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16. ABSTRACT

In much in the same way that the automobile disrupted horse and cart transportation in the 20th century, automated vehicles hold the potential to disrupt our current system of transportation in the 21st century. Experts predict that vehicles could be fully automated by as early as 2025 or as late as 2035. Methods are needed to help the public and private sector understand automated vehicle technologies and their system level effects. First, we explore the medium to long run effects of automated vehicles using the San Francisco Bay Area Metropolitan Transportation Commission's activity-based travel demand model (MTC-ABM). The simulation is unique in that it articulates the size and direction of change on travel for a wide range of automated vehicles scenarios. It is also one of a handful of studies that includes the secondary effects (trip generation, destination choice, and mode choice) in its simulations of the travel effects of automated vehicles. Second, we evaluate the potential to reduce the demand for personal automated vehicles given the introduction of an automated taxis service with plausible, but low per mile service costs. The analysis is conducted with an integrated model for the San Francisco Bay Area that includes the MTC-ABM combined with the agent-based MATSim model, which was customized for the region. This is the first study to evaluate the demand for an automated taxi service with individual driver values of time, the actual travel time cost they experience traveling on roadway network by time of day, and realistic but low estimates for automated vehicle taxi services. Third, we use the MTC-ABM and the MATSim dynamic assignment model to simulate different "first" mile transit access services, including ride-hailing (Uber and Lyft) and ridesharing (Uber Pool/Lyft Line and Via) with and without automated vehicles. The results provide insight into relative benefits of each service and automated vehicle technology and th

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Automated Vehicle Scenarios: Simulation of System-Level Travel Effects Using Agent-Based Demand and Supply Models in the San Francisco Bay Area

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National Center of Sustainable Transportation

University of California, Davis

Final Draft Research Report for the California Department of Transportation

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Abstract:

In much in the same way that the automobile disrupted horse and cart transportation in the 20th century, automated vehicles hold the potential to disrupt our current system of transportation in the 21st century. Experts predict that vehicles could be fully automated by as early as 2025 or as late as 2035. Methods are needed to help the public and private sector understand automated vehicle technologies and their system level effects. First, we explore the medium to long run effects of automated vehicles using the San Francisco Bay Area Metropolitan Transportation Commission's activity-based travel demand model (MTC-ABM). The simulation is unique in that it articulates the size and direction of change on travel for a wide range of automated vehicles scenarios. It is also one of a handful of studies that includes the secondary effects (trip generation, destination choice, and mode choice) in its simulations of the travel effects of automated vehicles. Second, we evaluate the potential to reduce the demand for personal automated vehicles given the introduction of an automated taxis service with plausible, but low per mile service costs. The analysis is conducted with an integrated model for the San Francisco Bay Area that includes the MTC-ABM combined with the agent-based MATSim model, which was customized for the region. This is the first study to evaluate the demand for an automated taxi service with individual driver values of time, the actual travel time cost they experience traveling on roadway network by time of day, and realistic but low estimates for automated vehicle taxi services. Third, we use the MTC-ABM and the MATSim dynamic assignment model to simulate different "first" mile transit access services, including ride-hailing (Uber and Lyft) and ridesharing (Uber Pool/Lyft Line and Via) with and without automated vehicles. The results provide insight into relative benefits of each service and automated vehicle technology and the potential market for these services.

Key Words: Automated Vehicles, Travel Demand Modeling, Agent Based Models, Transit Access

Executive Summary

In much in the same way that the automobile disrupted horse and cart transportation in the 20th century, automated vehicles hold the potential to disrupt our current system of transportation and the fabric of our built environment in the 21st century. Experts predict that vehicles could be fully automated by as early as 2025 or as late as 2035 (Underwood, 2015). The public sector is just beginning to understand automated vehicle technologies and to grapple with how to accommodate this technology in our current transportation system. The private sector has often pointed to short term congestion and environmental benefits of automated vehicle technology and appear to be unfamiliar with longer run effects of AVs that may offset these benefits.

Methods are needed to help the public and private sector understand automated vehicle technologies and their system level effects. How automated vehicle systems are integrated into our regional transportation systems could have significant negative and positive effects on congestion, vehicle miles traveled (VMT), greenhouse gas emissions (GHGs), energy consumption, and land development patterns. For example, one study estimates that automated vehicle technology could double greenhouse gas (GHG) emissions and energy consumption or reduce it by 50%, depending on the magnitude of different effects (Wadud et al., 2016). Understanding the potential impacts of automated vehicle technologies and services is critical to guiding their adoption in ways that improve multi-modal accessibility for all citizens and minimizes negative environmental effects.

The challenge, of course, is that automated vehicles have not yet been truly introduced into the transportation system and thus observed data is not available on how travelers will adopt and respond to automated vehicle technology. However, we do have travel survey data that capture typical daily travel patterns of individuals and households as well as estimates of individuals' willingness-to-pay and value of time for travel. In addition, we have the theoretical tools (activity-based travel demand models [ABMs] and dynamic assignment models [DTAs]), which use detailed travel activity data and transportation networks to replicate current and predict future traffic behavior.

In section two, we explore the medium to long run effects of automated vehicles using the San Francisco Bay Area Metropolitan Transportation Commission's activity-based travel demand model (MTC-ABM). We identify plausible automated vehicle scenario parameters, based on an extensive literature review, for changes in roadway capacity, automated vehicle passenger value of time, operating costs, and new auto travelers. Automated vehicle scenarios are operationalized, individually and in different combinations, in the MTC-ABM and the model is run to simulate their effect on mode choice, congestion, and VMT. The study is unique in that it articulates the size and direction of change on travel for a wide range of automated vehicles scenarios. It is one of a handful of studies that includes the secondary effects (trip generation, destination choice, and mode choice) in its simulations of the travel effects of automated vehicles.

The results of the scenarios simulated with the MTC-ABM model, which included individual effects of automated vehicles and combined effects, are summarized in the table below. Automated vehicles could effectively double roadway capacity by enabling the safe reduction of on-road vehicle headways. The results of this study show that a double of roadway capacity would significantly increase VMT and related GHG emissions (by 14%), reduce congestion (by 36%), increase motorized trips (especially transit during the peak hour), and reduce non-motorized trips. Autonomous vehicles, which cannot communicate with other vehicles, however, could increase on-road vehicles headway to avoid crashes and liability. A scenario was simulated in which roadway capacity was reduced by 20% and the results showed significant increases in vehicle hours of delay (198%) and increases in VMT and associated GHG emissions (11%), which was due to lengthy detours to avoid highly congestion areas. Another scenario was simulated in which the time burden of driving was reduced by 25% due to automated vehicle technology (i.e., former drivers could work and "play" while in the vehicle). The results show relatively modest increases in VMT, vehicle hours of delay, and drive alone and shared-ride vehicle trips (3%, 7%, and 1%, respectively) and reductions in transit and walk and bike trips (5% and 4%, respectively). Automated vehicle technology may improve vehicle fuel efficiency and reduce auto insurance costs. To represent these effects, a scenario was simulated in which the per mile cost of auto travel was reduced by 4 cents based on a review of the literature. The results show relatively modest increases in VMT, vehicle hours of delay, and drive alone and shared-ride vehicle trips (3%, 5%, and 1%, respectively) and reductions in transit and walk and bike trips (4%, each respectively). Automated vehicle technology may also allow people travel by car who currently cannot drive because of age, disability, or access to a vehicle to drive. A scenario was simulated in which the effects of relaxing the age restrictions for driving from 16 to 13, for all modes and purposes, and allowing households to use and automated vehicle even if the number of vehicles drop below the number of employed people in the household. The results indicate a significant increase in drive-alone vehicle trips (6%), and similarly large reductions in shared-ride (5%), transit (12%), and walk and bike trips (4%); however, overall increases in VMT and vehicle hours of delay were modest (2% and 1%). When all the effects of automated vehicle technology are combined in one scenario, the scenario show significant improvement in congestion (vehicle hours of delay are reduced by 70%), significant increases in drive alone trips (9%) and VMT (11%), and significant reductions in transit (20%) and walk and bike trips (12%). When the per mile cost of driving is added to the combined scenario, there are further improvements in congestion (-84% VHD), reductions in VMT (7%), significant increase in walk and bike travel (22%), increases in transit (6%) and drive alone trips (2%), and reductions in shared-ride vehicle trips (10%). In sum, automated vehicle technology, whether considering effects individually or collectively, are likely to increase VMT (and associated GHG impacts) from anywhere from 2% to 14%, may significantly improve congestion or worsen it somewhat due to induced travel, and are likely to undermine efforts to maintain or expand use of carpooling, transit, walk, and bike modes. Road pricing policies could counteract negative impacts; however, incentives for carpooling would need to be adjusted to be significant in the context of the travel time benefits of automated vehicles.

Percentage change in daily vehicle miles traveled (VMT), vehicle hours of delay (VHD), and drive alone, shared-ride, transit, walk, and bike trips for the automated vehicle scenarios relative to the base case.

