COVID-19 Public Transit Precautions: Trade-offs between Risk Reduction and Costs

Lily Hanig (lhanig@andrew.cmu.edu)
Carnegie Mellon University
Corey Harper
Carnegie Mellon University
Destenie Nock
Carnegie Mellon University

Research Article

Keywords: bus ridership, COVID-19 risk, cost-benefit analysis

Posted Date: October 25th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-997116/v1

COVID-19 Public Transit Precautions: Trade-offs between Risk Reduction and Costs

Lily Hanig*[1], Corey Harper[2, 3], and Destenie Nock[1, 2]

*Corresponding Author
[1]Engineering & Public Policy, Carnegie Mellon University
[2]Civil & Environmental Engineering, Carnegie Mellon University
[3]Heinz School of Public Policy and Information Systems, Carnegie Mellon University

2021

Abstract

The COVID-19 pandemic has spread globally; however, the risk of contracting COVID-19 on public transportation and its role in local spread remains unclear. Essential workers who are transit-dependent tend to be from low-income and minority populations and are faced with the risk of contracting COVID-19 each time they take a bus. We investigate bus ridership from April to September of 2020 and the risk of contracting COVID-19 on the bus by combining a transportation data analysis and an epidemiological model of COVID-19 risk. Our results show that 4% of county cases were contracted on the bus or from a bus-rider (first degree), disproportionately (52%) from trips that were over their mandated capacity. The risk of contracting COVID-19 on the bus was low, but socially worth mitigating. A cost-benefit analysis reveals that dispatching autonomous vehicles or deploying longer buses for passed-by passengers rather than allowing crowding have the lowest societal costs.

Introduction

The COVID-19 pandemic's level of global disruption to economic, environmental, and social aspects of society, over a relatively short period of time, are only comparable to the 1918 influenza pandemic and the world wars.[1] While the occurrence of global pandemics seems infrequent, there have been other near misses in recent years[2,3] meaning future pandemics are a possibility.[3] Transportation sector decisions play a role in mitigating the negative effects of the current pandemic and future disruptive events. Due to global trade (e.g., airplanes) COVID-19 was able to spread quickly around the world;[4] however, there is uncertainty regarding the impact that public transportation (i.e., buses) played in the local spread of the COVID-19 virus.

To date, most of the COVID-19 transportation literature investigates the role increased human mobility (planes,[4,5] long distance trains and buses,[5] subway usage,[6] general mobility[7]) plays in spreading COVID-19 because of the secondary and tertiary interactions once people leave public transportation modes. Yet even if people were using transportation modes that allowed them to isolate (e.g., single occupancy vehicles, bikes), interacting with people at the destination can still cause COVID-19 to spread. Thus, while public transit contributes (possibly largely) to spread in the way that it facilitates people going places where they interact with others;[4,5,6,7] even if people avoided public modes of transit, the COVID-19 risk would not be negated. A gap in the literature is an assessment of the risk of spreading COVID-19 within the confined space of the public transit vehicles (i.e., sitting on a public bus to get to your destination). Our specific contribution is as follows: while other papers assessed the COVID-19 risk of human mobility (facilitated by the public transit), we assess the COVID-19 risk of being on the public transit itself, in our case buses.

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.[8] Essential workers, such as grocers, health care workers, and public servants must still go to work in-person even during the strictest lock-downs.[9] Overall, public transit demand plummeted in the early weeks of the pandemic across the US,[10] but in areas with high essential worker and vulnerable populations, transit demand decreased less.[10] We investigate the effectiveness of COVID-19 passenger capacity limits in preventing the spread of the virus and evaluate how crowding reduction alternatives (e.g., longer buses or AVs) could have reduced the risk of contracting COVID-19 on the bus. While different transit modes each play their own role in the spread of COVID-19, we focus our analysis on buses due to this form of transportation making up the largest share of US public transit rides (46%).[11] Many public transit agencies (Chicago,[12] Oakland,[13] Pittsburgh[14]) have set per vehicle passenger capacity limits in an effort to increase the physical distance between passengers and promote public health safety. Several papers have shown that high-income passengers have more easily shifted away from public transit during the pandemic[10,15] because of alternative modes of transportation and jobs that allow for remote working. One paper found a positive correlation between a zip code's continued subway use during the COVID-19 pandemic and infection rates in that zip code,[6] as well as, a correlation between the socioeconomic vulnerability of zip codes and their subway ridership levels in New York City.[6] This indicates that low-income and minority essential workers riding the bus at higher rates during the pandemic when compared to their wealthier and white counterparts.[10]

Relatively high demand for transit in low-income areas presents an inequity in risk of contracting COVID-19 on transit. We seek to assess those risks and evaluate which policy alternatives mitigate them most effectively between allowing crowding as a baseline, dispatching additional or longer buses, or Autonomous Vehicles (AVs). Several papers investigate what role AVs may play in improving equity and accessibility of transportation[16,17,18,19,20] in pre-pandemic conditions. For example, Ezike et al. (2019) developed a travel demand model to assess how integrating AVs into the existing transit system could affect job accessibility and travel times for minority and low income populations.[16] Patterson (2020) highlights integrating fully autonomous vehicles into public transportation plans as key to reducing transportation access gaps in the Black community [20]. Harper et al. (2016) estimated the upper bound potential increase in travel demand for non-drivers, the elderly, and people with travel-restrictive medical conditions by assuming that these populations travel as much as a younger and/or healthier population.[19] Existing resilience literature has mainly focused on the role of automation for disaster management and the ability of unmanned aerial and ground vehicles to improve emergency response during hurricanes and earthquakes,[21],[22],[23].[24] Many of these unmanned systems don't transport humans and are more useful for surveillance and package delivery. We make a contribution to the AV equity and resilience literature by assessing the role of AVs for transporting essential workers to promote equity during a rare event like COVID-19 to help reduce risk disparities.

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. 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 vs. crowding problem, transit agencies could promote physical distancing while meeting demand through alternatives such as, dispatching more buses, dispatch longer 60-ft articulated buses as a substitute to the 40-ft buses on over-capacity routes, or in the near future, dispatch single-passenger AVs. Through our analysis we investigate the degree to which mitigation measures (e.g., longer buses and AVs) 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 contribute to the literature by exploring what role autonomous vehicles might play in rare events like the COVID-19 pandemic as a complement to public transit and the role different mitigation options might play in reducing the spread of COVID-19.

Results

Over-capacity on bus transport during COVID-19

To keep passengers safe, transit agencies set COVID-19 protocols like mandating masks and promoting physical-distancing.[12,13,14] To ensure physical distancing on the bus, several transit agencies set passenger capacities to less than half the bus's seating capacity to allow spreading out. When faced with an over-capacity decision, bus drivers have two choices: 1) potentially leave an essential worker without a ride to work or 2) allow them to enter an already at-capacity bus, increasing everyone's risk of contracting COVID-19. Our COVID-19 risk analysis (see Methods) is based in Allegheny County, PA where buses represent 86% of public transit rides for the county.[25] Local Transit data is sourced from the Port Authority, which has equipped their buses with automatic passenger counters allowing for an assessment of the number of people riding the bus on different bus routes by time of day.[25] 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 Figure 1. The average passenger load at bus stops in the lowest income census tracts dropped by 45% while the highest income census tracts saw a more dramatic drop of 59%. This indicates that low-income census tracts had higher continued-ridership and higher crowding rates throughout the pandemic.

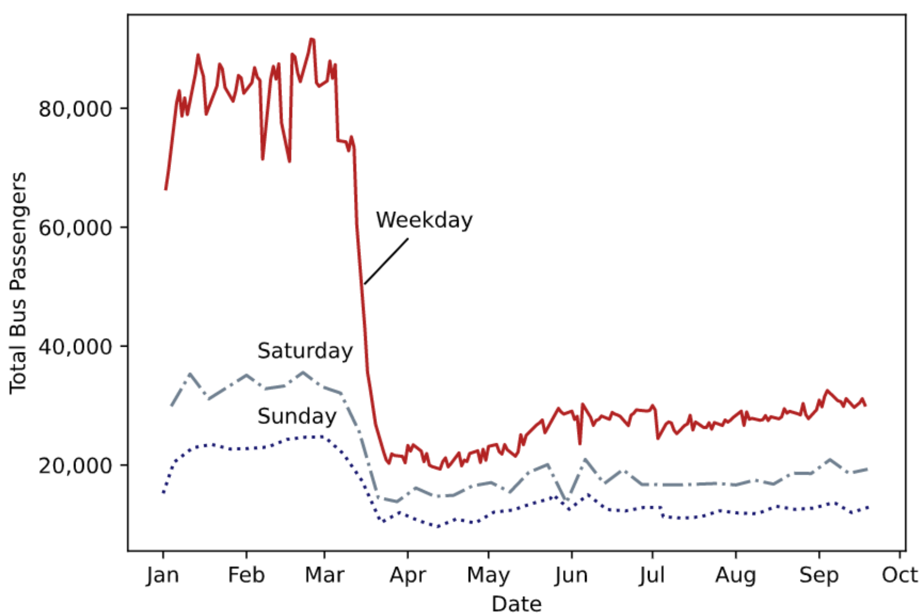


Figure 1: **Pandemic Bus Ridership By Day.** Weekday, Saturday, and Sunday total passenger count for Allegheny County from January 1st to September 20th 2020 excluding federal holidays.

