - \alpha_i)} \quad (5)$$

$$\text{where} \quad \binom{N_{\phi,i}}{\alpha_i} = \frac{N_{\phi,i}!}{\alpha_i!(N_{\phi,i} - \alpha_i)!} \quad (6)$$

4.3. Monte Carlo for each policy alternative

Eq. (5) shows the Bernoulli likelihood function used to represent the discrete probability for how many sick passengers (α_i) would be on a bus trip (i) given the percent of the population currently sick each day (ρ_d) and the number of people on the bus ($N_{\phi,i}$). The ϕ represents the set of five alternatives modeled in the Monte Carlo: allow crowding, extra buses, AVs, and longer buses (Eq. (8)).

Eq. (5):

$$P(\alpha_i) = \binom{N_{\phi,i}}{\alpha_i} \rho_d^{\alpha_i} (1 - \rho_d)^{(N_{\phi,i} - \alpha_i)} \quad (5)$$

$$\text{where} \quad \binom{N_{\phi,i}}{\alpha_i} = \frac{N_{\phi,i}!}{\alpha_i!(N_{\phi,i} - \alpha_i)!} \quad (6)$$

For the 'allowing crowding' and 'longer buses' alternative, all passengers would be allowed on the same bus ($\phi = 1$), so the number of people on the bus ($N_{\phi,i}$) is the peak load of passengers and the bus driver ($L_i + 1$). For the 'Extra buses' alternative, each trip would have a bus at-capacity with a bus driver ($C_i + 1$) and an overflow bus with the surplus riders and the bus driver ($s_i + 1$), which is the last passenger alternative in Eq. (8) ($\phi = 2$). In the 'extra buses' alternative, if more than one additional bus is required to keep the passenger loads at or below capacity ($Z_i > 1$), than there would be multiple buses running at-capacity (C_i) and one bus of overflow (s_i). The surplus (s_i) is therefore the peak passenger load of the original trip minus the capacity of the bus (C_i) times however many extra buses are required (Z_i) beyond the original bus (Eq. (7)). For the 'Autonomous vehicle' alternative ($\phi = 3$), all demand that exceeds the capacity would be given an autonomous vehicle, so the number of people on the bus is the bus capacity and

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[2] Probability curve found using the Make My Trip Count 2015 survey data of Allegheny County bus rider commute distances.

[3] The first bus is at capacity and the next bus has spill-over passengers until it is at capacity when an additional bus is dispatched.

the bus driver ($C_i + 1$). For the 'Transportation Network Company' alternative, the bus runs at capacity ($\phi = 2$) and a TNC is dispatched with a driver and passenger ($\phi = 4$) for all overcapacity riders ($L_i - C_i$).

$$s_i = L_i - (Z_i \times C_i) \tag{7}$$

$$N_{\phi,i} = \begin{cases} L_i + 1 & \phi = 1 \\ s_i + 1 & \phi = 2 \\ C_i + 1 & \phi = 3 \\ 2 & \phi = 4 \end{cases} \tag{8}$$

For the 'extra buses' alternative, there are two Bernoulli likelihood functions (Eqs. (9) and (10)), one for the at-capacity buses and one for the overflow buses. The total number of sick passengers (α_i) for each trip (i) in the 'extra buses' alternative is the number sick on each at-capacity bus ($\alpha_{i,1}$) plus the number sick on the overflow bus (Eq. (11)).

$$P(\alpha_{i,1}) = \binom{C_i + 1}{\alpha_{i,1}} \rho_d^{\alpha_{i,1}} (1 - \rho_d)^{(C_i+1)-\alpha_{i,1}} \tag{9}$$

$$P(\alpha_{i,2}) = \binom{s_i + 1}{\alpha_{i,2}} \rho_d^{\alpha_{i,2}} (1 - \rho_d)^{(s_i+1)-\alpha_{i,2}} \tag{10}$$

$$\alpha_i = (\alpha_{i,1} \times Z_i) + \alpha_{i,2} \tag{11}$$

$$P(\alpha_i) = \binom{2}{\alpha_i} \rho_d^{\alpha_i} (1 - \rho_d)^{(2-\alpha_i)} \tag{12}$$

For the 'TNC' alternative, there are two Bernoulli likelihood functions (Eqs. (9) and (13)), one for the at-capacity bus and one for the TNCs. The total number of sick passengers (α_i) for each trip (i) in the 'TNC' alternative is the number sick on the at-capacity bus ($\alpha_{i,1}$) plus the number sick on each TNC trip; A passenger and driver per TNC vehicle for each overcapacity rider (Eq. (14)).

$$P(\alpha_{i,3}) = \binom{2}{\alpha_{i,3}} \rho_d^{\alpha_{i,3}} (1 - \rho_d)^{(2-\alpha_{i,3})} \tag{13}$$

$$\alpha_i = \alpha_{i,1} + (L_i - C_i) \times \alpha_{i,3} \tag{14}$$

We run the Monte Carlo Analysis under thirteen sensitivity scenarios, baseline, and the lower and upper estimate for six variables: estimated unmet demand for the bus, the rate of COVID-19 among bus riders, mask efficiency among bus riders, the social cost of carbon used, and the cost per kilometer to dispatch TNCs and AVs. See Appendix C for the ranges of costs.

4.4. Vehicle costs

We break down the costs for bus trips (Eq. (15)), TNC rides, and AV rides (Eqs. (16)). The total bus operating cost (B) represents the cost to dispatch an additional bus for each trip (i) for the time in hours the trip takes (τ_i) at the hourly operating cost for the port authority (π_{bus}) for all bus trips that were overcapacity (I).

The TNC/AV operating cost (ζ_j) for the total AV trips (J) represents supplying each overcapacity rider (j) with a TNC/AV using the probability curve of commute lengths of Pittsburgh bus riders (in kilometers) (Pittsburghers for Public Transit, 2015) to find distance the traveled (M_j). We assume that the port authority would make an agreement with a TNC or AV dispatcher to meet rare-event demand, taking on the per-kilometers cost of the ride (π_{AV}), but not the cost of purchasing or storing the vehicle. See Appendix C for a further breakdown of the costs of each externality and the social costs.

$$B = \sum_{i=1}^{I} (\pi_{bus} \times \tau_i) \tag{15}$$

$$\zeta = \sum_{j=1}^{O} (\pi_{AV} \times M_j) \tag{16}$$

For the TNC and AV alternative, we assume the port authority will make a rare-event agreement with a TNC company/AV provider rather

than purchase and maintain their own light-duty vehicle fleet or AVs. We assume that for each TNC/AV ride, the port authority would bear paying the difference between the total cost of the ride and bus fare, but not the costs of purchasing a full fleet. Although uncommon, there is a precedent for TNC services to be dispatched in rare events. Uber committed to providing pandemic trips to people getting vaccinated and to essential riders (Uber, 2021; Gillaspia, 2021). In late 2020 when demand was lower than pre-pandemic levels, Uber estimates that 23% of public transit trips would have been cheaper with a ride-sharing service instead (Uber, 2021).

4.5. Infection calculation

Sick residents (σ_d) are assumed to be contagious for 20 days (d), including pre-symptomatic days. The percent sick in the county (ρ_d) is the total current cases divided by the county population (β). We use a random number generator in Python to model how many people would be contagious with COVID-19 on each bus trip given the number of people on each trip ($N_{\phi,1}$) including the bus driver, the average passenger trip length in hours (t), and the rate of COVID-19 in the county ρ_d.

Given the number of passengers modeled to have COVID-19 on the bus, we use an epidemiological model to find the probability of others on the bus contracting COVID-19 (I_{risk}) (Oliveira et al., 2021a; Gkantonas et al., 2021). Oliviera (2021) developed the epidemiological model and used several early-pandemic studies to calibrate and validate model assumptions (Oliveira et al., 2021a; World Health Organization, 2020; Miller et al., 2020; Morawska et al., 2020; Bourouiba, 2020; Wolfel et al., 2020; Buonanno et al., 2020; Burridge et al., 2021). The model constants (e.g., the effect of viral load, viral decay, settling rate, mask efficacy by type of mask, and exhalation rate by type of activity) are adjusted to SARS-CoV-2 (COVID-19) in the early stages of the pandemic to match the time period of the study (Gkantonas et al., 2021; Oliveira et al., 2021b). Other scenario-dependent constants are set to match typical bus conditions (e.g., ventilation rate, average mask efficacy, talking rate in the bus) (Venfilter, 2020; Environmental Protection Agency, 2021; Gkantonas et al., 2021). We assume 90% of passengers are sitting quietly and 10% are speaking; this assumption informs the exhalation rate in the model used. We also assume 100% of passengers are wearing a cloth mask and the masks are 35% effective (η_{mask}) (Environmental Protection Agency, 2021; Gkantonas et al., 2021). We assume passengers wear cloth masks (35% effective) based on the strict COVID-19 guidelines during the time period in our study and the minimal degree of N95 mask use in the early months of the pandemic; we run a sensitivity analysis on the mask efficiency to understand how sensitive our results are to the mask efficiency assumption and to model the extreme cases of 0% mask wearing and all passengers wearing N95 masks correctly.

The rate of concentration of viral particles in the air ($\frac{d\gamma}{dt}$) depends on the volume of the bus (V), the number of sick passengers (α_i), the mask efficiency of all passengers (η_{mask}), the COVID-19 particle generation of the sick passengers (G_v). While particles are emitted through sick passengers breathing, particles are also removed from the air through viral decay (λ), aerosol settling from gravity (κ), the rate that the air in the bus gets changed over (v), and any filtration that occurs (ψ).

$$\rho_d = \frac{\sum_{(d=-20)}^{0} \sigma_d}{\beta} \tag{17}$$

$$P(\alpha_i) = \binom{N_{\phi,i}}{\alpha_i} \rho_d^{\alpha_i} (1 - \rho_d)^{N_{\phi,i}-\alpha_i} \tag{18}$$

$$\frac{d\gamma}{dt} = \frac{\alpha_i \cdot (1 - \eta_{mask}) \cdot G_v}{V} - (\lambda + \kappa + v + \psi) \cdot \gamma \tag{19}$$

The above rate of particle concentration in the air ($\frac{d\gamma}{dt}$) is a linear first-order ordinary differential equations, which is integrated from t_0 to t, the average time each passenger spends on the bus.