Scenario	VMT	VHD	Drive Alone	Shared Ride	Transit	Walk and Bike
Increase Roadway Capacity (100%)	14%	-36%	1%	2%	8%	-5%
Reduce Roadway Capacity (20%)	11%	198%	-1%	1%	11%	-3%
Reduce Value of Drive Time (25%)	3%	7%	1%	1%	-5%	-4%
Reduce Operating Vehicle Costs ($0.04)	3%	5%	1%	1%	-4%	-4%
New Drivers	2%	1%	6%	-5%	-12%	-4%
Combined Effects	11%	-70%	9%	-3%	-20%	-12%
Road Pricing and Combined Effects	-7%	-84%	2%	-10%	6%	22%

In section three, we evaluate the potential to reduce the demand for personal automated vehicles given the introduction of an automated taxis service with plausible, but low per mile service costs. This figure is based on research from Fulton and Compostella (2018a and 2018b) and includes the amortized vehicle purchase cost over 100,000 miles of driving, fuel cost, insurance, maintenance, and cleaning for an automated vehicle with an internal combustion engine. We also evaluate how further reducing the per mile price of an automated vehicle taxi service, reducing the per mile operational costs of personal vehicles, and increasing the pricing of parking could influence market potential for an automated taxi service as well as regional VMT and greenhouse gas emissions. The analysis is conducted with an integrated model for the San Francisco Bay Area that includes the MTC-ABM combined with the agent-based MATSim model, which was customized for the region. Based on our review of the literature, this is the first study to evaluate the demand for an automated taxi service with individual driver values of time, the actual travel time cost they experience traveling on roadway network by time of day, and realistic but low estimates for automated vehicle taxi services. The results indicate a relatively modest market potential (4% to 6% for the automated taxi mode share) concentrated in the inner-city areas of the region, but one that expands outward as the relative cost of the automated taxi service decline. Similarly, average empty-vehicle travel time and distance is estimated to be relatively low for the region; however, as relative costs of the automated taxis service decline, these regional averages increase. Empty-vehicle distances in the outer areas of the region can be up to approximately ten times higher than inner city distances. The current study simulates a short-term time horizon and thus the increase in VMT is modest (about 1%) and CO_2 is estimated to be reduced due to improved vehicle flows from automated vehicle technology. As describe for the previous study in section two, over the longer run increases in VMT may be larger and reductions in GHG emissions from traffic flow improvements may be off-set by induced travel.

In section four, we use the MTC-ABM and the MATSim dynamic assignment model to understand the potential market demand for "first" mile transit access service. First, the MTC-ABM model and its estimated behavioral parameters are used to estimate the plausible high-end of those travelers who may switch to BART from all modes, if first mile service to the traveler's nearest BART station was significantly improved during the AM peak period. Second, we use the MTC-ABM estimated demand to simulate the travel time and cost benefits for each traveler (and their value of time) of different ride-hailing (Uber and Lyft) and ridesharing services (Uber Pool/Lyft Line and Via) with the MATSim model. User cost of the ride-hailing and ridesharing services are estimated for services that use conventional vehicles with a driver and automated vehicles. Study results indicated that Human driver first mile access services may benefit as many as one third or as few as about 12 percent of travelers who choose to travel by BART during the am peak period. Not surprisingly, when these services use automated vehicles (with significant labor cost reductions) these shares more than triple. Our results also suggest that it may be more challenging to provide travel time savings, relative to driving a personal vehicle and parking, with shared-ride services that have a common pick-up location rather than a home location. Many of those using the transit access modes live further away from BART stations and it may be harder to find a time-efficient pick up locations in these areas. However, this scenario did garner benefits for 4% more trips than did the human driven ride-hailing service. On the other hand, when automated vehicle technology was used for these services, the single passenger home-based pick up ride-hailing service increased benefits for almost 20% more trips.

1.0 Introduction

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In section three, we evaluate the potential to reduce the demand for personal automated vehicles given the introduction of an automated taxis service with plausible, but low per mile service costs. This figure is based on research from Fulton and Compostella (2018a and 2018b) and includes the amortized vehicle purchase cost over 100,000 miles of driving, fuel cost, insurance, maintenance, and cleaning for an automated vehicle with an internal combustion engine. The analysis is conducted with an integrated model for the San Francisco Bay Area that includes the MTC-ABM combined with the agent-based MATSim model, which was customized for the region. Based on our review of the literature, this is the first study to evaluate the demand for an automated taxi service with individual driver values of time, the actual travel time cost they experience traveling on roadway network by time of day, and realistic but low estimates for automated vehicle taxi services.

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2.0 Medium to Long Run Effects of Automated Vehicles in the San Francisco Bay Area

2.1 Introduction

In this study, we explore the medium to long run effects of automated vehicles using the San Francisco Bay Area Metropolitan Transportation Commission's activity-based travel demand model (MTC-ABM). We identify plausible automated vehicle scenario parameters, based on an extensive literature review, for changes in roadway capacity, automated vehicle passenger value of time, operating costs, and new auto travelers. Automated vehicle scenarios are operationalized, individually and in different combinations, in the MTC-ABM and the model is run to simulate their effect on mode choice, congestion, and VMT. The study is unique in that it articulates the size and direction of change on travel and GHG emissions from VMT for a wide range of automated vehicles scenarios. It is one of a handful of studies that includes the secondary effects (i.e., trip generation, destination choice, and mode choice) in its simulations of the travel effects of automated vehicles.

2.2 Literature Review

In this section, we summarize the modeling studies on personal automated vehicle technology with 100% market penetration, which capture the medium run to long run effects of automated vehicles by expanding the simulation of effects beyond route choice to land use, trip, destination, time of day, and/or mode choice. The methods and simulated scenarios are comparable to those simulated in this study. These studies and their results are described in Table 2.1. The studies simulate the effects of personally owned automated vehicles and automated taxi fleets with and without sharing by representing empty vehicle repositioning travel and changing roadway capacities, value of time (VOT), and the per mile cost of use. All studies assume 100% market penetration of fully automated or driverless vehicles.

Only one study represents the effects of personal automated vehicles on home location choice in Melbourne, Australia (Thakur et al., 2016). It uses a travel and land use model calibrated to regional MPO forecasts. The travel model represents destination and mode choice and uses a static assignment route choice model. A fleet of level 4 personal automated vehicles with full market penetration is represented by reducing traveler's value of time by 50%. The land use results show shifts in population locations from the inner suburbs (-4%) to the outer (+2%) and middle suburbs (+1%). Total VMT and average vehicle trip time grows by 30% and 24%, respectively, while transit mode share increases by 3 percentage points and transit mode share declines by 3 percentage points.

Regional MPO travel demand models are used to simulate personal automated vehicles with 100% market penetration in the cities of San Francisco (CA) and Seattle (WA) by increasing roadway capacity and reducing value of time. Gucwa (2014) uses the San Francisco Bay Area MPO regional activity-based travel demand model to simulate a 100% increase in roadway capacity with and without a 50% reduction in value of travel time and finds a 7.9% and 2%, respectively, increase in VMT. Childress et al. (2014) use an activity-based model for the Seattle region MPO and simulate a 30% increase in roadway capacity with and without a 65% reduction in value of time and a 50% reduction in parking costs. When roadway capacity is increased with and without a 65% reduction of value of travel time for high income individuals only VMT increases by 3.6% and 5%, respectively, and average travel delay declines by 17.6% to 14.3%, respectively. However, when the 65% reduction of value of time is applied to all individuals, parking costs are reduced, and roadway capacity is increased, total VMT increases by 19.6% and average delay increases by 17.3%. Childress et al. (2014) also examine changes in accessibility and VMT by zone from the simulated scenarios and find extreme increases in accessibility and VMT in outlying areas of the region and in some core urban areas, which suggest the potential for relocation of households and businesses to those areas. Note that the implied elasticity of demand for travel with respect to capacity increase is low for both these studies (0.002 and 0.012, respectively) relative to the empirical literature (as discussed in the next section). As a result, the increases in VMT and reductions in travel delay are likely underestimated.

The activity and agent-based travel demand model (POLARIS) is applied to the Ann Arbor (MI) region to evaluate different levels of personal automated vehicle market penetration rates, roadway capacity expansion, and value of time (Auld et al., 2017). The model represents trip, destination, mode, and dynamic assignment route choice. Auld et al. (2017) find that, when automated vehicle market penetration rates are at 100% and roadway capacity expands by 12% to 77%, VMT increases by 0.4% and 2% and average vehicle travel time is reduced by about 2% to 5%. When value of travel times of 25% and 75% are applied to market penetration rates of 20% and 70%, VMT increases from about 1% to 19% and average vehicle trip time increases from 2% to 30%. Changes in market penetration, roadway capacity, and value of times are combined and the results indicate an increase in VMT that ranges from 2% to 28% and average vehicle trip times that range from 2% to 30%. The authors note that the implied elasticity of demand for travel with respect to capacity for this study is 0.027 which is low compared with estimates in the empirical literature, as discussed in the next section.