The pandemic impacted both net-ridership, and the time of day that peak ridership occurred. 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), (Figure 2). During the pandemic the peak ridership shifted to be 2-4 PM and crowding decreased overall (Figure 2). In April and May 2 pm had a mean peak load of 9.62 passengers, 41% of the average PM peak load before the pandemic. 21% of 2-4 PM trips were over capacity compared to the overall average of 12%.

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 working from home, 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 (Figure 1), 21% of bus trips were over their COVID-19 capacity during the 2-4 PM time block from April to September.

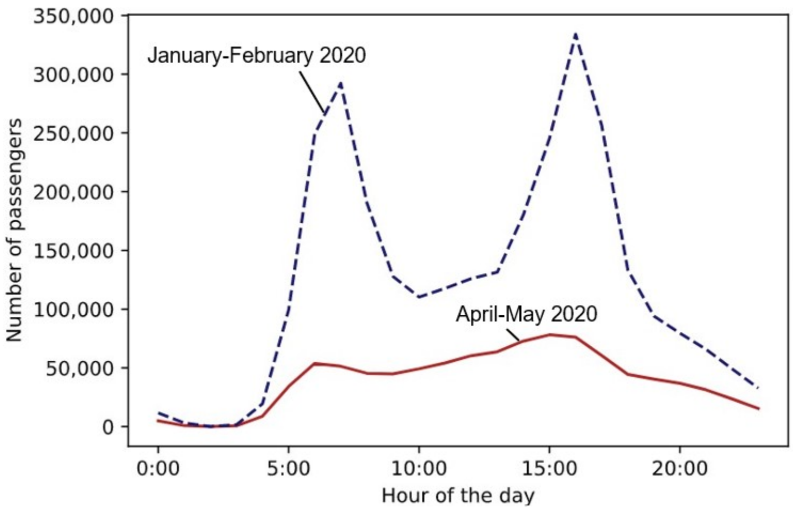


Figure 2: **Hourly Bus Load Before and During the Covid-19 Pandemic.** Aggregate peak bus loads by hour of the day pre-pandemic (January and February 2020) and in the early months of the pandemic (April and May 2020) for Allegheny County, PA.

We define the bus system baseline unmet demand as the total number of riders that surpassed the transit network's passenger COVID-19 limit, regardless of whether or not these passengers were allowed onto the bus. If the physical distancing guidelines were strictly enforced, the over-capacity riders would be passed by instead of picked up. Therefore, over-capacity riders represent known unmet demand of an at-capacity bus (see Methods). The commuters that are passed by are not recorded by the public transit agency, representing unknown unmet demand of the system (see Appendix for more limitations). As a result, the over-capacity riders represent the conservative, lower-bound of unmet demand on public transit during the pandemic. 12% of all Port Authority bus trips that occurred from April to September of 2020 were over their capacity (see Methods). During the observed period there were 5.8 million public transit passengers, 251 thousand (4%) of which exceeded COVID-19 passenger limitations. Some bus routes had days with an average of 7 or 8 too many passengers per trip. The majority of crowded rides had one or two extra riders.

Equity implications of mitigation measures

Previous transportation studies involving vulnerable populations have focused on inequalities related to disabled populations on public transit[26] as well as the distributional impacts of public transit decisions on equity indicators.[27] Other papers have explored the potential increases in travel demand from AVs serving elderly, disabled and other non-driving populations.[19] This is the first study the authors are aware of that assesses policy alternatives to mitigate crowding disparities between sub-groups (i.e. low-income and minority areas) during a public health crisis.

Inequities in bus service can manifest themselves in disproportionate wait-times and distances to bus stops, less frequent trips, or fewer safety precautions. Transit equity during the pandemic means that all passengers have similar access to transit (some aren't denied rides more often because of crowding) and that when passengers get on the bus, they face similar risk of contracting COVID-19; uneven distribution of crowding on the bus can lead to either of these inequities depending on if the bus driver denies a ride or allows crowding and the associated increased risk. If some areas or routes have frequently crowded trips, the passengers on those trips are more likely to be passed-over or have to enter a crowded (and therefore higher risk) bus.

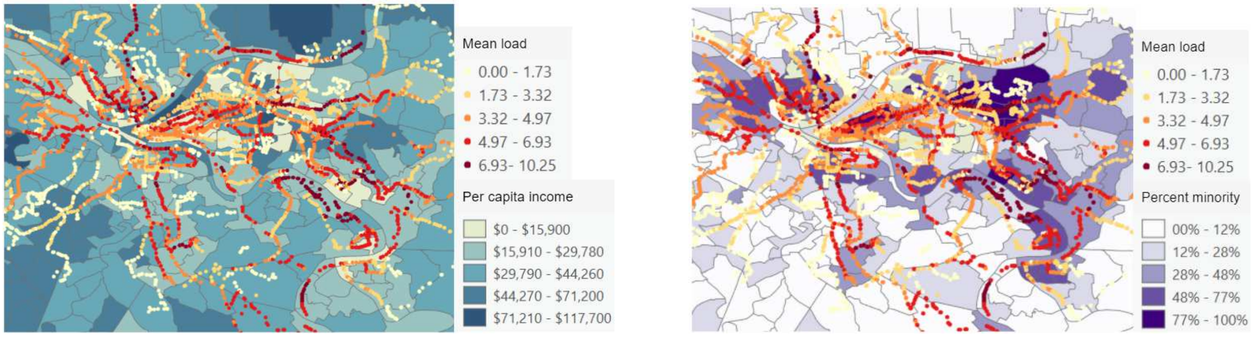
Figure 3 shows the average bus load from mid April to mid September at each bus stop in Allegheny County on top of American Community Survey designated census tracts. The darker the red dot, the higher average bus load at that stop; the darker the purple area, the higher percent ethnic minority of residents in that census tract. In Figure 3a the higher per capita census tracts had bus stops with a low mean load overall, particularly in the outer suburbs of the county.

Overall during the Spring of 2020, the 20% of lowest-income census tracts had almost twice the average passengers at bus stops compared to the highest income census tracts (4.2 passengers compared to 2.6 passengers on average). Low-income residents and under-represented demographics are more likely to be essential workers that have to commute during the pandemic (see Appendix C). Low-income residents are also more likely to be transit-dependent.[10] 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). 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 1 shows the average passenger load of the 335 census tracts with bus stops in them 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%.

Figure 4 presents average passenger loads of each census tract against the per capita income and ethnic minority percentage of the census tract. In the lower-left, passenger load (y-axis) is low for all of the highest-income census tracts, demonstrating ability to work-from-home or find alternative modes of transport. In the upper-middle plot in Figure 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



(a) (b)

Figure 3: **Mean Bus Loads By Stop.** The mean bus load 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).

Table 1: Socioeconomic characteristics of Census Tracts by Bus Stop Crowding. 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%

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%), but low ($25,000-$38,000) per capita income (Figure 4).

Overall Risk of Disease Spread

The key risk of concern to the public transit agency in 2020 was passengers spreading or contracting COVID-19 while on the bus due to crowding. We estimate the probability of contracting COVID-19 on the bus, from mid-April to mid-September, using a Bernoulli likelihood function and an epidemiological model of COVID-19 risk[28,29] we stochastically model how many passengers could have contracted COVID-19 per bus ride based on the percent of residents with COVID-19 per day in Allegheny County (see Methods and Appendix B). The model uses the peak bus load per trip and average time each passenger spent on each trip to model the risk of infection. We assume that COVID-19 is contagious for 20 days, accounting for some unrecorded asymptomatic carriers, people on the bus wear single-ply cloth masks that are 35% effective,[30,31] 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