Table 2
Percent of passengers and percent of trips over the port authority COVID-19 capacity by month.

Month	Total passengers	Overcapacity passengers	Overcapacity trips
April[a]	449,779	3.1%	8.9%
May	1,071,047	4.5%	12.7%
June	1,170,550	4.7%	13.2%
July	1,139,077	4.3%	12.1%
August	1,155,701	4.4%	12.0%
September[a]	788,436	4.3%	12.1%
Total	**5,774,590**	**4.3%**	**12.1%**

[a]April and September only include half of the month.

$$\gamma(t) = \frac{\alpha_i(1 - \eta_{mask})G_v}{V(\lambda + \kappa + \upsilon + \psi)} + \left(\gamma(t_0) - \frac{\alpha_i(1 - \eta_{mask})G_v}{V(\lambda + \kappa + \upsilon + \psi)} \right) \cdot e^{(\lambda + \kappa + \upsilon + \psi)(t - t_0)}$$

$$(20)$$

Given γ_t concentration of COVID-19 in the air, each non-sick passenger on the bus breathes in at an inhalation rate of Q_{inh} with masks blocking some η_{mask} of the γ_t intake. This inhalation occurs over the average time each passenger spends on the bus. We assume an initial viral intake ($N_{virus}(t_0) = 0$) of zero for uninfected passengers because we are only considering the COVID-19 contracted on the bus (not prior to the trip). $\kappa_p = 4.1 \times 10^2$ is dose–response constant for SARS-CoV (Watanabe et al., 2010). Given a risk probability (I_{risk}) and a number of people on the bus ($N_{\phi,i}$), the number of people that contract COVID-19 on each trip (ω_i) is modeled in the Monte Carlo using a Bernoulli likelihood function underlying a random number generator in Python.

$$N_{virus}(t) = (1 - \eta_{mask}) \int_{t_0}^{t} \gamma(t) \times Q_{inh} \, dt \qquad (21)$$

$$I_{risk} = 1 - e^{(-\frac{N_{virus}}{\kappa_p})} \qquad (22)$$

$$P(\omega_i) = \binom{N_{\phi,i}}{\omega_i} I_{risk}^{\omega_i}(1 - I_{risk})^{N_{\phi,i} - \omega_i} \qquad (23)$$

5. Results

5.1. Overcapacity on bus transport during COVID-19

The Pittsburgh Regional Transit set limits on how many passengers may ride on each type of bus to promote physical distancing and limit the spread of COVID-19 (Pittsburgh Regional Transit, 2020). Despite the COVID-19 capacities limitations, some buses had passenger loads above their mandated limit. Possible reasons for buses exceeding capacity include lack of knowledge about the set bus capacity limit, underestimating the current passenger load, or allowing the passenger on the bus despite the restriction. Table 2 shows the percent of overcapacity passengers and trips each month from mid-April to mid-September 2020. Throughout the first Spring of the COVID-19 pandemic, each month 4%–5% of riders were overcapacity, and 9%–13% of trips had overcapacity.

Our COVID-19 risk analysis is based in Allegheny County, PA where buses represent 86% of public transit rides for the county (Pittsburgh Regional Transit, 2019). In February 2020, the port authority had a total of 4.4 million passengers. Early in the COVID-19 pandemic (April 2020) total ridership dropped to 900,000 passengers (80% decrease), as seen in Fig. 2. The average passenger load at bus stops in the lowest income census tracts dropped by 45% while the highest income census tracts dropped by 59%. Low-income census tracts had higher continued ridership and higher crowding rates throughout the pandemic. Between January and February (before COVID-19), the peak ridership occurred between 7–9 AM (22.4 mean passenger load) and 4–6 PM (23.6 mean passenger load). During the pandemic, the peak ridership shifted to 2–4 PM and crowding decreased overall (See Appendix D for changes in ridership by the time of day). During the early months of the pandemic within 2–4 PM, 21% trips were over capacity compared to the overall average (12%).

5.2. Equity considerations

Fig. 3 shows the average busload from mid-April to mid-September, 2020 at each bus stop in Allegheny County on top of American Community Survey designated census tracts (United States Census Bureau, 2018). The darker the red dot, the higher the average busload at that stop; the darker the purple area, the higher percent ethnic minority of residents in that census tract. In Fig. 3(a) the higher per capita census tracts had bus stops with a low mean load overall, particularly in the outer suburbs of the county (See Appendix E for details on Allegheny County transit-dependent and essential worker demographics).

Fig. 3(a) shows that overall during the Spring of 2020, the 20% of lowest-income census tracts had almost twice the average passengers compared to the highest income census tracts (4.2 passengers compared to 2.6 passengers on average). Low-income residents and residents from an under-represented ethnic minority are more likely to be essential workers that have to commute during the pandemic (see Appendices E and F). Low-income residents are also more likely to be transit-dependent (Liu et al., 2020). Inability to work from home or shift to other modes of transit account for continued bus demand during the pandemic. We acknowledge that not every person on a bus passing through a lower-income census tract may be low-income themselves; however, the higher loads at bus stops in low-income and high-minority areas indicate that residents entering the buses near their homes in these census tracts are at higher risk of getting on a crowded bus.

The lowest 20% of census tracts by per capita income saw a 45% reduction in average passenger load (7.6 passengers to 4.2 passengers), while the 20% highest income census tracts saw a 59% reduction in average passenger load (6.3 to 2.6 passengers). Figs. 3(a) and 3(b) show that low-income and high-minority census tracts had marginally higher pre-pandemic ridership (about 2 extra passengers on average) coupled with a smaller reduction in ridership during the pandemic to yield more frequent crowding. During the early months of the pandemic (April–May), census tracts with high underrepresented minority populations had an average passenger load of 4.2 at their stops compared to low minority census tracts with an average passenger load of 2.8 riders.

Table 3 shows the average passenger load of the 335 census tracts with bus stops grouped into 5 quartiles by average passenger count. The census tracts with the lowest average load of less than 1.48 passengers on the bus at each stop are in census tracts with an average ethnic minority population of 14.4%, while the census tracts with the highest average passenger loads (greater than 4.86 passengers on the bus at each stop) have an average ethnic minority population of 41.7% (See Appendix F for details on the relationship between bus crowding per stop and census tract socioeconomic data).

5.3. Overall risk of disease spread

The key risk of concern to the public transit agency was passengers spreading or contracting COVID-19 while on the bus due to crowding. In our model, we assume that COVID-19 is contagious for 20 days (pre-symptomatic and symptomatic period for the Alpha variant from the Spring of 2020) (Widders et al., 2020), people on the bus wear cloth masks that are 35% effective (Environmental Protection Agency, 2021; Venfilter, 2020), and the probability that a passenger entering the bus has COVID-19 is equivalent to the percent of the population that has COVID-19 in Allegheny County that day. Allegheny County had 10,804 cases from mid-April to mid-September and our model estimates that 2% of those cases would have been contracted directly on the bus (234 cases). Using the average reproduction rate of COVID-19 in Pennsylvania over this period, a further 227 cases would have contracted COVID-19 from the infected bus passengers, giving a total first-degree community impact from infection of 4% of all cases at the county level from mid-April to mid-September 2020 (See 7 Limitations). We define zero-th degree of infection (direct infection) as cases modeled to be contracted on transportation and first degree of infection to be cases
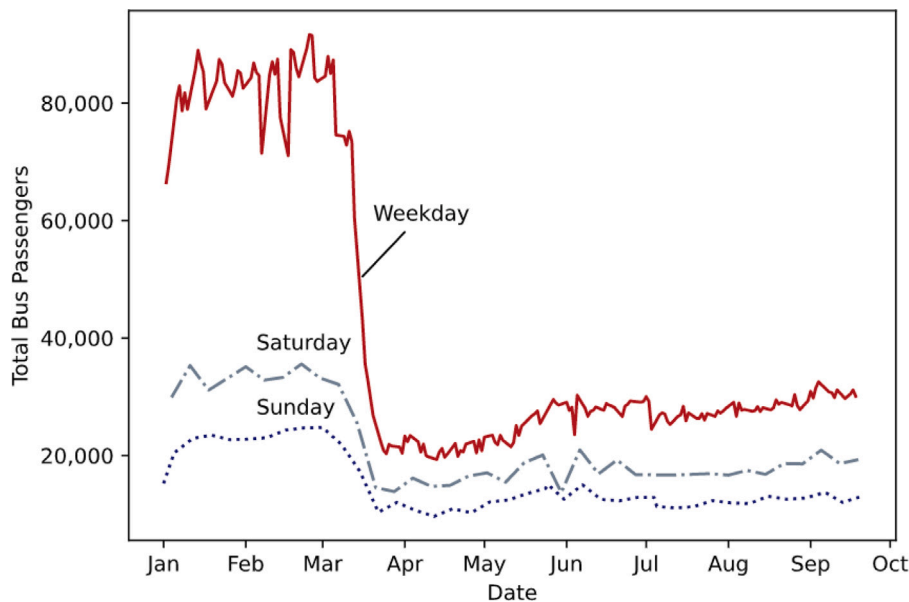
Fig. 2. Pandemic bus ridership by day. Total passenger count for Allegheny County from January 1st to September 20th, 2020 excluding federal holidays.

Table 3
Mean passenger load, per capita income, and percent ethnic minority of census tracts grouped by their mean bus stop passenger load in Allegheny County from mid-April to mid-September 2020.

Average passenger quartile	Average passenger count	Per capita income	Percent minority
0%–20%	0.87	$38,113	14.4%
20%–40%	2.23	$36,688	21.6%
40%–60%	3.36	$32,515	27.0%
60%–80%	4.24	$31,952	35.5%
80%–100%	5.96	$26,723	41.7%

Table 4
The number of passengers modeled to contract COVID-19 with a low disease-prevalence (April to September of 2020) and a high disease-prevalence in the community (August 2020 to January 2021) for direct bus infections (top) and including first-degree infections in the community (bottom).