Levin and Boyles (2015) modify the Austin (TX) regional MPO four step model to simulate personal automated vehicles with 100% market penetration in the downtown areas. This model represents destination, mode, and static assignment route choice. The model simulates personal automated vehicle travel by reducing vehicle following distances and jam densities to increase roadway capacity. The model also represents relocation travel and parking (e.g., to avoid parking cost vehicles will travel home after driving travelers to work). Levin and Boyles (2015) find that, in the peak period, the introduction of automated vehicles increase the disutility for parking and as a result 83% of total trips are round trips for repositioning. Vehicle trips increase by 275.5% while transit trips decline by 63%. However, average link speeds, weighted by length, are reduced by 9%.

Azevedo et al. (2016) examine the effect of a policy that prohibits personal vehicle travel in the central business district (CBD) of Singapore (i.e., transit access to CBD only) and introduces a fleet of shared automated vehicles with a fare that is 40% of the taxi fare. The policy is simulated with an activity and agent-based model (SimMobility) that makes use of local travel survey data, roadway and transit networks, and local taxi data. The model represents trip, destination, time-of-day, mode, and route choice. They find a 29 percentage point increase in the daily shared automated taxi mode, a 3 percentage point increase in transit mode share, and a 1 percentage point increase in both taxi and walk mode share.

Table 2.1. Summary of mid to long run scenario modeling studies.

Author	Location	Method	Travel Effects	AV	Scenario Parameters	Mode Choice	Total VMT	Travel Time	Land Use/Parking
Thakur et al. 2016	Melbourne, Australia	Travel & land use model calibrated to regional forecasts	Home location, destination, mode & SA route choice	100% Personal	50% VOT	+3 PP Car; -3 PP Transit	+30%	+24% Avg. VTT	Suburb pop.: +2% outer; -1% middle; -4% inner
Childress et al. 2014	Seattle, WA (US)	MPO regional activity-based travel model	Destination, mode & SA route choice	100% Personal	+30% road capacity	0 PP	+3.6%	-17.6 Avg. Delay	Outlying & some core high access & VMT increase
					+30% road capacity; 65% high income VOT	-1 PP Car	+5%	-14.3 Avg. Delay	
					+30% road capacity; 65% VOT; -50% parking cost	+1 PP Car; -2 PP Walk	+19.6%	+17.3 Avg. Delay	
Gucwa 2014	San Francisco, CA (US)	MPO regional activity-based travel model	Destination, mode & SA route choice	100% Personal	+100% road capacity	-	+2%	-	-
					+100% road capacity; 50% VOT		+7.9%		
Auld et al. 2017	Ann Arbor, MI (US)	Activity & agent-based travel model (POLARIS) with data from MPO (survey & network)	Trip, destination, mode & DTA route choice	100% Personal	+12% to +77% road capacity	-	+0.4% to +2%	-1.8% to -4.5% Avg. VTT	-
				20% Personal	25% to 75% VOT		+1.3% to +5%	+1.8% to +7.1% Avg. VTT	
				75% Personal	25% to 75% VOT		+5.7% to +18.6%	+8% to +30% Avg. VTT	
				20% Personal	25% to 75% VOT; +3% road capacity		+1.6% to +5.3%	+1.6% to +7.1% Avg. VTT	
				75% Personal	25% to 75% VOT; +12% road capacity		+4.3% to +12.7%	+3.2% to +15.9% Avg. VTT	
				100% Personal	25% to 75% VOT; +77% road capacity; AV Int.		+10% to +28.2%	+4.5% to +30.1% Avg. VTT	
Levin & Boyles 2015	Downtown Austin, TX (US)	Modified 4 Step Model & MPO travel data	Destination, mode & SA route choice (parking & repositioning)	100% Personal	Reduced following distance & jam densities	-63% transit trips; +274.5 vehicle trips	-	-9% Avg. Link Speed (weighted by length)	Increased parking disutility

Author	Location	Method	Travel Effects	AV	Scenario Parameters	Mode Choice	Total VMT	Travel Time	Land Use/Parking
Azevedo et al. 2016	CBD Singapore	Activity & agent travel model (SimMobility) with travel survey, network & taxi data	Trip, destination, time of day, mode & DTA route choice	Shared Taxi	No private vehicles; areas only accessed by transit; service cost 40% current taxi	+3% PP transit; +29% PP shared taxi; +1% PP taxi, +1% PP walk	-	-	-

AV=automated vehicles; VMT=vehicle miles traveled; SA=static assignment; DTA=dynamic traffic assignment; VOT=value of in vehicle travel time; PP=percentage point; Avg. VTT=average vehicle travel time.

2.2 Methods

The **San Francisco Bay Area MTC's ABM** belongs to the CT-RAMP (Coordinated Travel-Regional Activity Modeling Platform) family of ABMs developed by Parsons Brinkerhoff. The activities or day patterns that drive individuals' need to make travel-related choices in time and space are based on MTC's 2000 Bay Area Travel Behavior Survey. The data from this survey includes two-day travel diaries from 15,000 households. In the model, tours are the unit of analysis in a day pattern. A tour represents a closed or half-closed chain of trips starting and ending (in hourly increments) at home or at the workplace and includes at least one destination and at least two successive trips. The MTC ABM includes four mandatory tours (work, university, high school and grade school) and six non-mandatory tours (escort, shop, other maintenance, social/recreational, eat out and other discretionary). A more advanced feature of the CT-RAMP models is the representation of intra-household interactions among household members. All individuals and their socioeconomic characteristics in the MTC study area are generated through a statistical process known as a population synthesis, which expands survey samples (i.e., 2000 Public Use Microdata Sample and 2010 Census data) of households to represent the entire population. The 2010 zone system includes 1,454 zones. Static network assignment includes the following time periods: early off-peak (3 AM to 6 AM), morning peak (6 AM to 10AM), midday (10 AM to 3 PM), PM Peak (3 PM to 7 PM), and off-peak late (7 PM to 3 AM).

The MTC-ABM is run iteratively and at each iteration, tour and trip lists are generated for all individuals within the sample. Selection of alternative choices at each stage of the model depends on individual's socioeconomic characteristics and the relative attractiveness of the choice. The generated individual trips are aggregated as zonal origin and destination matrices and assigned to the network by mode (drive alone, shared rides, bike, walk, walk-transit and drive-transit) and by time period. After assignment, the updated network variables such as traffic volume and speeds and later, travel times are calculated and stored as average loaded network files to be used for next iteration. These new network values are used to derive zonal skims (e.g., in-vehicle travel time and wait time), which are subsequently input to the following model components: (1) trip generation by zonal accessibility logsums, (2) mode choice by the utility function, (3) trip distribution by mode choice logsum parameters, and (4) traffic assignment by the general cost function.

2.3 Scenarios

All scenarios assume 100% market penetration of personal automated vehicles in the same horizon year as the base case scenario for the MTC-ABM. Scenarios are simulated that examine plausible changes enabled by automated vehicle technology, including roadway capacity, value of travel time for drivers, monetary costs, and total drivers.

Roadway Capacity Increased by Automated Vehicles: Safety improvements from connected automated vehicles are expected to increase effective roadway capacity by enabling smaller vehicles and shorter headways and by reducing time delays due to accidents and improved operations. Shladover et al. (2012) conduct field tests and microsimulation modeling of connected automated vehicles at differing levels of market penetration and find increases in roadway capacity due to connected automated vehicles that range from 5% to 89%. Ambühl et al. (2016) use a mesoscopic model (VISSIM) to simulate an autonomous vehicle fleet with a simplified car following model, in which headways are reduced from two seconds for conventional vehicles to one half a second, on an abstract four by four gridded network (with 24 road links that are 120 meters long and two lanes in each direction) and report that the effective capacity of the network could be tripled by an automated vehicle fleet. Lioris et al. (2017) apply three queuing models to simulate automated vehicles with headways of three fourths of a second on an urban network with 16 intersections and 73 links. They show that both roadways and intersections can accommodate a doubling and tripling of roadway capacity with connected automated vehicles. In other words, intersections would not act as a bottleneck in a roadway network that served automated vehicles.

In addition, the literature suggests that the elasticity of VMT with respect to road capacity is 0.3 to 0.6 (short run) and 0.6 to 1.0 (long run) (Handy and Boarnet, 2015). Thus, if roadway capacity increases by 10% then VMT may increase by 3% to 6% in the short run and 6% to 10% in the long run.

In sum, the results of modeling and field studies, which largely consider reduced headways between automated vehicles, indicate that a fully automated vehicle fleet could approximately double or triple the effective capacity of existing roadways. As a result, in this scenario, roadway capacity is increased in the MTC-ABM network by 100% to represent reduced headways for connected automated vehicles in the following roadway facility classes: freeways, expressways, freeway ramps, special facilities, and toll plaza.

Roadway Capacity Reduced by Automated Vehicles: Autonomous vehicles, unlike connected automated vehicles, could result in a reduction in roadway capacity. Autonomous vehicles sense vehicles and objects around them but are not able to communicate with other vehicles as are connected automated vehicles and thus may not be able to safely reduce vehicle headways. Some suggest that autonomous vehicles may could be programmed to increase headways to improve safety and reduce accident liability. We were not able to find any literature that explored the magnitude of potential capacity reduction by autonomous vehicles. As a result, for purposes of this study, we assume that roadway capacity is increased by 20% in the MTC-ABM to represent increased headways for autonomous vehicles on freeways, expressways, freeway ramps, special facilities, and toll plaza.