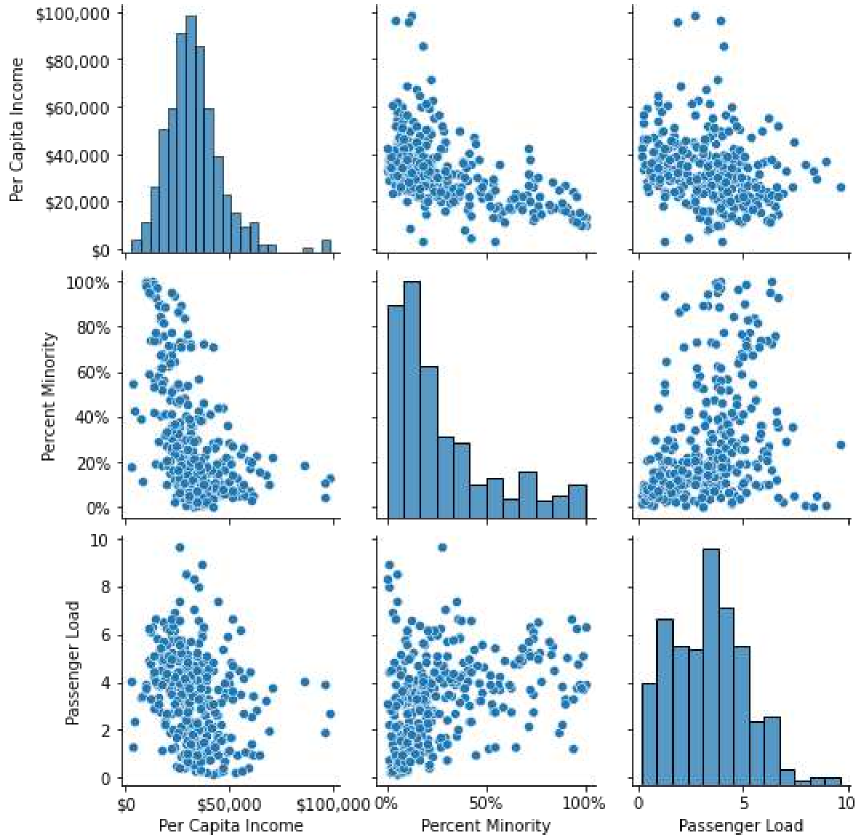


Figure 4: **Scatter Matrix of Census Tract bus and socioeconomic characteristics.** Scatter Matrix showing the relationship between the mean passenger load at the bus stops in each of the 335 census tracts in Allegheny County against the per capita income and ethnic minority percentage in the census tract.

directly on the bus (234 cases). Using the average reproduction rate of COVID-19 in Pennsylvania over this time 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 Limitations).

Figure 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[31] (see Methods and Appendix B).

In our base case we find that 4% of the cases in Allegheny in the early months were contracted from the transit system directly and in the community from riders on the transit system. We found 52% of all COVID-19 cases from the bus were contracted on over-capacity trips, despite making up only 12% of trips (121 cases out of 234). In our high COVID-19 rate scenario, we normalize the COVID-19 rate to the level of total cases in Allegheny County between August 6th 2020-January 10th 2021 onto the ridership from

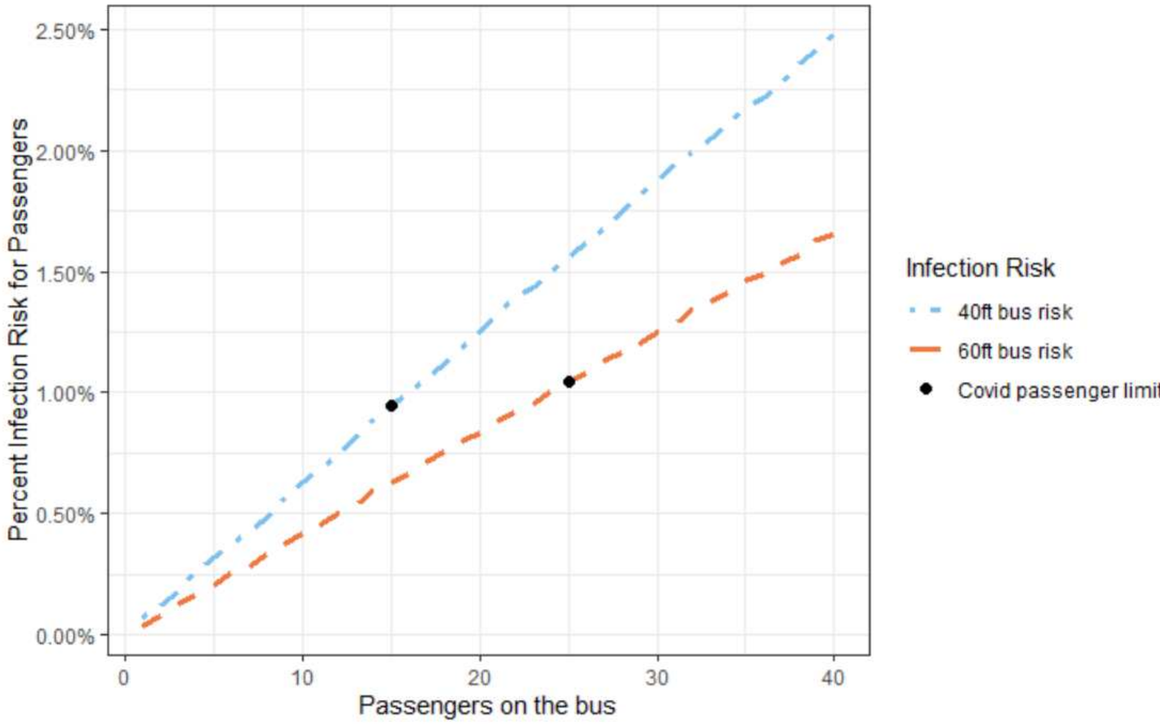


Figure 5: **Increased Infection Risk per Additional Passenger.** Simulation averaged over 100,000 runs of the percent of passengers that would get sick (y-axis) on a bus trip given a 10% COVID-19 rate among passengers on a 30 minute bus ride for each additional passenger on the bus (x-axis).

Spring 2020. When the COVID-19 rate is normalized to winter 2020 levels (52,300 total cases of COVID-19 , compared to the 10,804 cases in Spring) we find the total cases contracted on the bus increase by 440% (1037 contracted on the bus).

Table 2: Modeled Covid-19 contraction on crowded buses. The number of passengers modeled to contract COVID-19 with a low rate of COVID-19 in the community (April to September of 2020) and a high rate of COVID-19 in the community (August 2020 to January 2021) for direct bus infections (top) and including first degree of infections in the community (bottom).

	Over Capacity Bus Trips		**All Bus Trips**	
	Low COVID Rate	High COVID Rate	Low COVID Rate	High COVID Rate
Contracted on bus	121	394	234	1037
Including first degree	238	804	451	2116

We model the risk reduction if AVs are dispatched for each passenger that is over the covid-capacity of the bus. We assume there is no risk of infection in the AVs because COVID-19 spreads through the air[32] and an AV would be dispatched for each passenger so that they are not in contact with other passengers or with a driver. We find that if AVs are dispatched for over-capacity 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 (there is no reduction in cases contracted on non-crowded buses because AVs would only be dispatched for over-capacity passengers). As mentioned earlier, transit riders in low-income and high-minority census tracts ride on buses with higher passenger loads, placing them at higher risk of contracting COVID-19 from the transit system.

Uncertainty Analysis

There is inherent uncertainty in a driver's willingness to allow for crowding and the ranges of costs associated with various crowding reduction policies. We consider four transit alternatives: 1) allowing all unmet demand on the bus (i.e. ignoring COVID-19 guidelines), 2) dispatching a additional 40-ft buses to cover excess passenger demand that would have been passed-by the original bus fleet, 3) dispatching single-passenger capacity AVs for all unmet demand, and 4) dispatching 60-ft buses in place of 40-ft buses for trips with crowding. We chose to compare these alternatives because allowing crowding, dispatching extra buses, and dispatching longer buses are all within the capacity of the existing public transit bus fleet. We chose to investigate autonomous vehicles as an option to explore what role AVs may play to improve transit equity in rare events and because AVs allow for physical distancing because they do not require a driver (unlike other on-demand services like ride-sharing companies).

We run a Monte Carlo simulation for each of the 76,000 over-capacity trips in each of the four alternatives (allow crowding, extra buses, AVs, and longer buses). We focus on over-capacity trips for our Monte Carlo Analysis as these are the trips that did not obey the COVID-19 capacity limit set by the transit authority, putting passengers at increased risk of infection. We also vary the distance each over-capacity passenger would go if they took an AV, using the Make My Trip Count survey data[33] for an underlying probability distribution function of each passenger's total bus commute distance. The bus ridership data used for this analysis tracks bus load, not passenger origin-destination pairs. Therefore, it is not possible to discern the trip length of each person that takes the bus. Furthermore, single-trip bus rides often do not encompass a passenger's exact commute distance (e.i. bus transfers, indirect routes). To overcome these gaps in passenger-level data, the Make My Trip Count Survey is used to model the distance that each AV would need to go (see Appendix A for more details).

Figure 6 shows the number of passengers infected with COVID-19 in each simulation run of the Monte Carlo. The rate of COVID-19 in the county is used to stochastically model how many passengers would be sick on each trip. The number of people on the bus is stochastically represented in each run of the Monte Carlo analysis for each trip (see Methods). All four alternatives show a wide-range of infections in the Monte Carlo analysis with allowing crowding having the widest range of 83 to 165 infections from its least-infected run to its most-infected run, respectively. The allow crowding option has a 94% probability of having more than 100 infections, while the extra buses and longer buses have a 6% and 9% probability of causing more than 100 infections. The AV option only has a 1% probability of more than 100 infections. In Figure 6, none of the four alternatives reach zero, meaning that every alternative has a 100% probability of infecting at least one person.