COVID-19 rate:	Over capacity bus trips		All bus trips	
	Low	High	Low	High
Contracted on bus	121	394	234	1037
Including first-degree	238	804	451	2116

modeled to be contracted from a direct infection case using a per day reproduction rate for the state of Pennsylvania.

We found 52% of all COVID-19 cases from the bus were contracted on overcapacity trips, despite making up only 12% of trips (121 cases out of 234). In our high COVID-19 prevalence scenario, we normalize the COVID-19 prevalence to the level of total cases in Allegheny County between August 6th 2020–January 10th 2021 onto the ridership from Spring 2020. When the COVID-19 rate is normalized to winter levels (52,300 total cases of COVID-19, compared to the 10,804 cases in the previous spring) we find the total cases contracted on the bus increases by 440% (1037 contracted on the bus). In Table 4, The baseline number of modeled infections on the bus represent cases directly from the bus and including first-degree infection in the community. We Model infections looking only at trips that were overcapacity, and also looking at all trips. We model the recorded rate of COVID-19 in the community from April to September 2020 and we simulate the winter peak of COVID-19 onto spring 2020 demand.

We model the risk reduction if AVs are dispatched for each passenger over the bus's capacity. We assume there is no risk of infection in the AVs because COVID-19 spreads through the air (Center for Disease

Control, 2020) and an AV would be dispatched for each passenger, eliminating contact with other passengers or a driver. We find that if AVs are dispatched for overcapacity riders, the number of covid-cases contracted on crowded buses would be 41% of the base-case infections (71 infections). This would have meant 1% fewer total cases in the county.

5.4. Uncertainty analysis

There is uncertainty in the risk of contraction, the unmeasured unmet demand, the mask wearing adherence, and the range of projected costs associated with the modeled crowding reduction policies. We chose to compare the selected alternatives because allowing crowding, dispatching extra buses, dispatching longer buses are all within the capacity of the existing public transit bus fleet. We compare TNCs as an emerging form of public–private partnerships that some transit agencies used during the early period COVID-19 pandemic (Association, 2020). We investigated AVs as a future option to explore what role AVs may play to improve transit equity in rare events; AVs allow for physical distancing because they do not require a driver (unlike other on-demand services like current TNCs).

Fig. 4 shows the estimated number of passengers infected with COVID-19 by alternatives. The rate of COVID-19 in the county is used to stochastically model how many passengers would be sick on each trip (see Methods). All five alternatives show a wide range of infections in the Monte Carlo analysis — allowing crowding has the widest range of 83 to 165 infections from its least-infected run to its most-infected run, respectively. The allow crowding option and the TNC Dispatch option both have a 94% probability of causing more than 100 infections, while the extra buses and longer buses have a 6% and 9% probability of causing more than 100 infections (See Appendix G for details on risk by bus size). The AV option only has a 1% probability of more than 100
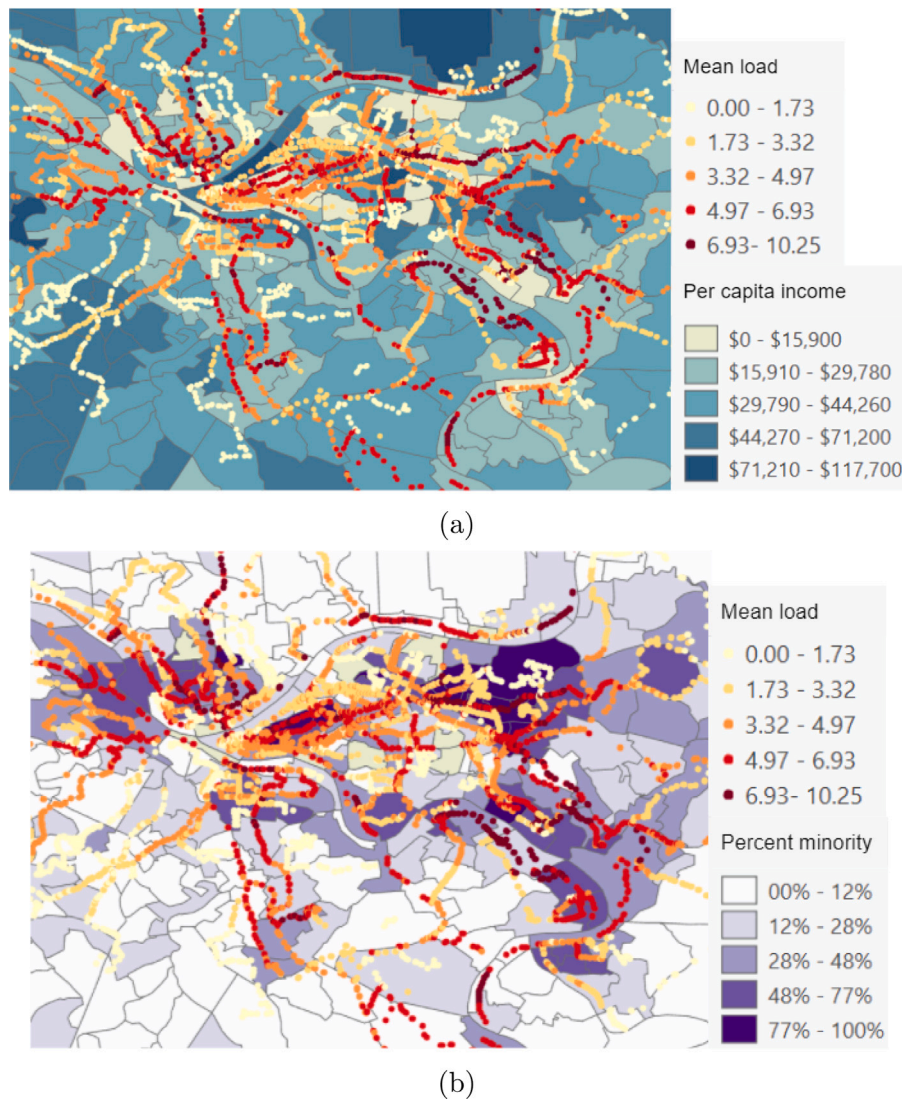
(a)

(b)

Fig. 3. Mean busloads by stop. The mean busload at each bus stop in Allegheny County from mid-April to mid-September 2020 on a map of census tracts with a color scale of per capita income (a) and percent ethnic minority (b).

infections. Note that, none of the five alternatives reach zero, meaning that each alternative retains some risk.

Fig. 5 presents the cost break down for each mitigation strategy. Allowing crowding costs $59 million in operation and social costs over the five months. Comparatively, AVs are the least costly option at $45 million (24% reduction) and longer buses are similar in cost at $46 million (22% reduction). Dispatching TNCs have the greatest total cost at $64 million (9% increase), followed by dispatching additional 40-ft buses has the greatest cost at $62 million (6% increase) due to the high operation costs of the extra buses. The least costly option when just considering expenses for the transit operator is to allow crowding on the bus ($17 million in operating costs for the crowded buses), then dispatch longer buses (same hourly costs), followed by dispatching AVs ($19 million), dispatching TNCs ($21 million) and finally dispatching additional buses ($31 million). However, when the social cost of passengers contracting COVID-19 is taken into consideration, dispatching AVs becomes more favorable. Allowing crowding has a social cost of lives lost from COVID-19 of $42 million, compared to AVs which would reduce the social cost of lives lost from COVID-19 to $24 million.

In Fig. 6, the measured overcapacity of the system represents the lower bound for unmet demand because it excludes any commuters that were barred from entering the bus. The upper bound for unmet demand is estimated as the average hourly demand between 2020 and