Value of Time Reduced by Automated Vehicles: Passengers in fully automated vehicles would be free to use in-vehicle travel time to work and "play" in their vehicle. As a result, the burden of in-vehicle travel time may be lessened. Ian Wallis Associates (2014) review the literature on the value of time of vehicle drivers compared to vehicle passengers. They find only five studies that directly address this issue and only one of these studies control for individual socio-demographic differences, such as income and age. In one U.K. study, the results of a stated preference and transfer price surveys[1] of vehicle drivers and passengers indicate that the average ratio for passenger value of time compared to driver value of time is 63% for commuter travel, 75% for other travel, and 78% for business travel (Hague Consulting Group, 1999 cited in Ian Wallis Associates, 2014). A study conducted in Australia, which employs a stated preference survey, finds that the value of travel time for passengers is 75% of drivers (Hensher, 1984 cited in Ian Wallis Associates, 2014). The results of stated preference and transfer price surveys administered in Sweden indicate no significant difference between passenger and driver value of travel time (cited in Ian Wallis Associates, 2014). In Denmark, a stated preference survey

[1] Stated preference surveys ask respondents to choose among different hypothetical options and experiment methods are typically employed to generate hypothetical choices. Transfer price surveys present hypothetical choices in relation to an existing or actual situation experienced by respondents.

shows that passenger value of travel time is 67% that of driver value of travel time, but when value of travel time is adjusted for income the value is 82% (Fosgerau et al., 2007 cited in Ian Wallis Associates, 2014). This study did not detect significant differences in value of travel time by trip purpose. The results of revealed[2] and stated preference surveys in Spain indicate that passenger value of time is 82% of the driver for work/education trips and 69% for all other trip purposes (Roman et al., 2007 cited in Ian Wallis Associates, 2014).

Studies that examine rail passengers' value of time spent on activities while traveling provide some insight into potential travel time benefits of automated vehicles. A survey of rail passengers in the U.K. indicates that only 13% of passengers engage in work or study while traveling, 98% of those passengers rate the time spent on those activities as of some use (59%) or very worthwhile (39%), and 62% to 85% of all passengers rate different non-work activities as of some use or very worthwhile (Lyons et al., 2007). Another study in the U.K., which uses revealed preference and stated preference surveys, finds that train travelers engage in a wider range of activities than car travelers and, on average, about 66 minutes were spent on work related activities by train passengers while only 6 minutes were spent on work related activities by car travelers (Batley et al., 2010). More recently, Malokin et al. (2015) conduct a revealed preference survey of commuters in the San Francisco-Sacramento transportation corridor in Northern California and extrapolate travel time benefits from productive time use during commuter rail and shared ride travel to estimate changes in commuter mode share for a hypothetical automated vehicle scenario. The results indicate that the drive alone mode share increases by 0.95 percentage points and shared ride mode share increases by 1.08 percentage points. However, one on-line survey, the results of which are stratified by gender, age, and income to closely represent the general population, finds that window gazing and relaxing is a more highly valued use of time than working in automated vehicles (Cyganski et al., 2015). However, Le Vine et al. (2015) question the equivalence of traveling in an automated vehicle and in a train due to differences in acceleration and deceleration dynamics, which have been found to impact travelers' comfort. They estimate that these dynamics are significantly worse in automated vehicles based on a microsimulation analysis.

A few surveys have been conducted that explore the factors that may motivate consumers to purchase an automated vehicle; however, the samples of these surveys are typically not representative of the general population in a specific geographic area. Bansal and Kockelman (2016) conduct an internet-based opinion survey and report that a significant number of respondents find the ability to engage in other tasks would contribute positively to purchasing an automated vehicle. These include texting or talking (74%), sleeping (52%), working (54%), and watching movies or playing games (46%). Menon et al. (2016) administer a survey to a university population in South Florida and find that 73% of respondents believe that more productive (than driving a conventional vehicle) use of travel time is a likely benefit of automated vehicles. On the other hand, Schoettle and Sivak's (2014a) internet-based survey of individuals in the U.K., the U.S., and Australia finds that 41% of respondents would continue watching the road even as passenger in an automated vehicle.

The ability to engage in other activities while traveling in an automated vehicle may reduce the time burden of travel. Potential reductions in the value of travel time from automated vehicles are largely extrapolated from the results of stated preference surveys of car passengers and rail passengers,

[2] Revealed preference surveys ask respondents questions about actual situations they experience

which may or may not be transferable to the experience automated vehicle passengers. The results of these studies vary widely, but 75% to 82% of current driver values of time may be reasonable. Studies also indicate that working may not be a common use of time for those traveling in automated vehicles.

In this scenario, the value of time for driving in a personal vehicle was reduced by 25%, which would influence the trip destination, mode choice, and traffic assignment in the model. By reducing the value of time for driving, auto travelers are more likely to take longer auto trips to more favored destinations, chose to travel by auto, and, perhaps, be less likely to avoid more direct routes due to congestion.

New Travelers Induced by Automated Vehicles: Fully automated vehicles could increase mobility for older adults, people with disabilities, young people without driver's licenses, and people living in poverty. The ability of these mobility-limited population groups to travel in automated vehicles, all things being equal, would tend to increase vehicle travel. Our review of the literature identified only four studies that attempt to quantify the magnitude of this increase.

Sivak and Schoettle (2014) conduct an on-line survey of young people (age 18 to 39) without a driver's license and ask the primary reason why they did not have a driver's license. The distribution of respondents without a driver's license aged 18 to 39 is consistent with that of the U.S. population (Schoettle and Sivak, 2014b). They find that four of these reasons would be eliminated by the availability of fully automated vehicles: too busy, disability, lack of driving knowledge, and legal issues. If respondents indicate one of those four reasons, then it is assumed that they would travel in a fully automated vehicle. The increase in total vehicle users was estimated by age group. These figures are then applied to the 2009 National Household Travel Survey (NHTS) data to estimate a 10.6% total average increase in annual VMT with fully automated vehicles for the U.S. population aged 18 to 39.

Brown et al. (2015) use data from the 2009 NHTS and the 2003 "Freedom to Travel Study" to estimate the increase in travel for youth, elderly, and disabled populations. They apply the travel rate of the top age decile (40 years old) to population segments from age 16 to 85. They estimate a total increase of 40% VMT per vehicle due to the availability of fully automated vehicles.

Wadud et al. (2016) use the 2009 NHTS to estimate the increase vehicle travel among those aged 62 and older that may result from the introduction of fully automated vehicles. Their analysis applies the driving rates of those aged 62 to everyone older than 62. The results indicate a 2% to 10% increase in VMT.

Harper et al. (2016) use data from the 2009 NHTS to estimate the potential increase in VMT by non-drivers, seniors (65 years and older), and individuals with travel-restrictive medical conditions. The study assumes that, with fully automated vehicles, non-drivers will use vehicles at the same rate as drivers, seniors will drive at the same rate as those under 65, and that working age adult drivers (19-64) with travel-restrictive medical conditions will travel at the same rate as working age adult drivers without medical conditions. They estimate a 14% increase in annual VMT for the U.S. population aged 19 and older.

In this scenario, we were able to relax the age restriction for driving from 16 to 13, for all modes and purposes, which makes driving more attractive relative to slow modes, public transit, walk, and bike. We also relaxed the auto sufficiency restriction. In the base case, the model classifies a household as auto sufficient if the number of autos in the household is greater than the number of the workers in a household. However, in this scenario a household is considered auto sufficient if the household has one or more autos. As a result, household members can use an automated taxi to meet their travel needs.

Operating Costs Reduced by Automated Vehicles: Attributes of automated vehicles will tend to reduce the variable per mile cost of operating a vehicle. The improved safety of automated vehicles should reduce insurance costs, which are about 3.3 cents per mile by about 60% to 80% (Wadud et al., 2016). It should also reduce the weight of the vehicle due to safety features. MacKenzie et al. (2014) estimate that removing this weight could reduce fuel consumption by 5.5%. Elasticity of VMT with respect to gas price is -0.03 to -0.10 (short run) and -0.13 to -0.30 (long run) (Circella et al., 2014).

In this scenario, we assume that the per mile cost of auto travel is reduced from 17.9 cents per mile to 14 cents per mile, which would influence mode choice in the model by making auto modes (drive alone, shared ride auto, and park-and-ride) more attractive than public transit, walk, and bike modes.

Combined Effects of Automated Vehicles: In this scenario we combined all changes included in following scenarios described above: increase roadway capacity, reduced value of time for driving, reduced operating costs, and new drivers.

Pricing Effects of Automated Vehicles: In this scenario, we doubled the per mile operated cost to 36 cents per miles for all auto travel and, as described above, increased roadway capacity, reduced by value of time for driving, and allowed for new drivers.