Figure 7 presents the cost breakdown for each mitigation strategy. Allowing crowding costs $59 million in operation and social costs over the five months. Comparatively, AVs are the cheapest option at $45 million (24% reduction) and longer buses are similar in cost at $46 million (21% reduction). 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 cheapest 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 in-place of

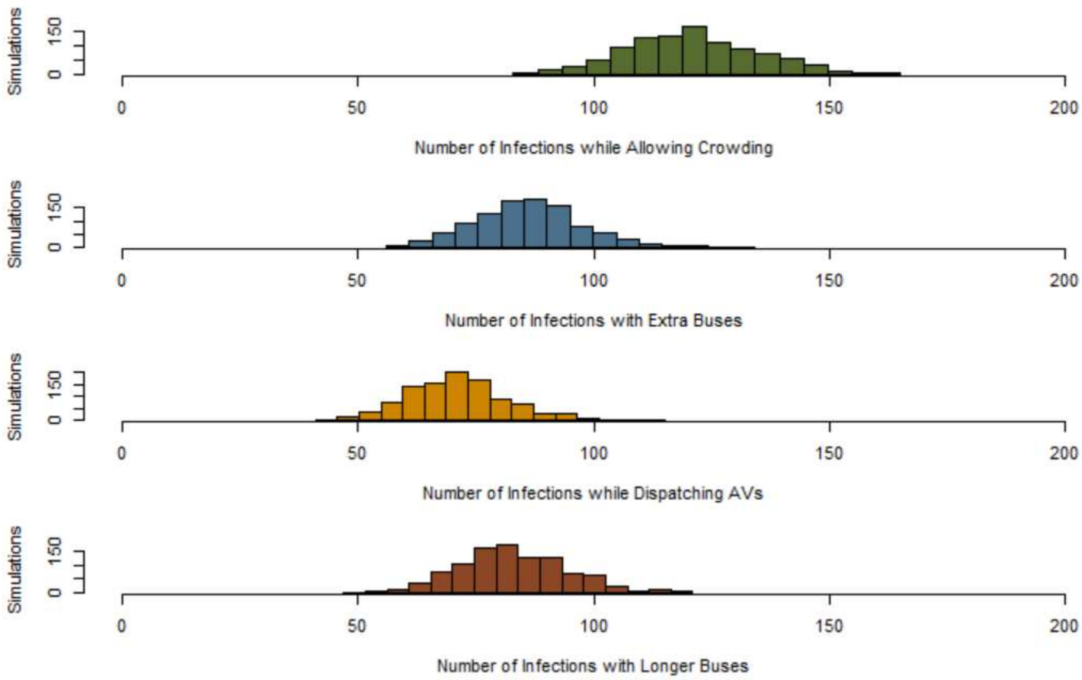


Figure 6: **Modeled Infections By Policy Alternative.** Histograms of the number of passengers estimated to contract COVID-19 in each policy alternative with baseline assumptions in the Monte Carlo analysis using the Freedman-Diaconis rule for selecting bin width from the Allowing Crowding alternative for all four alternatives.

shorter buses for crowded trips (same hourly costs), followed by dispatching AVs for passengers past the limit ($19 million), and finally dispatching additional buses to meet over-capacity demand ($31 million). However, when the social cost of passengers contracting COVID-19 and potentially dying gets 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 using a VSL of $5.05 million per death.

In Figure 7 we estimate the overall costs of operations, COVID-19 deaths, carbon and particulate emissions (social and health costs), marginal congestion, and increased traffic accidents associated with the different types of vehicles included in each alternative using a Monte Carlo Analysis. We assume a Value of Statistical Life (VSL) of $5.05 million,[34,35] a social cost of carbon of 51 $/ton of CO_2,[36] and an automated vehicle cost of $1.12 per mile to operate[37] in 2020 dollars for our base case. In Figure 8, the lower and upper bounds for the social cost of carbon (14 $/ton - 152 $/ton), the operating costs of AVs (0.65 $/mile - 2.47 $/mile), the unmet demand, and the COVID-19 rates in the county and the Value of a Statistical Life used for COVID-19 deaths ($1.3 - $11.6 million). The measured over-capacity 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 the average hourly demand between 2020 and 2018 levels.

In Figure 8, the Value of a Statistical Life represents the social cost of losing a life. 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 Figure 8 is sourced from the Department of Transportation,[38] which assumes transit risk is equal across age demographics (unlike COVID-19 , which is highest risk to older adults). Using the upper-bound VSL, it is less expensive to

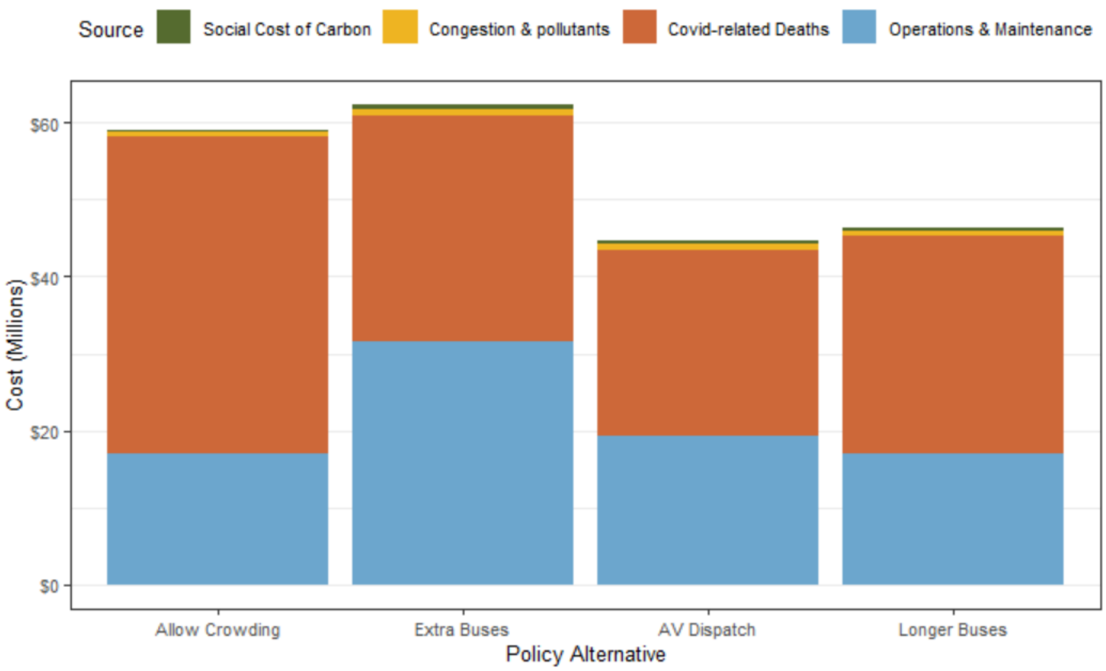


Figure 7: **Social Costs of Policy Alternatives.** Social Cost breakdown of each policy alternative considered to eliminate pandemic crowding on the bus.

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 cheaper ($110 million) than longer buses as well ($110 million). If the unmet demand of the system approaches its upper-bound, AVs are 36% cheaper ($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 the risk of contracting COVID-19 decreases by half.

Figure 9 shows the trade-off each policy alternative has between cost and infections. Black dots represent the baseline scenario (i.e., bus system demand from April to September 2020). Open circles 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 costs and infections in the baseline scenario; however, upon demand increases, longer buses have approximately twice the mean infections (214 infections) compared to AVs (111 infections). 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. If bus ridership is at baseline conditions when policy decisions are made but demand increases, the optimal decision shifts to be deployment of AVs. Longer buses have more uncertainty in their costs (range of $44 million) and infections (range of 131 infections) than AVs and extra buses given uncertainty in demand. Likewise, longer buses, extra buses, and AVs are preferred when compared to allowing crowding for costs (by at least $13 million) and infections (by at least 97 infections) for the upper demand scenario.

COVID-19 cases in Allegheny County remained low (10,804 cases among 1.2 million residents) over the duration of mid-April to mid-September. Pennsylvania maintained a reproduction rate of 0.97,[39] meaning that the average person in Pennsylvania that contracted COVID-19 in Pennsylvania in the Spring of 2020 infected one other person. Therefore the risk of contracting COVID-19 on the bus remained very low with