2018 levels. The Value of a Statistical Life represents the social cost of mitigating a small chance of death. If a low VSL ($1.33 Million) is used, allowing crowding on the bus becomes the most cost-competitive option because the increased COVID-19 risk is not valued as costly. The upper bound VSL ($11.6 Million) in Fig. 6 is sourced from the Department of Transportation (Department of Transportation, 2020), which assumes transit risk is equal across age demographics (unlike COVID-19, which is the highest risk to older adults). Using the upper bound VSL, it is less expensive to dispatch AVs ($76 million) than dispatching longer buses ($83 million). Similarly, if the rate of COVID-19 in the county is at its upper bound AVs are less costly ($99 million) than longer buses ($110 million). If the unmet demand of the system approaches its upper bound, AVs are 36% less costly ($59 million) than longer buses ($91 million). As the percentage of Allegheny residents with COVID-19 falls (to the lower bound representing half the true rate in the observed period), allowing crowding ($38 million) becomes cost-competitive with AVs ($34 million) because of the risk of contracting COVID-19 decreases, lowering the social costs. If all passengers properly wear N95 masks (assumed to have a 95% efficiency if worn properly), longer buses become the most cost-effective option ($21.5 million), followed by allowing crowding on the bus ($22.8 million), AV dispatch ($23.3 million), and TNC dispatch ($25.7 million); with complete mask compliance of high-efficiency masks, the added costs of
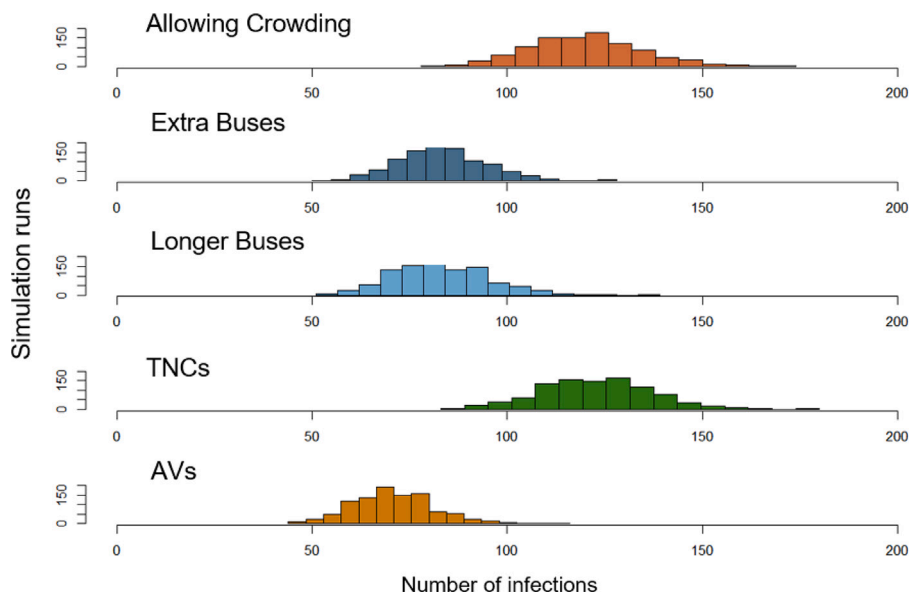
Fig. 4. Modeled infections by policy alternative. Number of passengers estimated to contract COVID-19 in each alternative with baseline assumptions in the Monte Carlo analysis using the Freedman–Diaconis rule for selecting bin width.
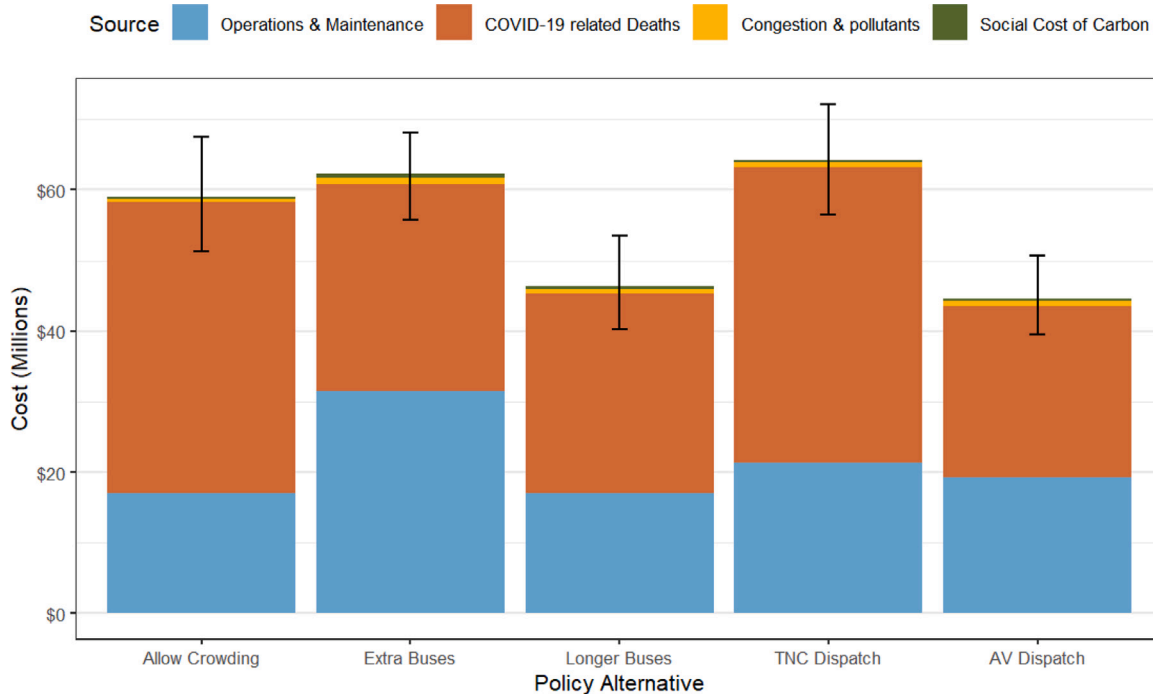

Fig. 5. Social costs of policy alternatives. Social Cost break down of each policy alternative considered to eliminate pandemic crowding on the bus. Error bars showing the 95th and 5th percentile COVID-19 related costs from the Monte Carlo Analysis.

dispatching AVs and TNCs do not get surpassed by the social cost of COVID-19 spread. In most scenarios, TNC were cost-competitive with dispatching extra buses, but the high mask efficiency scenario is the only option where TNC dispatch is cost competitive with dispatching longer buses. See Appendix I for the full table of cost and sensitivity results.

Fig. 7 shows the trade-offs between operational costs and direct infections on the bus for each policy alternative. The lower bound shows the baseline scenario (i.e., bus system demand from April to September 2020); the upper bound represent the upper bound of demand hourly ridership averaged between 2018 (pre-pandemic) and 2020 levels. We found that AVs and longer buses have similar number of infections

in the baseline scenario; however, upon demand increases, longer buses have approximately twice the mean infections (214 infections) compared to AVs (111 infections). On the other hand, longer buses yield higher direct social costs ($38 million) than AVs ($20 million). As demand reaches its upper bound, longer buses get crowded themselves and lose their risk mitigation ability. AVs continue to mitigate risk as demand increases, but at a higher cost per infection avoided. TNCs still have high social costs because each overcapacity passenger is in a TNC vehicle with a driver, so risk is not significantly mitigated on the aggregate (242 infections), resulting in infection and externality costs of $54 million. The additional vehicles required in the upper demand scenario for AVs and TNCs also result in relatively high operations,
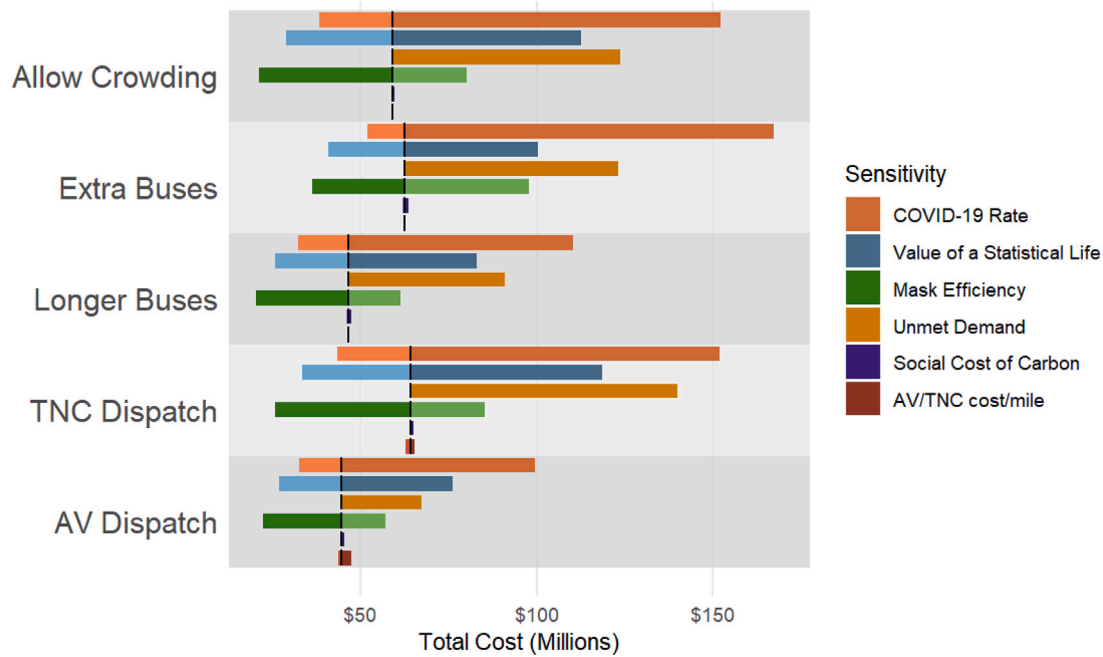
Fig. 6. Cost Sensitivity of each policy alternative to parameter bounds. The cost sensitivity to the lower and upper bound estimates of each parameter for each alternative with all other parameters held constant. The break down of parameter bounds can be found in Appendix C.

Table 5
Breakdown of costs in millions of $2020 for each policy alternative considered.

Cost $ millions USD2020	Operations & Maintenance	COVID-19 related deaths	Social cost of carbon	Congestion & Pollutants	Total
Allow crowding	17	41	0.32	0.51	59
Extra buses	31	29	0.58	0.94	62
Longer buses	17	28	0.47	0.56	46
TNC dispatch	21	42	0.36	0.77	64
AV Dispatch	19	24	0.36	0.77	45

emissions, pollution, and congestion costs ($ 1 million). Longer buses have more uncertainty in their total costs (range of $44 million) and infections (range of 131 infections) than AVs. Dispatching extra buses and dispatching TNCs both become costly in operational costs and social costs as demand increases coupled with less effective COVID-19 mitigation. TNCs cause a similar number of infections to longer buses in both scenarios; however, the operational costs are higher in both, as well.

5.5. Results tables

Table 5 shows the cost breakdowns for each policy alternative into their cost components seen graphically in Fig. 5. Table 6 shows the cost bounds for the 5th and 95th percent of COVID-19 cases for each alternative in Monte Carlo Analysis and the costs associated with the infection range.

Table 7 shows the numerical cost ranges for each policy alternative when each parameter is adjusted to its lower and upper bounds. The table can be seen graphically in Fig. 6. Some parameters do not impact price for certain alternatives so the bounds are ignored (e.g. AV price per-km does not impact the costs of buses). In the case of the unmet demand parameter, the baseline unmet demand already represents a lower-bound value.

6. Conclusions and policy implications

We investigate the spread of COVID-19 on a local transit authority and the cost-effectiveness of policy alternatives to mitigate the spread. Our model suggests 4% of the cases would have been contracted on

Table 6
Cost in millions of $2020 for the total social and operational costs of each policy alternative for the mean number of COVID-19 cases modeled in the Monte Carlo Analysis, the 5th percentile of cases, and the 95th percentile of cases.

Policy alternative	Mean total cost ($ Millions)	5% of infections ($ Millions)	95% of infections ($ Millions)
Allow crowding	59	52	67
Extra buses	62	56	68
Longer buses	46	41	53
TNC dispatch	64	56	72
AV dispatch	45	38	50

the bus or in the community from bus-riders in Allegheny County in the five-month period of April to September 2020. In the early months of the pandemic when both ridership and disease-prevalence in the community were low, the risk of contracting COVID-19 on the bus was almost negligible: 4% of cases were from the bus, but only 10,804 residents (<1% of residents) contracted COVID-19 in the county during this period: 394 total cases represent a small overall risk. Thus, transit during this time was a relatively low-risk activity, but with 1.2 million residents in the county, even a low possibility of contracting a deadly virus is worth mitigating.