2.4 Results

The scenario results for mode choice are presented in Table 2.2, which describe percentage change in total trips and mode shares, respectively. Roadway network results are shown in Table 2.3, which includes percentage changes in total VMT, vehicle trip volume, and vehicle hours of delay. Changes in VMT approximate the effect on GHG emission, as the two are closely related in a model set that does not represent any change in use of different vehicle types. All results are described in terms of change relative to the base case scenario.

The doubling of roadway capacity shows significant increases in VMT and trip volumes. VMT is increased by 22% in the peak period, 8% in the off-peak, and 14% for an average 24-hour daily period. Vehicle volumes are increased overall by 4%, with an increase of 6% in the peak and 1% in the off-peak period. The increase in peak hour travel offsets roadway capacity and associated auto travel time improvements and vehicle hours of delay are increased by 28%. However, significant reductions in vehicle hours of delay are forecast for the off-peak period (77%) where induced travel is significantly lower than peak hour travel. Over a 24-hour daily period, vehicle hours of travel are reduced by 36%. Increased roadway capacity and roadway speeds also increase the number of motorized trips (drive alone by 1%, shared-ride by 2%, and transit by 10%) during the peak period; however, walk and bike trips are reduced by 6% because travel time by these modes is relatively slower than modes that use the roadways. The implied elasticity of demand of VMT with respect to roadway capacity is 0.14, which is low relative to the literature and, because capacity was not expanded for all roadway types, it may be at the low end of reasonable for this scenario. The implied elasticity of demand for freeway VMT and capacity was 0.25. Note that this model set does not represent land use effects of new capacity.

The 20% reduction of roadway capacity for autonomous vehicles produces large increases in vehicle hours of delay: 416% for the peak period, 59% for the off-peak period, and 198% for the 24-hour daily period. Roadway volumes decline by 1% as more traveler make transit trips (11%) to avoid slower travel speeds. However, VMT increases, despite reductions in volumes, as drivers take longer routes to avoid congestion hot-spots.

The 25% reduction of value of time for driving reduces the number of transit and walk and bike trips 5% and 4%, respectively, and increases driving trips 1%. These changes in mode choice translate to daily increases in VMT of 3% and vehicle hours of delay of 7%. During the peak period, VMT increase by 4% and vehicle hours of delay increases by 18%.

When operating costs for autos are reduced by about 4 cents per mile, there is a shift from transit (4%) trips and walk and bike trips (4%) to drive-alone (1%) and shared-ride (1%) vehicle trips. VMT and vehicle volumes decline by about 3% and 2%, respectively, and vehicle hours of delay increase by 5%. The implied elasticity of VMT with respect to fuel price in this scenario is 0.11, which is on the high-end of short run estimates in the literature.

The new driver scenario simulates the effects of relaxing the age restriction for driving from 16 to 13, for all modes and purposes, and allowing households to use and automated vehicle even if the number of vehicle drop below the number of employed people in the household. The results indicated a significant increase in drive-alone vehicle trips (peak 7%, off-peak 4%, and 24-hour 6%), and similarly large reductions in shared-ride (peak 6%, off-peak 4%, and 24-hour 5%), transit (peak 11%, off-peak 13%, and 24-hour 12%), and walk and bike trips (peak 5%, off-peak 3%, and 24-hour 4%).

Dramatic mode shifts away from transit, walk, and bike mode choice are observed for the scenario in which several effects of automated vehicles area combined, including increased roadway capacity, reduced value of driving time and operating costs, and new drivers. Daily transit trips are reduced by 20%, walk and bike trips are reduced by 12%, and shared-driving trips are reduced by 3%. Drive alone trips increase by 11% during the peak period, 6% during the off-peak period, and 9% over the total 24-hour periods. Despite these changes in mode choice, vehicle hours of delay decline significantly (-56% for the peak, -79% for the off-peak, and -70% daily). VMT increases in this scenario (15% for the peak, 6 for the off-peak, and 11 daily) but the increase is less than the increase in the roadway capacity scenario. In the combined effect scenario, reduced congestion allows for more direct routes to destinations relatively to the increase highway capacity scenario. The San Francisco Bay area is a highly congested region and thus a significant number of travelers take less direct routes to avoid congested hot-spots.

The pricing and combined effects scenario includes a doubling of the base per mile operating cost (17.9 cents) and the automated vehicle effects of a doubling of roadway capacity, 25% reduction in value of driving time, and new drivers. With the exception of the non-trivial pain of higher road user fees, this scenario appears to provide the best system-level outcome in terms of reduced VMT, VHD, and increase transit, walk, and bike travel. Daily, we see reductions in VMT of 7%, vehicle volumes by 9%, and VHD by 84%. Walk and bike trips increase by 22% and transit trips increase by 6% over the average daily time period. The largest reduction in vehicle trips comes from the shared-ride vehicle mode. Drive alone trips increase by about 2% over a 24-hour period. This scenario shows that the current incentives for sharing rides (i.e., faster travel time in HOV lanes and reduced toll charges) may not be sufficient given the changes in travel time and costs from the introduction of automated vehicles into the transportation system.

Table 2.2. Percentage change in trips by mode for peak and off-peak periods for the automated vehicle scenarios.

Scenario	Time of Day	Drive Alone	Shared Ride	Transit	Walk and Bike
Base Case	Peak	6,269,541	4,955,338	791,508	1,346,109
	Off-Peak	5,350,847	3,836,884	384,401	1,279,525
	Total	11,620,388	8,792,222	1,175,909	2,625,634
Increase Roadway Capacity (100%)	Peak	1%	2%	10%	-6%
	Off-Peak	0%	1%	5%	-3%
	Total	1%	2%	8%	-5%
Reduce Roadway Capacity (20%)	Peak	-3%	0%	10%	-6%
	Off-Peak	2%	2%	12%	0%
	Total	-1%	1%	11%	-3%
Reduce Value of Drive Time (25%)	Peak	1%	1%	-5%	-4%
	Off-Peak	1%	1%	-5%	-4%
	Total	1%	1%	-5%	-4%
Reduce Operating Vehicle Costs ($0.04)	Peak	1%	1%	-4%	-5%
	Off-Peak	1%	1%	-4%	-4%
	Total	1%	1%	-4%	-4%
New Drivers	Peak	7%	-6%	-11%	-5%
	Off-Peak	5%	-3%	-13%	-3%
	Total	6%	-5%	-12%	-4%
Combined Effects	Peak	11%	-3%	-19%	-13%
	Off-Peak	6%	-2%	-23%	-11%
	Total	9%	-3%	-20%	-12%
Road Pricing and Combined Effects	Peak	4%	-11%	10%	23%
	Off-Peak	-1%	-8%	-1%	20%
	Total	2%	-10%	6%	22%

Table 2.3. Percentage change in vehicle miles traveled (VMT), volume of vehicles (VOL), and vehicle hours of delay (VHD) for peak and off-peak periods for the automated vehicle scenarios from the base case.

Scenario	Time of Day	VMT	VOL	VHD
Base Case	Peak	86,883,585	176,476,827	334,246
	Off-Peak	99,744,968	204,064,211	527,911
	Total	207,969,628	378,077,830	2,566,657
Increase Roadway Capacity (100%)	Peak	22%	6%	28%
	Off-Peak	8%	1%	-77%
	Total	14%	4%	-36%
Reduce Roadway Capacity (20%)	Peak	12%	-2%	416%
	Off-Peak	11%	1%	59%
	Total	11%	-1%	198%
Reduce Value of Drive Time (25%)	Peak	4%	0%	18%
	Off-Peak	2%	0%	1%
	Total	3%	0%	7%
Reduce Operating Vehicle Costs (4 cents)	Peak	3%	3%	14%
	Off-Peak	3%	2%	-1%
	Total	3%	2%	5%
New Drivers	Peak	3%	0%	11%
	Off-Peak	1%	0%	-4%
	Total	2%	0%	1%
Combined Effects	Peak	15%	10%	-56%
	Off-Peak	6%	6%	-79%
	Total	11%	8%	-70%
Road Pricing and Combined Effects	Peak	-6%	-10%	-80%
	Off-Peak	-7%	-8%	-86%
	Total	-7%	-9%	-84%

2.5 Conclusion

In sum, automated vehicle technology, whether considering effects individually or collectively, are likely to increase VMT (and associated GHG impacts) from anywhere from 2% to 14%, may significantly improve congestion or worsen it somewhat due to induced travel, and are likely to undermine efforts to maintain or expand use of carpooling, transit, walk, and bike modes. Road pricing policies could counteract negative impacts; however, incentives for carpooling would need to be adjusted to be significant in the context of the travel time benefits of automated vehicles.