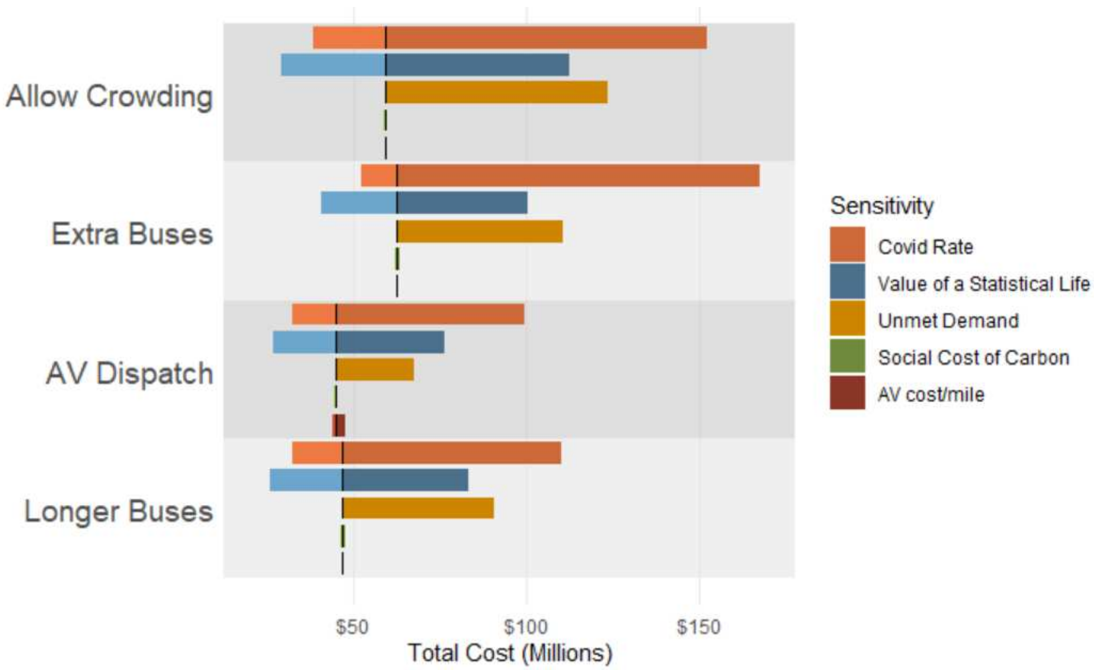


Figure 8: **Cost Sensitivity of each policy alternative to parameter bounds.** Tornado plot showing the cost sensitivity to the lower and upper bound estimates of each parameter for each alternative.

an estimated 2% of total county cases contracted directly on the bus and half of those contracted on over-capacity buses. When COVID-19 rates are at their peak, the risk of crowding on the bus becomes much higher. In the scenario where COVID-19 rates are normalized to the winter peak, the case count increases from 121 passengers contracting COVID-19 on over-capacity buses to 394 passengers contracting COVID-19 on over-capacity buses (more than three times as many cases). For both high COVID-19 rates (>2000 cases per week) and high ridership (mean peak load of 13 passengers per trip) AVs are more cost-effective than dispatching longer buses for over-capacity trips because the cost of COVID-19 infections to society surpasses the costs to dispatch single-occupancy vehicles. At the baseline for the Spring of 2020, given the COVID-19 rates and transit demand that occurred, the costs to dispatch longer buses ($46 million) and AVs ($45 million) are nearly even alternatives in terms of total costs to the transit agency and the community at large.

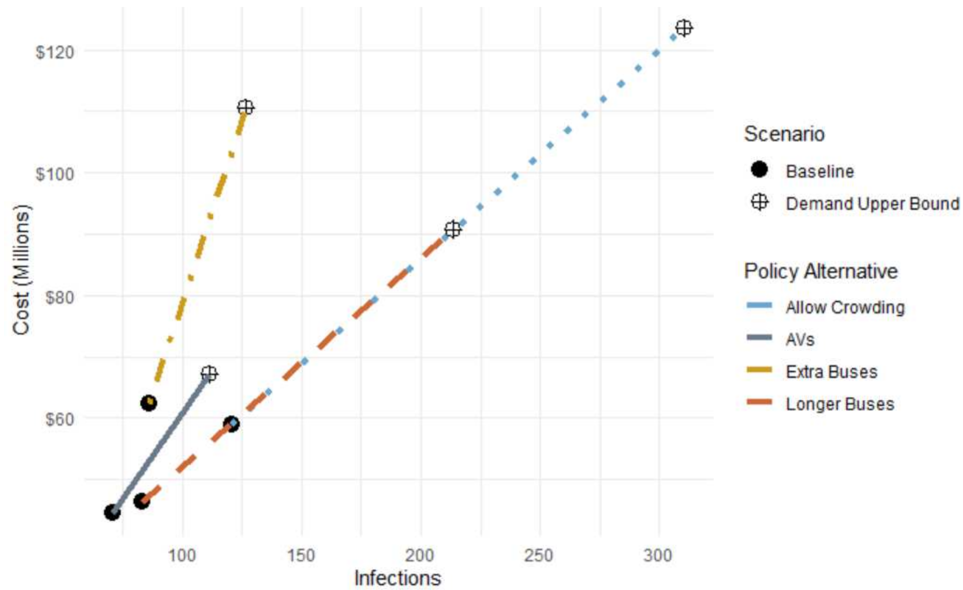


Figure 9: **Cost and Infection Sensitivity to Bus Demand.** Trade-off between overall cost and infections incurred for each policy alternative across bus demand bounds. The lower left shows the baseline case of over-capacity in the system; the upper right point represents the scenario where bus demand is averaged hourly with pre-pandemic bus demand, giving an upper limit of possible pandemic bus demand.

Conclusions and Policy Implications

We assess 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 in the county would have been contracted on the bus or in the community from bus-riders in Allegheny County in the five month time period of April to September 2020. In the early months of the pandemic when both ridership and the rate of COVID-19 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, and 234 cases total cases represent a small overall risk. Thus, transit during this time was a fairly 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 early months of the pandemic only 12% of trips were over-capacity, but these trips accounted for over half (52%) of COVID-19 cases modeled to be contracted on the bus. The risk of contracting COVID-19 on the bus was not evenly distributed throughout the community. 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 on the bus. This largely reflects inability to work from home during the pandemic or inability to use alternative modes of transportation.

Strategies that minimize crowding on the bus without leaving people without a ride are important for transit equity. Among the strategies considered, we find that allowing crowding on the bus causes the highest number of infections and dispatching a single-person AV for each over-capacity rider causes the fewest infections. Dispatching longer buses and dispatching extra buses cause similar levels of infection. If AVs were dispatched for over-capacity passengers that would possibly yield a 41% decrease in cases contracted on crowded buses (half of the cases contracted on the bus were contracted on crowded buses), which could have yielded a 1% reduction in total cases in the county. This reduction is small, but still translates to about 100 avoided cases in the county.

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 yield similar costs and are the most effective methods when considering the cost to operate, the social cost of COVID-19 risk, the social cost of extra vehicle emissions, and other externalities like marginal increased congestion. The longer buses allow increased ability to physically distance with only marginal increases in emissions and operations costs compared to the 40-ft buses. The Port Authority did choose 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 would become crowded enough to justify the cost of dispatching Autonomous Vehicles (AVs) for over-capacity passengers.

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 (and all residents indirectly through taxes), society more broadly takes on the social cost of emissions and increased road congestion, but the riders bare the costs associated with increased risk of contracting COVID-19 while riding the bus. 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. In the event that 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.

In Figure 8, 'Allowing crowding' was more costly than AVs and longer buses to society in all scenarios. Additionally, when COVID-19 cases are at half the rate they were in the early months of the pandemic and demand for transit remained low, 'Allowing Crowding' became cost competitive (if only 0.05% of the county had contracted COVID-19 as a lower-bound). This implies that in a pandemic setting, mitigation strategies on public transit to allow for physical distancing (e.g., making transit agreements with AV dispatchers or sending out longer buses in-place of standard buses for crowded trips) is 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 of sitting on the bus for airborne diseases. However, some trips (12%) still met or 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.

Methods

In this section we present our method for evaluating the costs of deploying COVID-19 mitigation alternatives for a bus public transportation system, which include AVs, extra buses, and longer buses. We start by identifying the scope of the analysis and unmet demand within the system. After that, we detail our methods for quantifying costs, benefits, externalities, and changes in COVID-19 risk for each option. Finally, we discuss our methods for considering the range of uncertainty inherent to the risks and externalities with a Monte Carlo Analysis.

Public transit in Allegheny County has limited passenger capacity on buses in order to promote physical distancing between commuters, (10 passengers for 35-ft buses, 15 passengers for 40-ft buses, and 25 passengers for 60-ft buses). Continued use of the bus system by essential worker commuters places them at a higher risk of contracting COVID-19[40] due to their reliance on the public transit system in dense urban settings.

The method for measuring crowding on the bus is defined in Equation 1. The total number of over-capacity passengers (O) is the sum of over capacity (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 over-capacity is the difference between the load and capacity. If the peak load is less than or equal to the capacity, the over-capacity (O_i) is zero.

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

$$O = \sum_{i=1}^{I} O_i \tag{2}$$

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).

$$Z_i = \lfloor \frac{L_i}{C_i} \rfloor \tag{3}$$

Monte Carlo

A Monte Carlo simulation is conducted to compare how the range of costs change under varying AV trip length (probability curve found using the Make My Trip Count 2015 survey data of Allegheny County bus rider commute distances), and the stochastic uncertainty of increased risk of contracting COVID-19 on the bus. The total cost includes operating costs ($/mile), marginal congestion, accident, & emissions costs ($/mile), the value of a statistical life from COVID-19 risk, and the social cost of vehicle emissions.