We found that in the spring and summer of 2020 only 12% of trips were overcapacity, but accounted for over half (52%) of modeled COVID-19 cases contracted on the bus. The buses were more crowded on average in low-income and high ethnic minority census tracts (with an average passenger load almost twice as high per bus stop), leaving residents in these census tracts at higher risk of contracting COVID-19
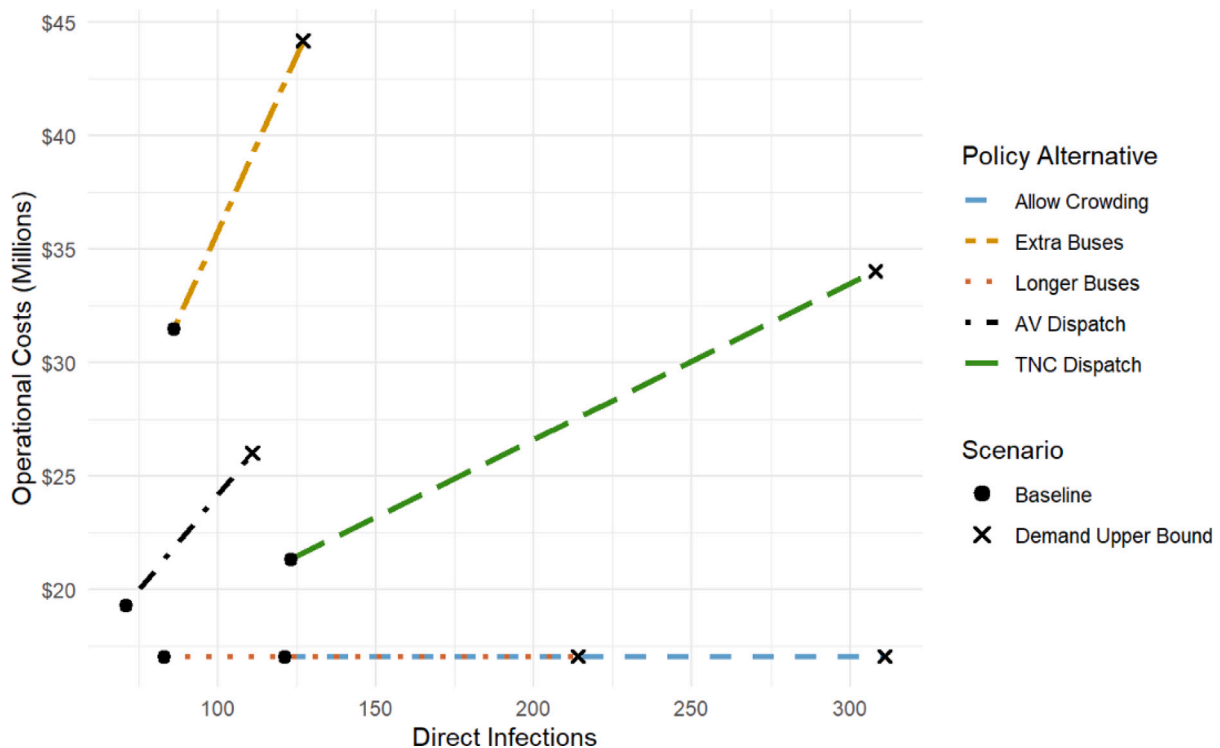
Fig. 7. Operational costs and infection sensitivity to bus demand. Trade-offs between operational cost and direct infections of COVID-19 on the bus across bus demand bounds. Direct infections are cases modeled to be contracted on the bus, and do not include secondary infections resulting from arriving at a person's destination. The solid circle shows the baseline case of overcapacity in the system; the *x* represents the scenario where bus demand is halfway back to pre-pandemic bus demand on an hourly basis, giving an upper bound for pandemic bus demand.

Table 7

Sensitivity Analysis of cost (in millions of $2020) of each policy alternative to the lower and upper bounds of five parameters considered in the model.

	Total cost range in $2020 millions		
Parameter adjusted	Allowing crowding	Extra buses	Longer buses
Midpoint cost	*59.1*	*62.3*	*46.4*
AV/TNC cost/km	–	–	–
Social cost of carbon	(58.8–59.7)	(61.9–63.5)	(46.0– 47.3)
Mask efficiency	(22.8–111.2)	(36.3–97.8)	(21.5–83.1)
Unmet demand	(59.1–123.6)	(62.3–123.2)	(46.4–90.8)
Value of a statistical life	(28.8–112.5)	(40.8–100.3)	(25.6–83.1)
COVID-19 rate	(38.4–152.1)	(51.9–153.9)	(32.2–110.3)
Parameter adjusted	TNC dispatch	AV dispatch	
Midpoint cost	*64.3*	*44.6*	
AV & TNC cost/km	(62.7–65.4)	(43.7–47.4)	
Social cost of carbon	(64.0–65.0)	(44.4–45.4)	
Mask efficiency	(25.7–85.2)	(23.3–75.7)	
Unmet demand	(64.3–140.0)	(44.6–67.3)	
Value of a statistical life	(33.5–118.6)	(26.9–76.0)	
COVID-19 rate	(43.3–152.0)	(32.4–99.5)	

on the bus. This largely reflects the inability to work from home or the inability to use alternative modes of transportation.

We consider strategies that minimize crowding on the bus without leaving people without a ride; we find that dispatching TNC rides and allowing crowding on the bus cause the highest number of infections (242 and 239 infections); while dispatching a single-person AV for each overcapacity rider causes the fewest infections (140 direct infections) for overcapacity trips. Dispatching longer buses and dispatching extra buses cause similar levels of infection (164 and 169 direct infections). We modeled that dispatching AVs for overcapacity passengers yields a 41% decrease in cases contracted on crowded buses (half of the cases contracted on the bus were contracted on crowded buses), equivalent

to a 1% reduction in total cases in the county for the spring of 2020. This reduction translates to about 100 avoided cases.

Although the risk from April to September of 2020 was low, when the rate of COVID-19 is normalized to early winter 2021 levels, case counts increase by about four-fold. The risk is still low compared to total passenger trips that occur, even in a high COVID-19 scenario. Given a 3% death rate among COVID-19 cases in Allegheny County in the early months of the pandemic, even a low-risk can be costly (tens of millions in social costs for the loss of life from transit-related infection of COVID-19).

We found that dispatching 60-ft articulated buses as a substitute for 40-ft buses for crowded trips or dispatching autonomous vehicles both yield similar costs and are the most effective methods when considering the cost to operate, the social cost of COVID-19, the social cost of vehicle emissions, and other externalities. The longer buses allow increased ability to physically distance with only marginal increases in emissions and operations costs. The Port Authority chose to dispatch 60-ft articulated buses in place of 40-ft buses for frequently-crowded trips beginning in November 2020. AVs become significantly more favorable as the rate of COVID-19 increases to winter-peak levels and when total transit demand gets closer to pre-pandemic levels. This is because the 60-ft articulated buses become crowded enough to justify the cost of dispatching AVs for overcapacity passengers.

When mask efficiency is modeled at 95% (all passengers properly wear N95 masks at all times), longer buses are the most cost-effective option ($19.2 million), followed closely by allowing crowding ($19.5 million), and AVs ($ 21.4 million) because the additional operational and social costs of dispatching extra vehicles outweigh the benefits when transmission on the bus is low due to effective mask-wearing of high efficiency masks.

It is important to note that the costs are not distributed evenly within the community across the policy alternatives considered. Transit authorities take on the cost of operations for vehicles, society more

broadly takes on the social cost of emissions and increased road congestion, but the riders and their networks bear the costs of increased risk of contracting COVID-19 on the bus. Low-income and high ethnic minority areas had more crowded buses. Given the mean infections per alternative in the Monte Carlo analysis, dispatching AVs possibly represents 41% fewer COVID-19 cases from crowded buses in the early days of the pandemic than allowing crowding (although the overall risk is low); dispatching extra buses and longer buses represented a 31% and 29% decrease, respectively. If unmet demand is at its upper bound, 199 fewer cases (65% fewer) are contracted from the bus system when AVs are dispatched for additional passengers.

This paper provides a framework for tying together models of COVID-19 spread in an indoor space (e.g., a vehicle) with public transportation data to compare alternatives and test sensitivity to decisions such as mask adherence and maximum passenger load. The county does not measure COVID-19 cases contracted on the bus; therefore, we provide a framework for modeling, estimating, and comparing rates of spread in different scenarios that cannot be attained directly. Due to the challenges of validating estimates we run thirteen sensitivity scenarios for each of the five alternatives considered to understand how sensitive our results are to each assumption made and to give bounds of estimation.

We take existing, validated approaches for modeling the spread of COVID-19 in an indoor space (e.g., inside a vehicle) and apply the model in a novel way to public transportation data. We go beyond modeling the hypothetical spread of COVID-19 on a single hypothetical bus and instead model the spread across 76,000 bus trips, running each trip modeled 1000 times in a Monte Carlo simulation. This approach allows the combination of multiple dynamic models. By running the Monte Carlo simulation repeatedly for each alternative and scenario, we can see the convergence of results of dynamic, random probability events. Specifically, we use a Monte Carlo analysis because the rate of COVID-19 in the community is low enough that many bus trips, will not have a passenger with COVID-19. Running the simulation allows us to capture this real-world randomness. This framework and approach of combining an epidemiological model with real-world trips in a dynamic simulation can be extended by researchers to compare transportation alternatives, model future disease spread, and test the sensitivity of the model to different policies.