3.0 Relative Demand for Automated Taxis and Personal Vehicles Using Agent-Based Demand and Supply Models in the San Francisco Bay Area

3.1 Introduction

In this section, we evaluate the potential to reduce the demand for personal automated vehicles given the introduction of an automated taxis service with plausible, but low per mile service costs. This figure is based on research from Fulton and Compostella (2018a and 2018b) and includes the amortized vehicle purchase cost over 100,000 miles of driving, fuel cost, insurance, maintenance, and cleaning for an automated vehicle with an internal combustion engine. As the results of the previous section show, vehicle miles traveled (VMT) and associated greenhouse gas emissions could increase significantly, if automated personal vehicles largely replaced conventional personal vehicles. The analysis is conducted with an integrated model for the San Francisco Bay Area that includes the Metropolitan Planning Commissions' activity-based travel demand model (MTC-ABM) combined with the agent-based MATSim model, which was customized for the region. Based on our review of the literature, this is the first study to evaluate the demand for an automated taxi service with individual driver values of time, the actual travel time cost they experience traveling on roadway network by time of day, and realistic but low estimates for automated vehicle taxi services.

3.2 Literature Review

In this section, we review studies that simulate automated taxis scenarios with methods similar to those employed in this study. See Table 3.1. Faganant and Kockelman (2014) simulate an automated taxi fleet in a small downtown of Austin-like city. Travel demand is randomly generated with limited reference to the 2009 National Household Travel Survey (NHTS). The physical representation of this downtown is a 10-mile by 10-mile gridded areas without a physical representation of roadway networks. As a result, automated taxis are simulated with constant peak and off-peak travel speeds for a typical weekday. They find that VMT increases by about 11%. Life-cycle energy and GHG emission effects are also calculated using estimates of VMT, fleet size, and parking for base and automated taxi scenarios and show reductions in energy use by 12% and GHGs by 6%.

Later studies conducted by Faganant, Kockelman, and others (Fagnant et al., 2015 and Faganant and Kockelman, 2016) improve their representation of daily travel in Austin (TX) by increasing the size of the core city to a 12-mile by 24-mile area, using a roadway network with link-level travel times, and using origin and destination travel demand data from the regional Metropolitan Planning Organization's (MPO's) four step model. They also use the MATSim dynamic assignment model (Horni et al., 2016). The results from the improved modeling of the automated taxi fleet in Fagnant et al. (2015) show lower increases in VMT (8%) and improved energy use and GHG reductions (14% and 7.6%, respectively). The increase in VMT in the shared automated taxi ranged from 17% to 52% of the increase for the automated taxi scenario.

Chen and Kockelman (2016) simulate an automated electric taxi fleet that competes with other modes by per mile cost of use and with travel time benefits in a hypothetical mid-sized region (100-mile by 100-mile gridded area) similar to Austin (TX). The agent-based MATSim framework is implemented with MPO trip generation rates by population densities, trip length distributions from the 2009 NHTS, and fixed peak and off-peak travel speeds that vary by area type (downtown, urban, suburban, and exurban). The model represents both mode and DTA route choice with vehicle repositioning. In these scenarios, value of time is reduced to 25%, 35%, and 50% of current value of travel time and per mile charges are 75 cents, 85 cents, and one dollar. As value of time and average per mile cost increases average trip length decreases. When the automated electric taxi service costs 85 cents per mile, average trip distance increases by 20 to 29 percent at 25% and 35% values of travel time and declines somewhat (4%) at 50% value of travel time. At 35% value of travel time, average trip distance increases by 20% and 35% when per mile costs are 75 and 85 cents, respectively, but declines (3%) when per mile costs are one dollar. This study shows that at the right per mile cost an automated vehicle fleet may not increase VMT and congestion.

Bischoff and Maciejewski (Maciejewski and Bischoff, 2016; Bischoff and Maciejewski, 2016; and Bischoff et al., 2017) examine automated taxis and shared taxis in Berlin, Germany with the MATSim modeling framework, which includes a dynamic assignment model with vehicle relocation capabilities. The model uses local travel behavior data to dynamically schedule automated vehicle fleets for an average weekday (Maciejewski et al., 2017). Maciejewski and Bischoff (2016) simulate different levels of market penetrations for automated taxis (20% to 100%). They find that the share of empty drive time to total drive time ranges from 17% to 19%. Bischoff and Maciejewski (2016) examine the share of empty ride per zones from an automated taxi service at 100% market penetration. They find that the city average is 16%, but in the city center it is much lower (10% or less) and in outlying areas it is much higher (22% to 45%).

Another study (de Alameidia Correia and van Arem 2016) examines the effects of a fully automated personal vehicle fleet with an agent-based model that represents mode choice and dynamic assignment route choice with parking and repositioning in Delft, Netherlands, which is a small city in South Holland. The model uses roadway and transit networks and mode choice coefficients and generalized cost functions from Arentz and Molin (2013). This study examines a fully automated vehicle fleet and varies the paid and free parking and value of travel time (reduced by 50%) and finds that paid parking significantly increases empty vehicle location travel, VMT, and vehicle hours of delay and reduces car mode share and total vehicle parking time. The largest increase in VMT and empty vehicle miles traveled (325% and 87.4%, respectively) and the greatest decline in total vehicle parking time (8.7%) was in the scenario where parking charges were implemented everywhere. Congestion or vehicle hours of delay grew the most (824%) where there was a charge for parking everywhere except for two peripheral lots. Reduced value of time in the paid parking scenarios increases VMT and total vehicle parking time in scenarios with free parking limited to the periphery, but dampens the increase in empty vehicle relocation travel and vehicle hours of delay. Overall, the share of repositioning travel ranges from 11% to 65%, the increase in car mode share ranges from -26 percentage points to 31 percentage points, VMT grows from 17% to 325%, vehicle hours of delay increases from 20% to 699%, and total vehicle parking time ranges from -7% to 25%.

Martinez and Christ (2015) use a SA route choice model with a rule-based mode choice model (using proximity and trip length) to simulate an automated taxi fleet with and without transit. The models use population attributes and travel demand data from a local travel survey and travel times are based on hourly updated link speeds from a roadway network. However, automated taxis with and without transit see increases in VMT (88% and 43%, respectively) due to empty vehicle travel and the elimination of bus routes.

Table 3.1 Summary of relevant travel scenario modeling studies.

Author(s)	Location	Method	Travel Effects	AV	Scenario	Empty travel	Total VMT	Energy & GHGs
Faganant & Kockelman 2014	Hypothetical US city similar to Austin, TX	Agent-based model; 10 by 10 mi. gridded area; demand randomly generated with some basis in 2009 NHTS; constant peak and off-peak speeds (no network)	DTA route choice with relocation travel	100% Taxi	-	-	+10.7%	-12% energy; -5.6% GHG
Fagnant et al. 2015	Austin, TX	Agent-based dynamic assignment (MATSim); 12 by 24 mi. core city; demand from MPO 4 step model; network with link-level travel times	DTA route choice with relocation travel	100% Taxi	-	-	+8.0%	-14% energy; -7.6% GHG
Faganant & Kockelman 2016	Austin, TX	Same as above	Same as above	100% Taxi & Shared Taxi	Taxi Taxi & Shared Taxi Taxi & Shared Taxi + 30% TT Taxi & Shared Taxi + 40% TT	-	+8.7% +4.5% +2.7% +1.5%	-
Chen & Kockelman 2016	Hypothetical mid-sized city like Austin, TX	Agent-based (MATSim); MPO trip generation rates; 2009 NHTS TD; fixed vehicle speeds	Mode & DTA route choice with vehicle repositioning	Electric Taxi Share	25% VOT & $0.85/mile 35% VOT & $0.85/mile 50% VOT & $0.85/mile 35% VOT & $0.75/mile	7.2% 7.7% 9.1% 6.8%	+29% Avg. TD +20% Avg. TD -4% Avg. TD +35% Avg. TD	-
Maciejewski & Bischoff 2016	Berlin, Germany	Agent-based (MATSim): dynamically schedules fleet in response to demand; Berlin travel behavior data	DTA route choice with repositioning travel	Taxi Share	20% 40% 60% 80% 100%	19% 18% 17% 17% 17%	-	-
Bischoff & Maciejewski 2016	Berlin, Germany	Same as above	Same as above	100% Taxi	regional average city center outlying areas	16% 10% or less 22% to 45%	-	-
de Alameidia Correia &	Small city Delft, Netherlands	Agent-based model with travel survey data, networks; mode choice	Mode & DTA route choice with parking	100% Person al	Free home parking & 2 free peripheral lots	11.5%	+17.3%	-

Author(s)	Location	Method	Travel Effects	AV	Scenario	Empty travel	Total VMT	Energy & GHGs
van Arem 2016	(South Holland)	coefficients & generalized cost functions from Arentz and Molin, 2013	and vehicle repositioning		Paid parking everywhere (same price)	87.4%	+325.6%	-
					Free parking everywhere	10.8%	+20.9%	
					2 free peripheral parking lots	64.8%	+142.6%	
					1 free peripheral parking lots	53.2%	+119.1%	
					50% VOT	10.3%	+49.4%	
					50% VOT & 2 free peripheral parking lots	62.8%	+190.3%	
					50% VOT & no free parking except 1 lot	50.4%	+165.7%	
Martinez & Christ 2015	Lisbon, Portugal	Model with population & travel demand from travel survey data; travel times based on hourly updated link occupancy	SA route choice & rule based mode choice (proximity & trip length)	100% Taxi	No Transit		+88.2%	-
					Transit		+43.2%	

AV=Automated Vehicles; VMT=Vehicle Miles Traveled; NHTS=National Household Travel Survey;DTA=Dynamic Traffic Assignment; TT=Travel Time; VOT= Value of Time; TD=Travel Distance; GHG=Greenhouse Gas Emissions

3.3 Method

In this study, the San Francisco Bay Area activity-based travel demand model (MTC-ABM) is integrated with an application of the MATSim framework that includes dynamic traffic assignment model (DTA) and the choice to use a personal auto or an automated taxi based on an individuals' value of time and per mile cost of each mode. ABMs typically use static traffic assignment models because DTA's involve long computational times to simulate real urban networks. In static assignment models the detailed output from ABMs, individuals' attributes and travel activities, are aggregated into vehicle flows by origin and destination location for different daily time periods (e.g., am peak, off-peak, and pm peak). To avoid these long computational times MATsim uses a spatial queue model, rather than simulating car-following and lane-changing details, for significantly faster computational speeds. This gives MATSim the capability to run large simulation scenarios within a reasonable time.