We run the Monte Carlo Simulation to simulate passengers sick on each bus trip (76,000 trips) for each of the four dispatch alternatives under 11 sensitivity scenarios (baseline, and the lower and upper estimate for 5 variables) 1000 times. See (Appendix B) for convergence and Monte Carlo run justification. Each simulation used the probability density function of commute trip lengths to assign a commute distance to each AV ride. The number of people with COVID-19 on each bus trip are assigned using Bernoulli Likelihood functions (Equation 5) and a random number generator in Python, an epidemiological model[28,29] is then used 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.

In each run we model the risk of contracting COVID-19 with four dispatch alternatives. In the first alternative, we assume crowding is allowed and we model the risk of contracting COVID-19[29] with all passengers on the same bus. In the second alternative, extra buses are dispatched for the over-capacity passengers (the first bus is at-capacity and the next bus has spill-over passengers until it is at capacity). In the third alternative, we assume all over-capacity passengers are taking single-passenger AVs. We model the risk of contracting COVID-19 on the at-capacity bus and assume a risk of zero for the single-passenger AV trips. We assign a commute distance using a random number generator to each over-capacity passenger.[33] In the fourth 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. The COVID-19 risk calculator assumes a well-mixed room.[28] To find the number of people that enter the bus sick we use a rate of sickness for that day within the county. Equation 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 20 days which accounts for the pre-symptomatic and symptomatic period of illness.

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

Equation 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 four alternatives modeled in the Monte Carlo: allow crowding, extra buses, AVs, and longer buses (Equation 8).

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

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

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 'Autonomous vehicle' alternative ($\phi = 2$), 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 the bus driver ($C_i + 1$). 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 Equation 8 ($phi = 3$). 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 (Equation 7).

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

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

For the 'extra buses' alternative, there are two Bernoulli likelihood functions (Equations 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 of sick passengers on the overflow bus (Equation 11).

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

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

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

Infection Calculation

Sick residents (σ_d) are assumed to be contagious for 20 total days (d), including pre-symptomatic days. The percent sick in the county (ρ_d) is the total current cases divided by the Allegheny 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}).[29,28] We assume 90% are sitting quietly and 10% of passengers are sitting and speaking. We also assume 100% of passengers are wearing a cloth mask and the masks are 35% effective (η_{mask})[30] to account for some improper mask wearing.

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 being emitted through sick passengers breathing, particles are also being 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).

$$\rho_d = \frac{\sum_{(d=-20)}^{0} \sigma_d}{\beta} \tag{12}$$

$$P(\alpha_i) = \binom{N_{\phi,i}}{\alpha_i} \rho_d^{\alpha_i} (1 - \rho_d)^{N_{\phi,i}-\alpha_i} \frac{d\gamma}{dt} = \frac{\alpha_i \cdot (1 - \eta_{mask}) \cdot G_v}{V} - (\lambda + \kappa + v + \psi) \cdot \gamma \tag{13}$$

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

$$\gamma(t) = \frac{\alpha_i(1 - \eta_{mask})G_v}{V(\lambda + \kappa + v + \psi)} + \left(\gamma(t_0) - \frac{\alpha_i(1 - \eta_{mask})G_v}{V(\lambda + \kappa + v + \psi)}\right) \cdot e^{(\lambda+\kappa+v+\psi)(t-t_0)} \tag{14}$$

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 non-sick passengers of zero 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.[41] 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.

$$N_{virus}(t) = (1-\eta_{mask}) \int_{t_0}^{t} \gamma(t) \times Q_{inh}\, dt \tag{15}$$

$$I_{risk} = 1 - e^{(-\frac{N_{virus}}{\kappa_p})} \tag{16}$$

$$P(\omega_i) = \binom{N_{\phi,i}}{\omega_i} I_{risk}^{\omega_i} (1-I_{risk})^{N_{\phi,i}-\omega_i} \tag{17}$$

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 ($N_{\phi,i} = 2-41$).

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

Equations 13 to 17 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

Vehicle Costs

A key assumption in our vehicle costs is that the Port Authority makes a rare-event agreement with an AV provider rather than purchase and maintain their own AVs. We assume that for each AV ride, the port authority would bear paying the difference between the total cost of the AV ride and bus fare, but not the costs of purchasing a full fleet. Although uncommon, there is a precedent for ride-sourcing services to be dispatched in rare events. Uber committed to providing pandemic trips to people getting vaccinated and to essential riders.[42,43] Likewise, Uber estimates that 1-6% of all US public transportation trips could be replaced with a ride-sharing trip at a decreased cost to the transit operator.[42] 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.[42]

We breakdown the costs for bus trips (Equation 19) and AV rides (Equations 20). 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 over-capacity (I).

The AV operating cost (ζ_j) for the total AV trips (J) represents supplying each over-capacity rider (j) with an AV using the probability curve of commute lengths of Pittsburgh bus riders (in miles)[33] to find distance traveled (M_j). We assume that the Port Authority would make an agreement with an AV dispatcher to meet rare-event demand; therefore taking on the per mile cost of the AV ride (π_{AV}), but not the cost of purchasing or storing the vehicle.

$$B = \sum_{i=1}^{I} (\pi_{bus} \times \tau_i) \tag{19}$$

$$\zeta = \sum_{j=1}^{O} (\pi_{AV} \times M_j) \tag{20}$$

Externalities

In addition to the operating costs, 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 time period observed and a Value of Statistical Life (VSL) year adjusted for COVID-19.[34,38,35] A Social Cost of Carbon is used to account for the negative externalities of increased emissions from additional vehicles.[36] Marginal externalities from increased congestion, traffic, and pollution are derived from Perry et al. 2007.[44] Table 3 shows the breakdown of costs used for each alternative and cost component per vehicle dispatched.

Table 3: Input values used for the lower, mid, and upper bound estimates of vehicle costs per mile or per hour of operation per vehicle.

Alternative	Operational Cost	VSL[34,38,35]	Social Cost of Carbon[36]	Externalities
Allow Crowding	188.09 $\frac{\$}{hr}$	(1.33 | 5.05 | 11.6) \$M	(0.05 | 0.18 | 0.54) $\frac{\$}{mile}$	0.30 $\frac{\$}{mile}$
Extra Buses	188.09 $\frac{\$}{hr}$	(1.33 | 5.05 | 11.6) \$M	(0.05 | 0.18 | 0.54) $\frac{\$}{mile}$	0.30 $\frac{\$}{mile}$
Longer Buses	188.09 $\frac{\$}{hr}$	(1.33 | 5.05 | 11.6) \$M	(0.06 | 0.23 | 0.68) $\frac{\$}{mile}$	0.33 $\frac{\$}{mile}$
AVs	(0.65 | 1.12 | 2.47) $\frac{\$}{mile}$	(1.33 | 5.05 | 11.6) \$M	(0.01 | 0.02 | 0.07) $\frac{\$}{mile}$	0.13 $\frac{\$}{mile}$

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 mile are theoretical and derived from cost estimates[37] and current transportation network company costs.[43] 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 the current COVID-19 pandemic conditions to future transit decisions during 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 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, breathing level, airflow, and air mixing on the bus. 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[45] 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. Over the course of the pandemic perceived risk and its influence on human behavior will impact the spread of COVID-19. By the late-spring of 2021 COVID-19 vaccines had become widely available. Vaccines impact the overall risk of COVID-19 to society; in particular, they lower the risk of death among the vaccinated. 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.

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.[34] 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. In the case of COVID-19 mitigation strategies, placing a value on them can be difficult if the reduced risk of infection isn't well 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[46]) 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 because they are variable, hard to quantify, and outside of the scope of societal costs considered here.

When a bus is at its covid-mandated passenger capacity, the bus driver can pass a person by or pick them up. Using passenger counts, we can find the number of passengers that travelled above the passenger limit (breaking the covid-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 half-way back to pre-pandemic levels. However, we cannot directly measure the passed-by passengers from the original bus trips.

We consider four alternatives: allow crowding and dispatching more buses, longer buses, or autonomous vehicles. 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 like Uber or Lyft. 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.

Acknowledgements

We would like to thank the Block Center for Technology and Society at Carnegie Melon University. This material is based upon work supported by the National Science Foundation Graduate Research Fellowship under Grant No. DGE1745016 & DGE2140739.

Author Contributions

L.H. led the study design, data acquisition and analysis, interpretation of results, and manuscript preparation. C.H. contributed to study acquisition and design, and manuscript editing. D.N. Contributed to study acquisition and design, and manuscript editing.

Competing Interests

The authors have no conflicts of interest to declare.

Data Availability

The repository for this project can be found at `https://github.com/Lilyhanig/transit_covid_precautions`. The raw bus data is too large to share on Github. For access, please email lhanig@andrew.cmu.edu.

Code Availability

The repository for this project can be found at `https://github.com/Lilyhanig/transit_covid_precautions`.

Appendix A Data Sources

PAAC ridership data Port Authority of Allegheny County (PAAC) has provided bus ridership data for 2018- September of 2020. This data is used to calculate over-capacity ridership during the COVID-19 pandemic. The data comes from automatic passenger counters equipped on all PAAC buses providing location, time, and load of each bus at each stop. However, the bus data only gives explicit information on the numbers of bus passengers, it does not measure unmet demand. If a person gets passed by, this unmet demand is not directly recorded in the PAAC ridership data. The data also does not provide demographic data of the passengers. It is also load-based, not agent-based; at each bus stop the change in load is recorded (passengers on/off), but passengers are not tracked from their origin to their destination.