For policymakers, this work can be used to understand the role that public transportation has in the spread of airborne diseases and compare risks modeled across alternatives. Importantly, it can also help public transit agencies better understand how different policy and operational decisions (e.g., mask efficacy, passenger limitations, and dispatching longer buses) affect public health and the associated economic costs and societal benefits. Our framework is useful for policymakers and transit agencies particularly early in the spread of a novel airborne disease because it gives insight into the sensitivity of spread and the bounds of results to different policy decisions when there is a high degree of uncertainty about the future of the disease. Given that public transit serves a vital role in providing mobility especially to those in underserved populations, understanding the range of possibilities (e.g., the upper bound of COVID-19 spread if passenger demand increases) can help inform decision making and improve health equity. Additionally, our results can help inform communication by comparing modeled risk on the bus to perceived risk of riding the bus by the general public; with this understanding, policymakers can adjust messaging and protocol to help passengers make safety and transportation decisions.

Our results imply that in a pandemic setting, mitigation strategies on public transit to allow for physical distancing are cost-justified to society compared to crowded buses. The risk for a given passenger trip was low due to adherence to mask policies, an overall decrease in demand, short average bus trips, and the low-risk atmosphere for airborne diseases of sitting on the bus. However, some trips (12%) still surpassed their mandated passenger limit for sufficient physical distancing, and for these trips, it would be worthwhile for transit agencies to pursue alternatives like AVs and longer buses to alleviate crowding.

7. Limitations

This paper compares several alternatives for mitigating the risk of COVID-19 for public transit users. As one alternative to over-crowded buses, we assess the role that AVs could play in mitigating infection risk during the COVID-19 pandemic. AV technology is still developing, meaning costs per kilometer are theoretical and derived from cost estimates (Bösch et al., 2018) and current transportation network company costs (Gillaspia, 2021). The estimated costs may fall as AVs become commercially available. Likewise, no pandemic is exactly alike in its incubation period, contagiousness, or policy climate. Therefore, caution must be taken when applying lessons learned from early COVID-19 pandemic conditions to transit decisions during future rare events. However, our insights can create a baseline to guide future disease-spread mitigation decisions for assessing the risk of illnesses spreading throughout the public transit system.

There are also limitations to modeling COVID-19. The epidemiological model reflects the current understanding of how COVID-19 spreads and assumptions about bus conditions that are dependent on human behavior and adherence to policies, such as mask-wearing adherence, exhalation rate, airflow & ventilation, and air mixing on the bus (Gkantonas et al., 2021; Oliveira et al., 2021b; Environmental Protection Agency, 2021; Venfilter, 2020). It also uses COVID-19 rates and a reproduction rate from the first six months of the pandemic for the baseline analysis. The pandemic continues to evolve in its contagiousness and reproduction rate as the virus mutates and adapts (Center for Disease Control, 2021a) and as vaccines are deployed. Additionally, policy climate and perceived risk influence demand for public transportation and adherence to mitigating measures like mask-wearing and physical distancing. By the spring of 2021, COVID-19 vaccines had become widely available in Allegheny County. Vaccines impact the overall risk of COVID-19 to society. The social cost of COVID-19 on the bus when vaccines are widely disseminated is not considered in this paper, due to our goal of understanding risks in the early stages of the pandemic. Further work could be done to test the sensitivity of results to evolving COVID-19 viral load efficacy, the impact of vaccines, and the rate of spread. This paper provides a framework for comparing pandemic scenarios on public transportation given the difficulty of validating disease spread on public transportation.

When a bus is at its COVID-19 passenger capacity, the bus driver can pass a person by or pick them up. Using passenger counts, we can find the number of riders per trip above the passenger limit (breaking the COVID-19 policies); there is inherent uncertainty in measuring the unmet demand of passengers. We approximate the upper bound of total demand as the average between baseline (2018) hourly demand and early pandemic (2020) hourly demand. This provides an indication of how the system would operate if public transit demand were halfway back to pre-pandemic levels. However, we cannot directly measure the passed-by passengers from the original bus trips.

The value of Statistical Life (VSL) is a useful metric for accounting for what people are willing to pay to reduce small marginal risks when conducting a policy-related benefit–cost analysis. The VSL gets measured indirectly through people's willingness to pay to avoid a given risk or through labor markets (Viscusi and Aldy, 2008). Estimating VSL has inherent limitations because it does not get measured directly and because it involves knowing the change in marginal risk that the VSL represents. For COVID-19 mitigation strategies, placing a value on them can be difficult if the reduced risk of infection is poorly understood.

COVID-19 has large social costs beyond death that are not encompassed in a VSL estimate. A person that contracts COVID-19 may incur high medical expenses, they may need to miss work for weeks (or months in the case of long-haul COVID-19 (Mayo Clinic, 2021)) or even lose their job. A covid-19 patient will also have the personal costs of feeling sick for weeks and of long-term symptoms like loss of smell. The non-death-related social costs of covid are not included in this analysis

Table A.1
Symbol table A: Infection calculations.

Symbol	Variable	Unit
i, I	each bus trip, total bus trips	
d, D	each day, total Days	
ϕ	set of dispatch alternatives	discrete choices
L_i	peak passenger load	passengers
C_i	mandated bus capacity	passengers
O_i	over capacity ridership	passengers
Z_i	extra buses dispatched	buses
s_i	surplus passengers	passengers
ρ_d	probability of sick passenger	
σ_d	diagnoses each day	people
β	total Population	people
$N_{\phi,i}$	number of people on the bus	passengers
α_i	number of sick people on the bus	passengers
η_{mask}	mask efficiency	
γ	particle concentration	$\frac{PFU}{m^3}$
G_v	particle generation	particles/h
λ	viral decay	$\frac{1}{h}$
κ	settling of aerosol droplets	$\frac{1}{h}$
υ	air changes per hour	$\frac{1}{h}$
ψ	deposition probability	
t	average passenger time on bus	Hr
V	bus volume	m^3
N_{virus}	viral particles inhaled	particles/h
Q_{inh}	inhalation rate	$1/cm^3$
κ_p	reciprocal probability that a single pathogen will initiate response	
I_{risk}	infection probability	
ω_i	COVID-19 cases contracted per trip	passengers

Table A.2
Symbol table B: Operational costs.

Symbol	Variable	Unit
B	bus operation costs	$
π_{bus}	hourly bus costs	$/h
τ_i	full route time	h
ζ	TNC/AV operation costs	$
π_{AV}	hourly TNC/AV costs	$/h
M_j	TNC/AV costs per kilometer	$/km

because they are variable, hard to quantify, and outside of the scope of societal costs considered here.

None of our transportation alternatives consider passengers opting for other transport modes (e.g., walking, driving) when the bus is at its capacity. We leave the economic value of public transportation per rider and the social costs of unserved demand for future work. During the pandemic there were real riders that were passed by at-capacity buses; these passengers had real social costs like being late for work or the fare to take an alternative service such as a TNC. We do not consider passing by passengers as an acceptable alternative because it does not meet the baseline goals of meeting all bus demand while keeping passenger COVID-19 risk low.

We assess the societal costs of COVID-19 spreading between passengers on the bus and we set our system bounds at one degree of infection in our costs to account for any people that would be infected directly from bus riders. Several papers have looked at the impacts that different modes of transit have played in the spread of COVID-19 (Christidis and Christodoulou, 2020; Zheng et al., 2020; Carrión et al., 2021; Nouvellet et al., 2021) and therefore account for the infections not just potentially caused on transit, but the total cascading infection count from transit promoting increased human mobility. We assume that most passengers could find a private mode of transportation if the bus is not an option, thus we are not assessing the cascading role that the bus system plays in increasing human mobility and COVID-19 spread as a result. Instead, we investigate the specific risk of contracting COVID-19 on the bus itself and model the COVID-19 cases that can be attributed to the bus and to bus riders directly.

CRediT authorship contribution statement

Lily Hanig: Study design, Data acquisition, Analysis, Interpretation of results, Writing – original draft. **Corey D. Harper:** Study acquisition and design, Writing – review & editing. **Destenie Nock:** Study acquisition and design, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Lily Hanin reports financial support was provided by National Science Foundation. Destenie Nock reports financial support was provided by Block Center for Technology and Society at Carnegie Mellon University. Corey Harper reports financial support was provided by US Department of Transportation.

Data & code availability

The repository for this project can be found at https://github.com/Lilyhanig/transit_covid_precautions. Bus ridership data can be requested from Pittsburgh Regional Transit.

Appendix A. Variable table

Tables A.1 & A.2 show the variables and their units for the infection and cost calculations.
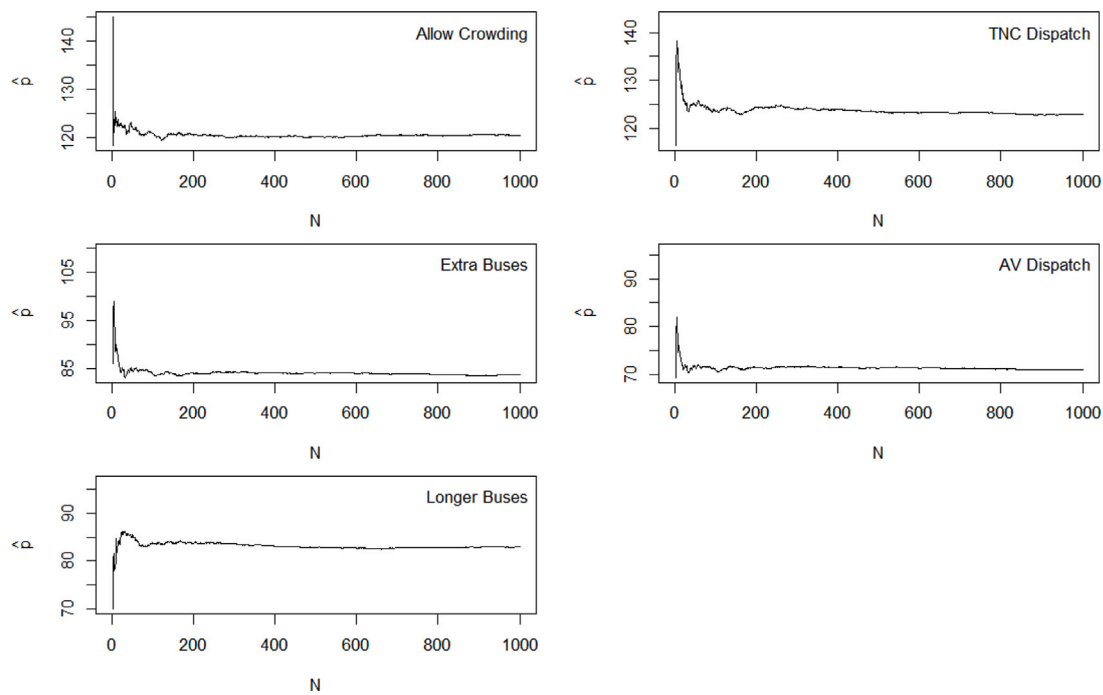
Fig. B.1. Convergence plot for the Monte Carlo Analysis for each policy alternative. By halfway through the total runs (N = 500) the average infection was within 0.5 infections (less than 1 person).