The integration of MATSim with the MTC-ABM required conversion of the MTC ABM population trip list into the MATSim format. Python scripts were developed to automate the conversion of the MTC trip list (travel activity by person/household attribute) to the format required by MATSim. The conversion of the trips list required the refinement of trip departure time by hour to minute. The 2000 Bay Area Transportation Survey was used to estimate the distribution of trip departure time by 15-minute intervals by hour within each time-period and by county. Trips within each hour from the model are then randomly selected and then assigned departure times within the hour based on weighting factors developed from this distribution. Individual value of time was included in the trip list. These estimates are available from the MTC ABM and are based on a stated preference survey conducted in the San Francisco Bay Area. Value of time is log normally distributed and segmented by four income groups (low, med, high, and very high). This variable is important in estimating the generalized cost function for each person.

MATSim (Multi-Agent Transport Simulation) includes two main components (1) simulation of travel demand on a physical network and (2) the decisions travelers make in response to current traveling conditions (Ziemke, et al., 2014). Dubernet and Axhausen (2013) provide a concise description of MATsim and its basic steps:

(1) Initial demand: All agents have an initial daily plan, which serves as a starting point in the iterative improvement process.
(2) Mobility simulation: Plans of all agents are executed concurrently, to allow estimating the influence of the plans of the agents of each other. This step typically uses a queue simulation to simulate car traffic, which gives estimates of the congested travel time.
(3) Scoring: The information from the simulation is used to estimate the score of each individual plan. This information typically takes the form of travel times and time spent performing activities. This experienced utility is used to update the score associated with the plan.
(4) Re-planning: Then, part of the agents select a past plan based on the experienced score, following a Logit like selection probability; the other agents copy and mutate one of their past plans. If the number of plans in an agent's memory exceeds a predefined threshold, the worst plan is deleted, pushing the evolution toward plans with higher scores. Steps 2 to 4 are then iterated until the system reaches a stable state. Typical replanning strategies include least cost rerouting using travel time estimates from the previous iteration, departure time mutation, and mode mutation at the sub-tour level.

While it is possible to simulate a full population with MATSim, for computational reasons often only a fraction of agents is simulated. This is a widely used approach that scores robust results, also with regard to automated vehicle simulations (Horni et al., 2016; Bischoff and Maciejeweski, 2016).

MATSim comes with a module that simulates the effects of automated taxi fleets. The corresponding MATSim extension is able to dispatch vehicles online, i.e. during simulation runtime. The advantage of this method is a realistic distribution of waiting and travel times for the synthetic population, depending on the fleet parameters. Vehicle dispatch is handled by using a fleet-wide optimization approach. To handle large fleets within reasonable computational times, the dispatch algorithm follows a simple, but efficient, heuristic which may be described by two states. First, in times of oversupply (i.e., during off-peak periods), the closest vehicle is dispatched when a new ride request is made. Second, in times of undersupply, a vehicle, once it is available, is dispatched to the closest waiting request. This may lead to longer wait times for people sending requests from remote locations but leads to an efficient fleet utilization. Since automated taxis will need to travel empty in between customers, additional vehicle miles will be travelled. In combination with mode choice, several pricing schemes may be applied to the automated taxi service. Various fare structures can be represented, including subscription, flagfall, distance, and time-based fares. These may also be analyzed on a detailed spatio-temporal level.

MATSim also simulates the flow effects of automated vehicles and combined traffic of automated vehicles and conventionally driven vehicles. Automated vehicles are expected to increase road capacity due to their more efficient behavior (smaller gaps between vehicles, improved interaction at intersection, etc.). However, the actual improvement is hard to be precisely estimated. Recent studies suggest the improvement to be in the range of 1.5 and 2.0 for only-automated vehicle traffic, and in the case of traffic with mixed automated vehicles and conventionally driven vehicles, the relative improvement is expected to scale almost proportionally to the share of automated vehicles. In other words, an automated vehicle consumes 1.5 to 2.0 times less of the nominal flow capacity, measured in passenger cars per hour, compared to a conventionally driven vehicles of the same size, though they both occupy the same amount of space on the road.

The logic of the mixed vehicular traffic module can be illustrated in the following way. If 1,200 vehicles per hour are allowed to leave a link and all of them are conventionally driven vehicles, everything remains the same. If automated vehicles only require half the amount of flow capacity of a conventionally driven vehicles, 800 automated vehicles travelling on the link during an hour would leave enough throughput for 800 additional conventionally driven vehicles. Thus, the actual flow capacity would be 1,600. If only automated vehicles travel the link during an hour, the effective capacity would increase to 2,400 vehicles.

3.4 Scenarios

The relative demand for automated taxis and personal automated vehicles was simulated with the automated taxi module in MATSim with an estimated average fare of 48 cents per mile based on research conducted by Fulton and Compostella (2018a and 2018b). The figure includes the amortized vehicle purchase cost over 100,000 miles of driving, fuel cost, insurance, maintenance, and cleaning for an automated vehicle with an internal combustion engine. Personal vehicle travel was simulated in MATSim with the base case per mile operational cost from the MTC-ABM, which is about 20 cents per mile in the year equivalent to the 48 cents per mile estimated by Fulton and Compostella (2018a and

2018b). Both the automated taxi and personal automated vehicles are charged bridge tolls as represented in the MTC-ABM. However, personal automated vehicles still park and incur the average zonal parking charges, as represented in the MTC-ABM, and walk time penalties, which were assumed to be 15 minutes per trip. However, automated taxis do not pay the parking charge or experience the walk time penalty. As discussed above, the value of time for each potential personal vehicle driver or automated taxi passenger is represented in the model. As a result, the choice to drive a personal automated vehicle or taxi is based on the relative trade-offs between the total time (roadway travel time and parking walk time penalty) and cost (per mile, parking, and bridge tolls) for each mode given an individuals' value of time. Total demand is obtained from the drive alone mode share from the MTC-ABM and is held constant in this analysis. Four alternative scenarios are simulated as described in Table 3.2. For the vehicle flow of automated taxis, a flow improvement factor of 1.5 is assumed.

Table 3.2 Summary of scenarios.

AV Taxi Scenarios	**Per Mile Automated Taxi Fare**	**Per Mile Personal Vehicle Cost**	**Average Zonal Parking Costs**
Base Case	No AV Taxi	20 cents	MTC-ABM values
Mean Cost AV Taxi	48 cents	20 cents	
Low Cost AV Taxi	36 cents	20 cents	
Mean Cost AV Taxi + High Cost Personal Vehicle	48 cents	23 cents	
Mean Cost AV Taxi + Doubled Parking Costs	48 cents	20 cents	Double MTC-ABM Values

3.5 Results

The travel and greenhouse gas emission (CO_2) results are presented in Table 3.3 below. The automated taxi mode share varies from about 4% with the mean estimated per mile fare cost of 48 cents to a high of about 6% for the lower per mile automated taxi fare of 36 cents. Doubling parking pricing produces modest improvement over the 48 cents automated taxi scenario because of the limited spatial distribution of paid parking in the region. These results are somewhat lower than Chen and Kockelman (2016). Our study evaluated lower per mile service costs but held value of time constant from the base case and used network generated travel times (as opposed to fixed average travel times). The highest density of automated taxi trips has origins and destinations where parking prices are high. Figures 3.1 shows the location of parking costs. Figure 3.2 shows the location of trip origins. This helps explain the relatively modest share of empty vehicle travel time and travel distance, less than 9%, in the scenarios and the relatively short wait time, which range from 2 to 4 minutes. Overall, however, VMT increases modestly, percentage change ranges from 1% to 2%, due to increase empty vehicle travel. However, CO_2 emission decrease by 7% to 12% because of the flow improvements assumed in the simulated scenarios. The spatial distribution of empty travel time is illustrated for each scenario in Figure 3.3.