American Community Survey 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.

Transit App data Transit App is a route finding app used for all types of transportation.[47] Transit app records bus demand 'sessions' from the app opening and mapping a bus route inside the Allegheny County bounds. The app does not provide information on if the app user chose to get on the bus, but it gives a reflection of bus demand. Transit app provides demand during the pandemic for all of Allegheny County per hour per date as a percent 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 a date falls on and then averaging that with the three nearest of that day of the week in 2018. For example, if March 15th is a Sunday in 2020, Transit App will average Sunday March 11^{th} 2018, Sunday March 18^{th} 2018, and Sunday March 25^{th} 2018, so that it does not compare a Sunday in one year to a Tuesday in another year.

Make My Trip Count Survey 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 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.

IPUMS - 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 can provide some representation of the demographics of bus commuters in Allegheny County by career.

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 ($I = 76,000$). Figure 10 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 rate, 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 4 shows the average number

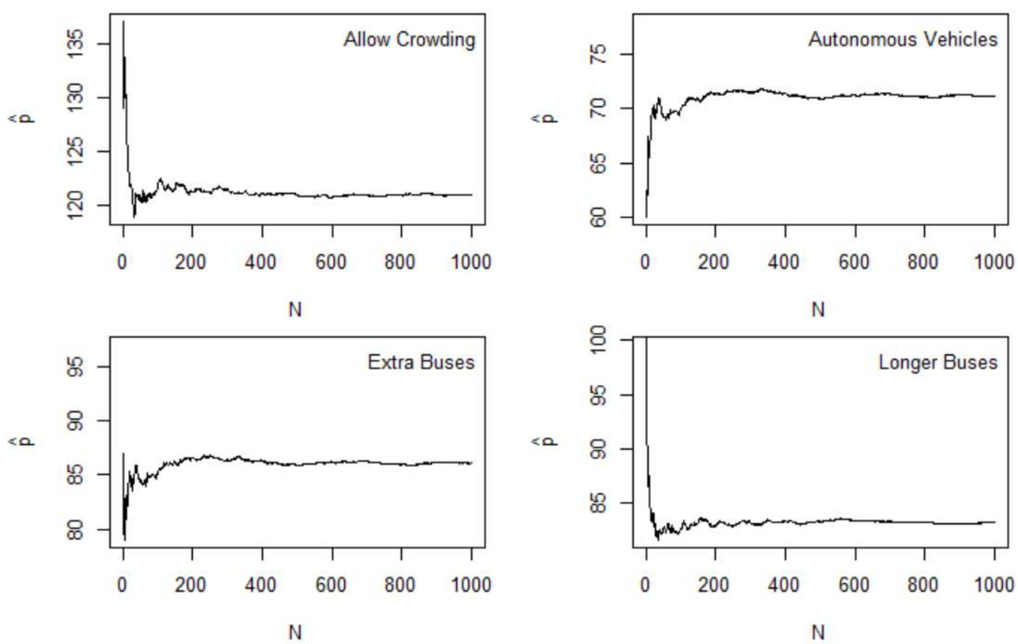


Figure 10: Convergence plot for the Monte Carlo Analysis for each policy alternative. By halfway through the total runs (N=500) the average infection was within 0.25 infections (less than 1 person).

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 four alternatives, the mean infections at the half-way point in simulation runs were within 0.25 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.

Table 4: Average infections for each alternative after 500 and 1000 runs of the Monte Carlo Analysis for the baseline scenario with the change between the 500^{th} run $\hat{\mathbf{p}}$ and the 1000^{th} run $\hat{\mathbf{p}}$.

Policy Alternative	$\hat{p}(n = 500)$	$\hat{p}(n = 10000)$	Δ
Allow Crowding	121.000	121.032	-0.032
Extra Buses	85.856	86.102	-0.246
AVs	70.892	71.136	-0.244
Longer Buses	83.274	83.190	0.084

Appendix C   Pandemic Transit 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.[9] 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 partial capacity of recreational and non-essential facilities like gyms, bars, and salons.[9] Business as usual in this report refers to pre-pandemic business operations.

Transit user demographics across the phases and in pre-pandemic data are found from the Integrated Public Use Micro data Series (IPUMS – USA)[48] 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.[9]

Figure 11 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.

Table 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

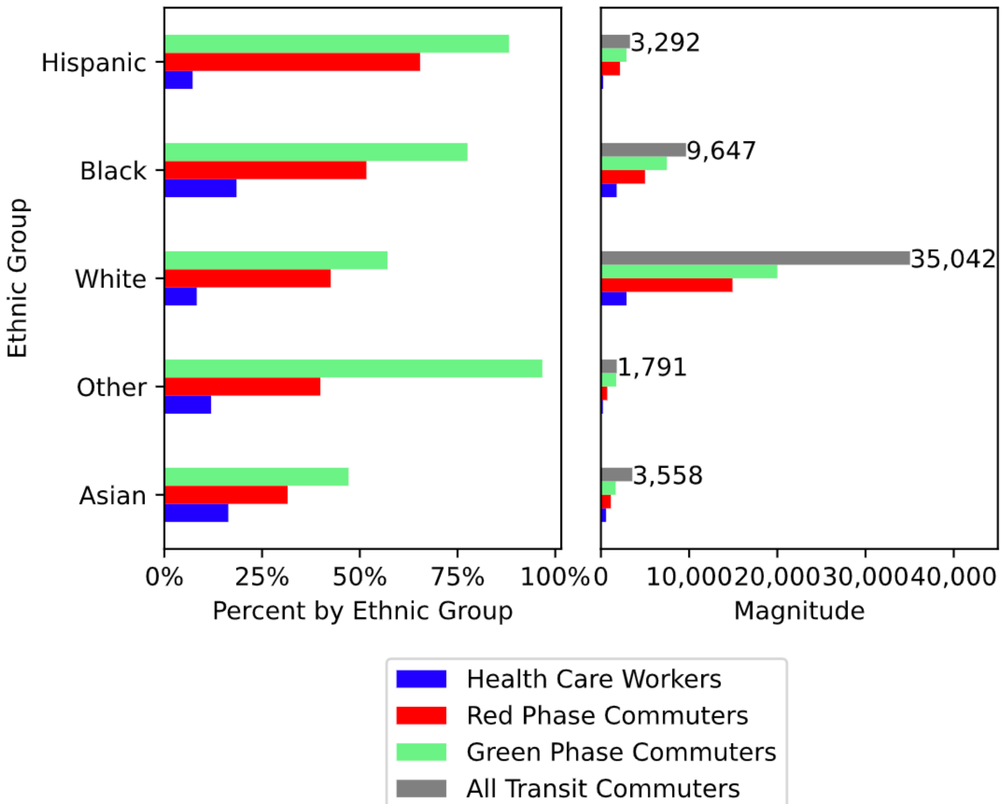


Figure 11: **Bus Commuter Demographics by Pandemic Lockdown Phase.** Commuters by demographic during red-phase of the COVID-19 Lockdown (only essential services), green-phase of lockdown (Retail partially open with restrictions), and among healthcare workers.

Appendix D Unmet Demand

The Port Authority for Allegheny County set limits on how many passengers may ride on each type of bus to promote physical-distancing and limit the spread of COVID-19.[14] Despite the COVID-19 capacities limitations, some buses had passenger loads above their mandated limit. Possible reasons for buses exceeding capacity include lacking knowledge of the set bus capacity, lacking knowledge of the current passenger load, or allowing the passenger on the bus despite the restriction. Table 6 shows the percent of over capacity passengers and trips each month from mid-April to mid-September 2020. Throughout the first Spring of the COVID-19 pandemic, 4-5% of riders were over-capacity each month, and 9-13% of trips had over-capacity each month.

Table 6: Percent of passengers and percent of trips over the Port Authority COVID-19 capacity by month. * April and September only include half of the month.

Month	Total Passengers	Over Capacity Passengers	Over Capacity Trips
April*	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*	788,436	4.3%	12.1%
Total	**250,851**	5,774,590	**4.3%**

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 with in the pandemic. Even if a bus is not at its capacity, some commuters may choose to wait for the next bus or 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.

Appendix E Variable Table

Table 7: Symbol Table A: Infection Calculations

symbol	variable	unit
i	each bus trip	
I	total bus trips	trips
d	each day	
D	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/hr
λ	viral decay	$\frac{1}{hr}$
κ	settling of aerosol droplets	$\frac{1}{hr}$
v	air changes per hour	$\frac{1}{hr}$
ψ	deposition probability	
t	average passenger time on bus	Hr
V	bus volume	m^3
N_{virus}	viral particles inhaled	particles/hr
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 8: Symbol Table B: Operational Costs

symbol	variable	unit
B	bus operation costs	\$
π_{bus}	hourly bus costs	\$/hr
τ_i	full route time	hr
ζ	AV operation costs	\$
π_{AV}	hourly AV costs	\$/hr
M_j	AV costs per mile	\$/mile

References

[1] "Historical evidence for economic effects of COVID-19". In: *European Journal of Health Economics* 21 (2020). DOI: https://doi.org/10.1007/s10198-020-01206-8.