Table B.3

Average infections for each alternative after 500 and 1000 runs of the Monte Carlo Analysis for the baseline scenario with the change between the 500th run p̂ and the 1000th run p̂.

Policy Alternative	$\hat{p}(n = 500)$	$\hat{p}(n = 1000)$	Δ
Allowing crowding	120.23	120.44	0.21
Extra buses	84.01	83.62	0.39
Longer buses	82.88	82.99	0.11
TNCs	123.50	122.98	0.52
AVs	71.36	71.14	0.22

Appendix B. Monte Carlo convergence

The Monte Carlo Analysis is run 1000 times (N=1000) for each policy alternative ($\phi = 4$) and for all trips ($I = 76,000$). Fig. B.1 shows the average number of infections after each run of the simulation until N = 1000. For each policy alternative, the infection average had converged to within 0.25 infections (less than one person) by halfway through. The cumulative average number of infections at N = 1000 is significantly more sensitive to assumptions about demand, the COVID-19 prevalence, and mask wearing (variance in the hundreds of infections) than by the number of simulation runs (variance within 1 infection). 76,000 trips are simulated in each run causing the average for total infections to converge quickly.

Table B.3 shows the average number of infections per cumulative simulation run at 500 runs and 1000 runs, as well as the difference between the mean infections at each point. For all five alternatives, the mean infections at the half-way point in simulation runs were within 0.5 infections of the mean infection for all simulation runs. This shows that convergence within the Monte Carlo Simulation occurred quickly within the run count. At 1000 runs, the mean infection rate is much more sensitive to assumptions of the input parameters (like COVID-19 rate in the community or levels on bus demand) than to the number of simulation runs within the Monte Carlo analysis.

Appendix C. Externality costs

In addition to the operating costs for buses, AVs, and TNCs (Pittsburgh Regional Transit, 2018; Bösch et al., 2018; Gillaspia, 2021; Uber, 2021), each dispatch alternative comes with externalities that need to be taken into account. The cost of COVID-19 is found using a death rate of 3% (recorded deaths per recorded cases) for Allegheny County in the period observed and a Value of Statistical Life (VSL) year adjusted for COVID-19 (Viscusi and Aldy, 2008; Department of Transportation, 2020; Conover, 2020). We use a VSL year adjusted for Covid-19 of $5.05 Million in $2020 with a range of $1.33–11.6 Million for sensitivity analysis. A Social Cost of Carbon is used to account for the negative externalities of increased emissions from additional vehicles (Interagency Working Group on the Social Cost of Green House Gases, 2021). We use 51 $/ton for the social cost of Carbon and a range of 14–152 $/ton for the sensitivity analysis. Marginal externalities from increased congestion, traffic & noise, and pollution are derived from Parry et al. (2007) and are adjusted to $2020. Table C.4 shows the breakdown of costs used for each alternative and cost component per vehicle dispatched.

Appendix D. Changes in daily ridership

Pre-pandemic, the Port Authority dispatched its peak number of buses between 4–5 pm to match peak ridership with an average of 315 bus trips in that hour; in April and May, the Port Authority dispatched an average of 211 bus trips from 4–5 pm, 67% of the bus trips they were running pre-pandemic. Although the peak ridership shifted to occur from 2–3 pm, peak bus dispatch still occurred at 4–5 pm, which could be one reason the county saw crowding on the bus. The shift away from typical commute times indicates that office workers who made up the bulk of the peak hour riders pre-pandemic were now avoiding transit, leaving transit-dependent essential workers as the primary riders on the bus fleet. To mitigate the spread of COVID-19, the Port Authority set passenger capacity limits for their 35-ft bus (10 passengers), 40-ft bus (15 passengers), and 60-ft articulated bus (25 passengers). Although pandemic ridership was overall lower than pre-pandemic levels (Fig. 2), 21% of bus trips were over their COVID-19 capacity during the 2–4 PM time block from April to September (see Fig. D.2).
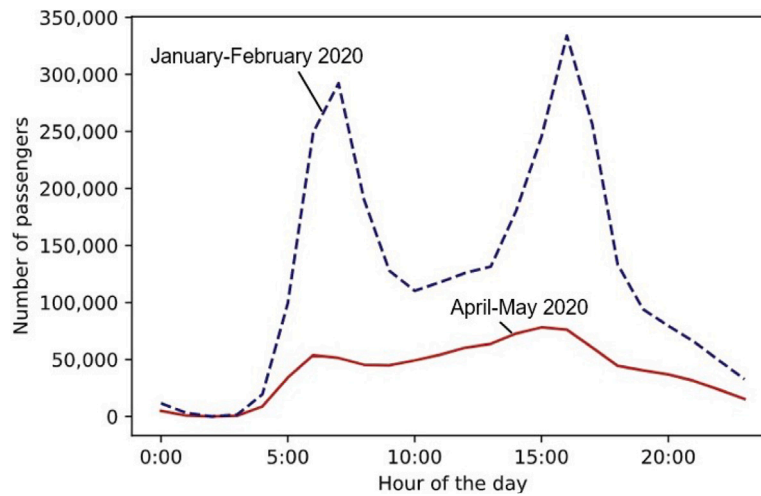
Fig. D.2. Hourly bus load before and during the Covid-19 pandemic. Aggregate peak bus loads by the hour of the day pre-pandemic (January and February 2020) and in the early months of the pandemic (April and May 2020) for Allegheny County, PA.

Table C.4
Input values used for the lower, mid, and upper bound estimates of vehicle costs per kilometer or per hour of operation per vehicle. (1) (Pittsburgh Regional Transit, 2019), (2) (Interagency Working Group on the Social Cost of Green House Gases, 2021), (3) (Parry et al., 2007).

$/kilometer	Operations	Social Cost of Carbon	Congestion & Traffic	Pollutants
	(1)	(2)	(3)	(3)
Allow crowding	188 $/h	0.11 (0.03–0.34)	0.09	0.10
Extra buses	188 $/h	0.11 (0.03–0.34)	0.09	0.10
Longer buses	188 $/h	0.14 (0.04–0.42)	0.11	0.10
TNCs	1.32 (0.83–1.65)	0.01 (0.004–0.04)	0.07	0.02
AVs	0.70 (0.40–1.53)	0.01 (0.004–0.04)	0.07	0.02

Appendix E. Pandemic commuter demographics

Pittsburgh, Pennsylvania has experienced both full and partial quarantines throughout the COVID-19 pandemic. The city of Pittsburgh refers to full-lockdown quarantine as 'red phase' and requires that only essential services, including healthcare workers and grocery stores, operate at normal capacity (Governor Tom Wolf, 2020). The first phase of re-opening from red phase, known as 'yellow phase', allows for restaurants and hotels to open up at partial capacity. 'green phase' is a further re-opening of businesses that includes a partial capacity of recreational and non-essential facilities like gyms and bars (Governor Tom Wolf, 2020). Table E.5 shows the restrictions on businesses during each lockdown phase of the pandemic.

Transit user demographics across the phases and in pre-pandemic data are found from the Integrated Public Use Micro data Series (IPUMS – USA) (Integrated Public Use Microdata Series, 2020) 2018 transportation survey. Pennsylvania Governor Tom Wolf's mandates on business operations in each phase were applied to the 2018 baseline data to calculate demographics of transit commuters throughout the pandemic (Governor Tom Wolf, 2020).

Fig. E.3 shows that during both red and green phase, transit commuters that cannot work from home are disproportionately Hispanic and Black. Healthcare commuters in Allegheny County are also disproportionately black. Therefore, any situation where pandemic commuters are placed at increased risk of contracting COVID-19 will disproportionately place ethnic minorities at an increased risk of contracting COVID-19.

Appendix F. Further bus load demographic details

Fig. F.4 presents average passenger loads of each census tract against the per capita income and the ethnic minority percentage of the census tract. In the lower-left, passenger load (y-axis) is low for all

Table E.5
Pennsylvania residential mobility restrictions during Red, Yellow, and Green phase of the lockdown.

Red Phase	
Life Sustaining Businesses Only	Follow business and building safety orders
Schools	Closed for in-person instruction
Restaurants	Carry-out only

Yellow Phase	
Schools	Closed for in-person instruction
Restaurants	carry-out & outdoor dining
Indoor Retail	Open & follow Guidelines
Indoor Recreation	closed
Health & Wellness	closed
Entertainment	closed

Green Phase	
Schools	Open for in-person instruction
Restaurants	25–50% capacity
Indoor Retail	Open & follow Guidelines
Indoor Recreation	50% capacity
Health & Wellness	50% capacity
Entertainment	50% capacity

of the highest-income census tracts, demonstrating the ability to work-from-home or find alternative modes of transport. In the upper-middle plot in Fig. F.4, per capita income and percent minority of the census tracts are correlated with the highest-income census tracts having a low-minority population. When comparing percent minority on the x-axis to percent load on the y-axis (bottom-middle) we see that the load trends upward as the population of the census tract has a higher percent minority. Although the load trends upward with percent minority, the highest (more than 8) average load census tracts had relatively low minority populations (less than 28%) and also low ($25,000–$38,000) per capita income (Fig. F.4).
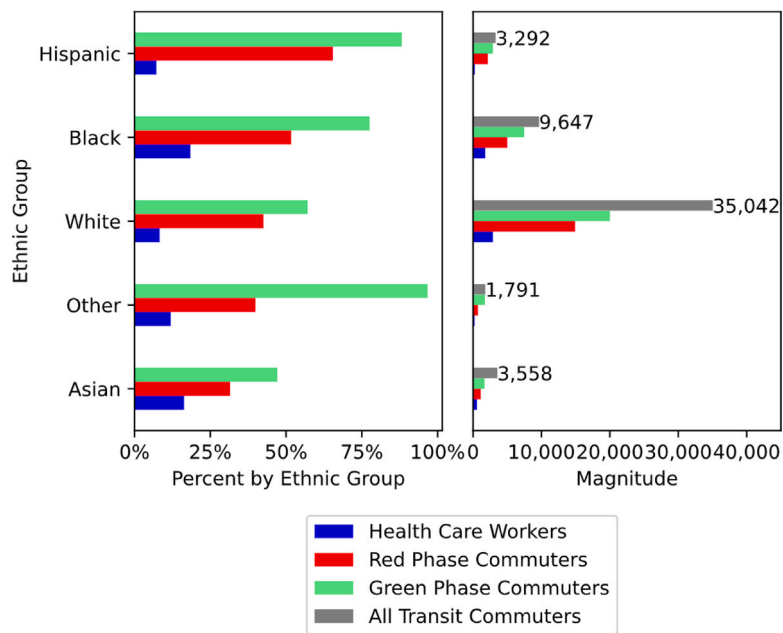
Fig. E.3. Bus commuter demographics by pandemic lockdown phase. Commuters by demographic during red phase of the COVID-19 Lockdown (only essential services), green phase of lockdown (Retail partially open with restrictions), and among healthcare workers.
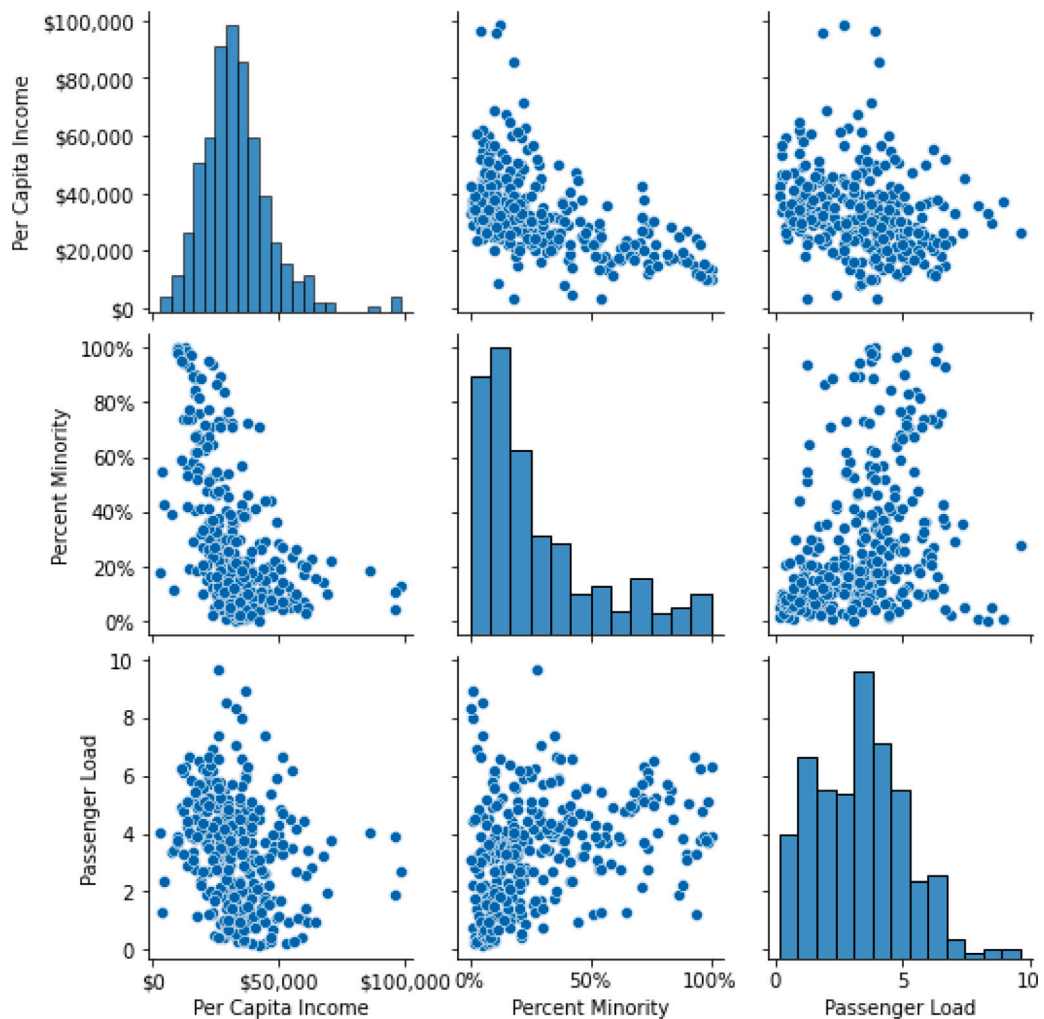

Fig. F.4. Scatter matrix of census tract bus and socioeconomic characteristics. Scatter Matrix showing the relationship between the mean passenger load at the bus stops in each of the 335 census tracts in Allegheny County against the per capita income and ethnic minority percentage in the census tract.
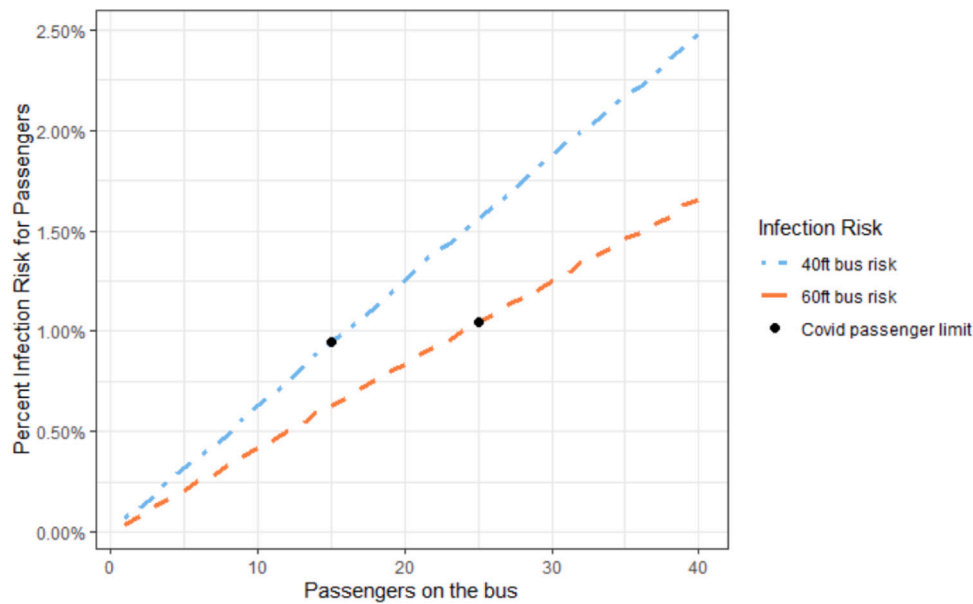
Fig. G.5. Increased infection risk per additional passenger. Simulation averaged over 100,000 runs of the percent of passengers that would get sick (y-axis) on a bus trip given a 10% COVID-19 rate among passengers on a 30-minute bus ride for each additional rider on the bus.

Appendix G. Infection risk across different bus sizes

To model the increased risk of contracting COVID-19 as the bus becomes more crowded for 40-ft and 60-ft buses, a constant rate of COVID-19 in the population of 10% ($\rho = 10\%$) is used and a Monte Carlo is run 100,000 times modeling a single trip with a passenger load of 1 to 40 in 1 person increments with a bus driver ($N_{\phi,i} = 2 - 41$).

$$P(\alpha_i) = \binom{N_{\phi,i}}{\alpha_i} \rho^{\alpha_i} (1 - I_{risk})^{N_{\phi,i} - \alpha_i} \tag{G.1}$$

Eqs. (19) to (23) (see Methods for details) are then used to find the number of people sick for each of the 100,000 runs for a passenger load of 1–40 for both 40-ft and 60-ft buses with the volume of the bus (V) representing the key difference in risk.

$$\rho_d = \frac{\sum_{(d=-20)}^{0} \sigma_d}{\beta} \tag{G.2}$$

$$P(\alpha_i) = \binom{N_{\phi,i}}{\alpha_i} \rho_d^{\alpha_i} (1 - \rho_d)^{N_{\phi,i} - \alpha_i} \tag{G.3}$$

$$\frac{d\gamma}{dt} = \frac{\alpha_i \cdot (1 - \eta_{mask}) \cdot G_v}{V} - (\lambda + \kappa + \upsilon + \psi) \cdot \gamma \tag{G.4}$$

$$\gamma(t) = \frac{\alpha_i (1 - \eta_{mask}) G_v}{V(\lambda + \kappa + \upsilon + \psi)} + \left(\gamma(t_0) - \frac{\alpha_i (1 - \eta_{mask}) G_v}{V(\lambda + \kappa + \upsilon + \psi)} \right) \cdot e^{(\lambda + \kappa + \upsilon + \psi)(t - t_0)} \tag{G.5}$$

Fig. G.5 shows the average number of passengers that would get sick if 10% of the bus passengers have COVID-19. At the passenger-limits set by the Port Authority, both the 40ft and 60ft buses have similar risk (within 0.3%) of contracting COVID-19; for a bus at its COVID-19 passenger limit, if 10% of passengers are sick, the likelihood of contracting COVID-19 is 1%. Every passenger on the 40-ft bus increases the risk by 0.06% and on the 60-ft bus by 0.04%. As the bus gets more crowded, the risk increases faster on the 40-ft bus, such that on a very crowded bus (40 passengers) a 40-ft bus is almost 1% riskier than a 60-ft bus. The low spread rate in general results from the assumption that passengers are sitting on the bus for a limited time with good airflow and wearing one-ply cloth masks (Venfilter, 2020) (see Methods).

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