[2] Betsy Mckay. *The Epidemics That Didn't Happen*. 2021. URL: https://www.wsj.com/livecoverage/covid-2021-04-29/card/DSfr0c505zzRycVpYxBd.

[3] Knowable Magazine. *Pandemics in recent history*. 2020. URL: https://knowablemagazine.org/article/health-disease/2020/pandemics-recent-history.

[4] "The Predictive Capacity of Air Travel Patterns during the Global Spread of the COVID-19 Pandemic: Risk, Uncertainty and Randomness". In: *Environmental Research and Public Health* 17 (10 2020). DOI: https://doi.org/10.3390/ijerph17103356.

[5] "Spatial transmission of COVID-19 via public and private transportation in China". In: *Travel Medicine and Infectious Disease* (2020). DOI: https://doi.org/10.1016/j.tmaid.2020.101626.

[6] "Neighborhood-level disparities and subway utilization during the COVID-19 pandemic in New York City". In: *Nature Communications* 12.3692 (2021). DOI: https://doi.org/10.1038/s41467-021-24088-7.

[7] "Reduction in mobility and COVID-19 transmission". In: *Nature Communications* 12.1090 (2021). DOI: https://doi.org/10.1038/s41467-021-21358-2.

[8] *Transit Is Essential: 2.8 Million U.S. Essential Workers Ride Transit to Their Jobs*. 2020. URL: https://transitcenter.org/2-8-million-u-s-essential-workers-ride-transit-to-their-jobs/.

[9] Governor Tom Wolf. *Process to Reopen Pennsylvania*. 2020. URL: https://www.governor.pa.gov/process-to-reopen-pennsylvania/.

[10] *The impacts of COVID-19 pandemic on public transit demand in the United States*. 2020. DOI: https://doi.org/10.1371/journal.pone.0242476.

[11] 2019. URL: https://www.census.gov/content/dam/Census/library/publications/2021/acs/acs-48.pdf.

[12] *Coronavirus: Operations - CTA*. 2020. URL: https://www.transitchicago.com/coronavirus/operations/#capacity.

[13] *Updated Covid-19 Guidelines*. 2020. URL: https://www.alamedaca.gov/ALERTS-COVID-19/Updated-Guidelines.

[14] Port Authority of Allegheny County. *Port Authority of Allegheny County Coronavirus (Covid-19)*. 2020. URL: https://www.portauthority.org/covid-19/coronavirus/.

[15] Wilbur et al. *Impact of COVID-19 on Public Transit Accessibility and Ridership*. 2020. URL: https://arxiv.org/abs/2008.02413.

[16] "Examining the Equity Impacts of Autonomous Vehicles: A Travel Demand Model Approach". In: *Transportation Research Record: Journal of the Transportation Research Board* (2019). DOI: https://doi.org/10.1177/0361198119836971.

[17] *Autonomous vehicles: The next jump in Accessibilities?* 2017. DOI: https://doi.org/10.1016/j.retrec.2017.03.005.

[18] *Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations*. 2015. DOI: https://doi.org/10.1016/j.tra.2015.04.003.

[19] "Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions". In: *Transportation Research Part C: Emerging Technologies* 72 (2016). DOI: https://doi.org/10.1016/j.trc.2016.09.003.

[20] Regan F. Patterson. *New Routes to Equity: The Future of Transportation in the Black Community*. 2020. URL: https://www.cbcfinc.org/wp-content/uploads/2020/10/NewRoutestoEquity-Final5.pdf.

[21] "Autonomous drones for assisting rescue services within the context of natural disasters". In: (2014). DOI: https://doi.org/10.1109/URSIGASS.2014.6929384.

[22] "Potential applications of unmanned ground and aerial vehicles to mitigate challenges of transport and logistics-related critical success factors in the humanitarian supply chain". In: *Asian Journal of Sustainability and Social Responsibility* 3 (2020). DOI: https://doi.org/10.1186/s41180-020-0033-7.

[23] "Automating humanitarian missions with a heterogeneous fleet of vehicles". In: *Annual Reviews in Control* 38 (2 2014). DOI: https://doi.org/10.1016/j.arcontrol.2014.09.008.

[24] "Cyber-physical Systems can Make Emergency Response Smart". In: *Procedia Engineering* 107 (). DOI: https://doi.org/10.1016/j.proeng.2015.06.086.

[25] Port Authority of Allegheny County. *Operating and Capital Improvement Budget*. 2019. URL: https://www.portauthority.org/contentassets/a87b421c115246c29b635b79f090cace/budgetbook2019.pdf.

[26] M.T. McCluskey. "Rethinking equality and difference: Disability discrimination in public transportation". In: 97 (1987). URL: https://digitalcommons.law.yale.edu/cgi/viewcontent.cgi?referer=&httpsredir=1&article=7136&context=ylj.

[27] Tierra S. Bills and Joan L. Walker. "Looking beyond the mean for equity analysis: Examining distributional impacts of transportation improvements". In: *Transport Policy* 54 (2017), pp. 61–69. ISSN: 0967-070X. DOI: https://doi.org/10.1016/j.tranpol.2016.08.003.

[28] *airborne.cam: a risk calculator of SARS-CoV-2 aerosol transmission under well-mixed ventilation conditions*. 2021. URL: https://airborne.cam/airbornedotcam.pdf.

[29] "Evolution of spray and aerosol from respiratory releases: theoretical estimates for insight on viral transmission". In: *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* (2021). DOI: https://doi.org/10.1098/rspa.2020.0584.

[30] *EPA Researchers Test Effectiveness of Face Masks, Disinfection Methods Against COVID-19*. 2021. URL: https://www.epa.gov/sciencematters/epa-researchers-test-effectiveness-face-masks-disinfection-methods-against-covid-19.

[31] *Comparative Guide to Norms for the Classification of Air Filters*. URL: https://www.venfilter.com/normativa/comparative-guide-norms-classification-air-filters.

[32] CDC. *Scientific Brief: SARS-CoV-2 and Potential Airborne Transmission*. 2020. URL: https://www.cdc.gov/coronavirus/2019-ncov/more/scientific-brief-sars-cov-2.html.

[33] *Make My Trip Count Survey*. 2015.

[34] "Adjusting the Value of a Statistical Life for Age and Cohort Effects". In: *The Review of Economics and Statistics* 573 (2008). URL: https://scholarship.law.vanderbilt.edu/faculty-publications/49.

[35] Chris Conover. *The Social Cost Of The First 200,000 Lives Lost To Covid-19*. 2020. URL: https://www.forbes.com/sites/theapothecary/2020/09/24/how-to-value-the-first-200000-lives-lost-to-covid-19/?sh=161e43b73780.

[36] Interagency Working Group on the Social Cost of Green House Gases. *Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide Interim Estimates under Executive Order 13990*. 2021. URL: https://www.whitehouse.gov/wp-content/uploads/2021/02/TechnicalSupportDocument_SocialCostofCarbonMethaneNitrousOxide.pdf.

[37] "Cost-Based Analysis of Autonomous Mobility Services". In: *Transport Policy* 64 (2018). DOI: https://doi.org/10.1016/j.tranpol.2017.09.005.

[38] Department of Transportation. *Departmental Guidance on Valuation of a Statistical Life in Economic Analysis*. 2020. URL: https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis.

[39] The Delphi Group Carnegie Mellon. *Changing Metrics and Additional Resources*. 2020. URL: https://rt.live/us/PA.

[40] Mutambuzi et all. *Occupation and risk of severe COVID-19: prospective cohort study of 120 075 UK Biobank participants*. 2020. URL: https://oem.bmj.com/content/early/2020/12/01/oemed-2020-106731.

[41] In: *Risk Analysis* 7 (2010). DOI: 10.1111/j.1539-6924.2010.01427.x.

[42] *Towards a New Model of Public Transportation*. 2021. URL: https://d1nyezh1ys8wfo.cloudfront.net/static/PDFs/Transit+Horizons+vF.pdf.

[43] Daniel Gillaspia. *how much does Uber charge per mile?* 2021. URL: https://www.uponarriving.com/uber-charge-per-mile/.

[44] *Automobile Externalities and Policies*. 2007. DOI: 10.1257/jel.45.2.373.

[45] Center for Disease Control. *Delta Variant: What we Know About the Science*. 2021. URL: https://www.cdc.gov/coronavirus/2019-ncov/variants/delta-variant.html.

[46] *COVID-19 (coronavirus): Long-term effects*. 2021. URL: https://www.mayoclinic.org/diseases-conditions/coronavirus/in-depth/coronavirus-long-term-effects/art-20490351.

[47] Transit App. *Hourly Covid-19 Transit Demand Data*. 2020. URL: https://transitapp.com.

[48] IPUMS. *What Is IPUMS USA*. 2020. URL: https://usa.ipums.org/usa/intro.shtml.