The spatial distribution of trip origins and ratio of empty vehicle distance by trip origins are illustrated in Figures 3.2 and 3.3, respectively. When the mean 48 cent per mile cost of using an automated taxi is simulated, then trips are concentrated in downtown urban areas and the inner suburban ring of the region where empty vehicle travel is low. As the relative price of using the automated taxi is reduce in subsequent scenarios, then there is an increase in the number of trip origins with significantly higher levels of empty vehicle travel distance (up to a ten-fold increase) in the outer areas of the region. The relative monetary cost of an automated taxi services is negatively correlated with distance from the central business district. This result is consistent with Bischoff and Maciejewski (2016)

Table 3.3 Summary of Travel and Greenhouse Gas Emissions Results

Scenarios	AV Taxi Mode Share	% Empty Vehicle Time	% Empty Vehicle Distance	Percentage Change in VMT	Change in CO_2 (metric tons)	Average Wait Time (minutes)
Mean AV Cost	4.1%	6.6%	3.4%	1%	-7%	2.4
Low AV Cost	6.2%	8.1%	7.3%	2%	-12%	4.1
Mean AV Cost and High Cost Personal Vehicle	5.4%	8.5%	6.5%	1%	-10%	3.9
Mean AV Cost Doubled Parking Costs	5.0%	8.5%	5.8%	1%	-9%	3.6

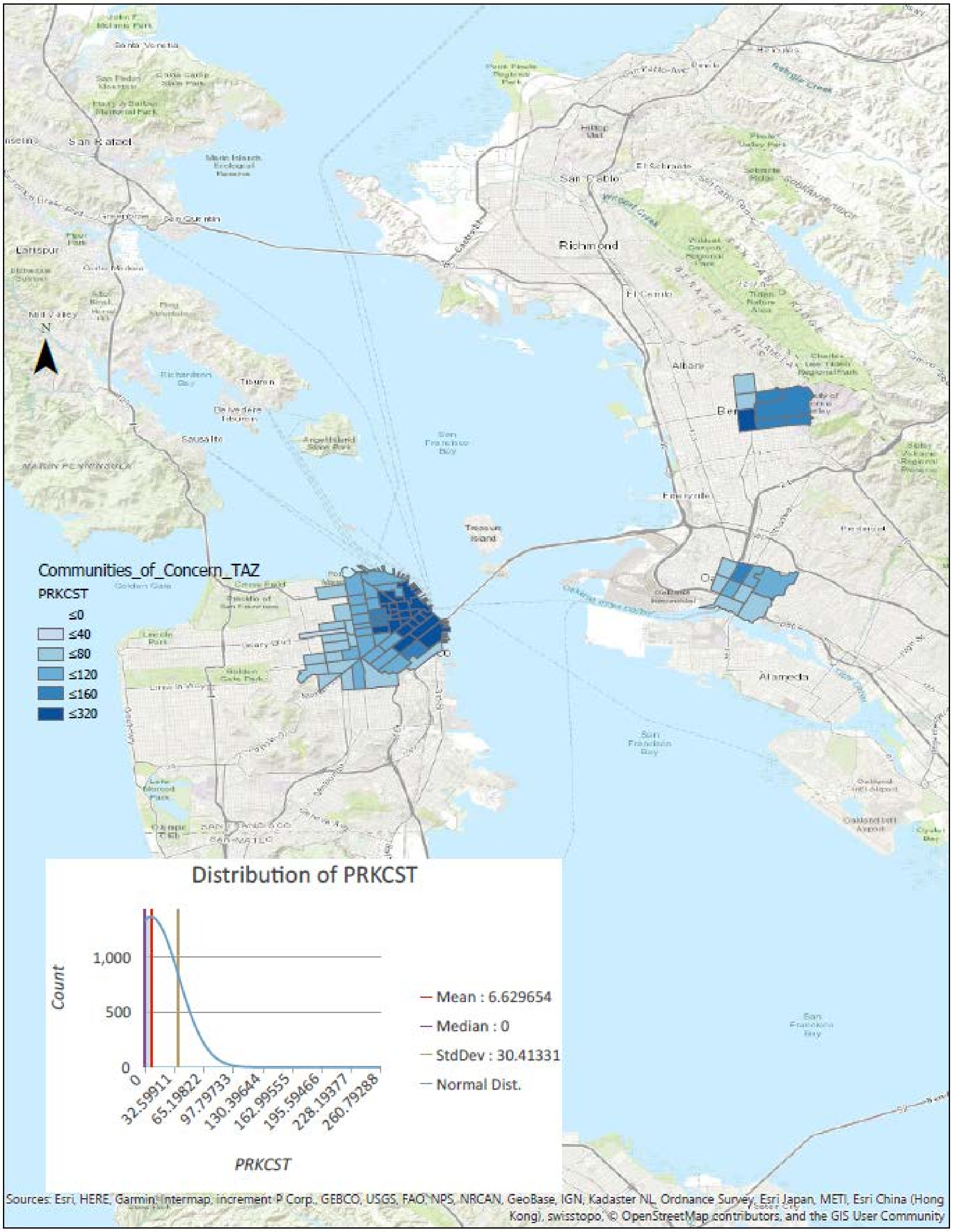


Figure 3.1 Spatial distribution of parking cost (PRKCST) as represented in the MTC-ABM base case scenario.

Figure 3.2 Spatial distribution of trip origins (tripsStarting).

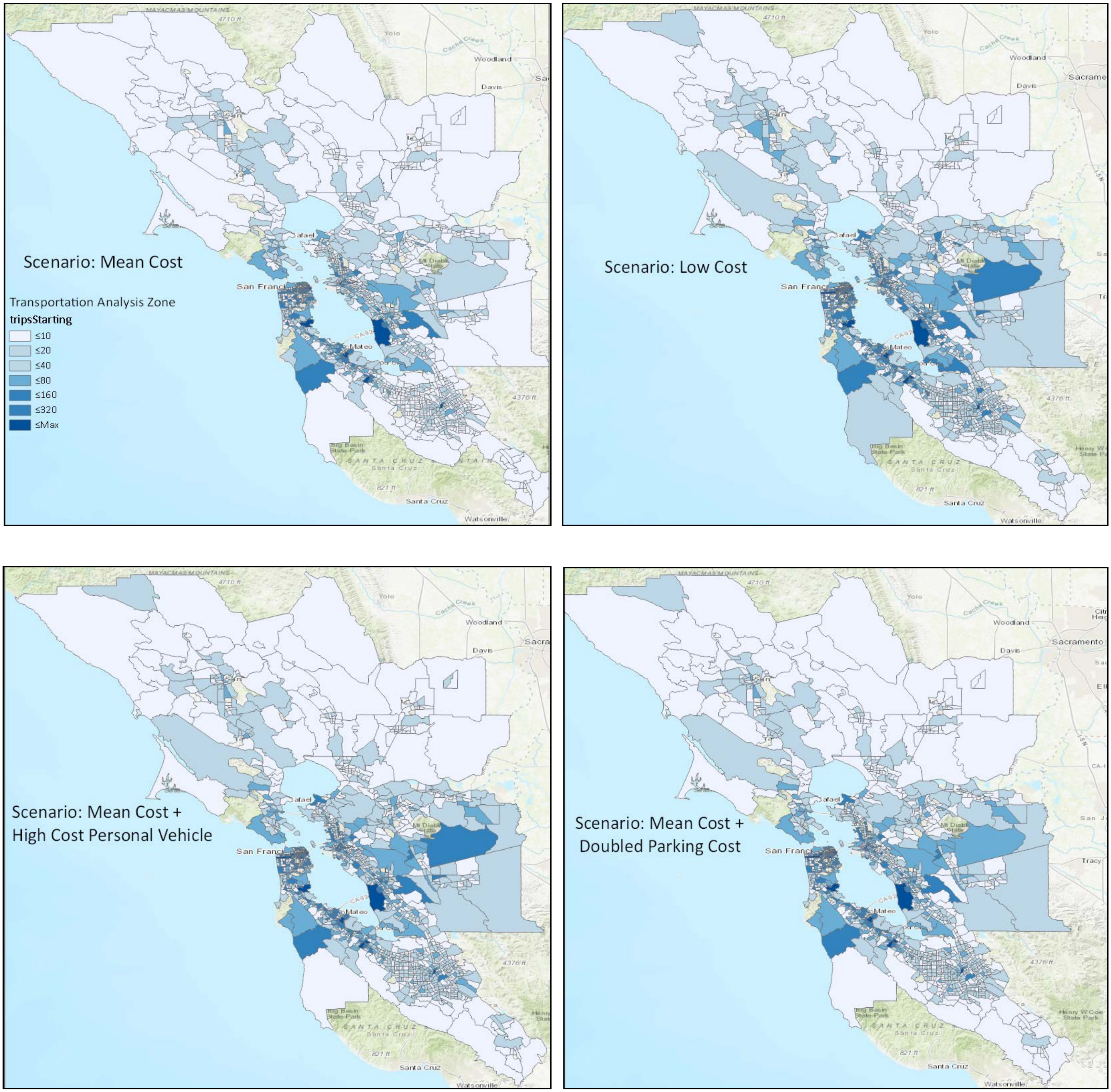
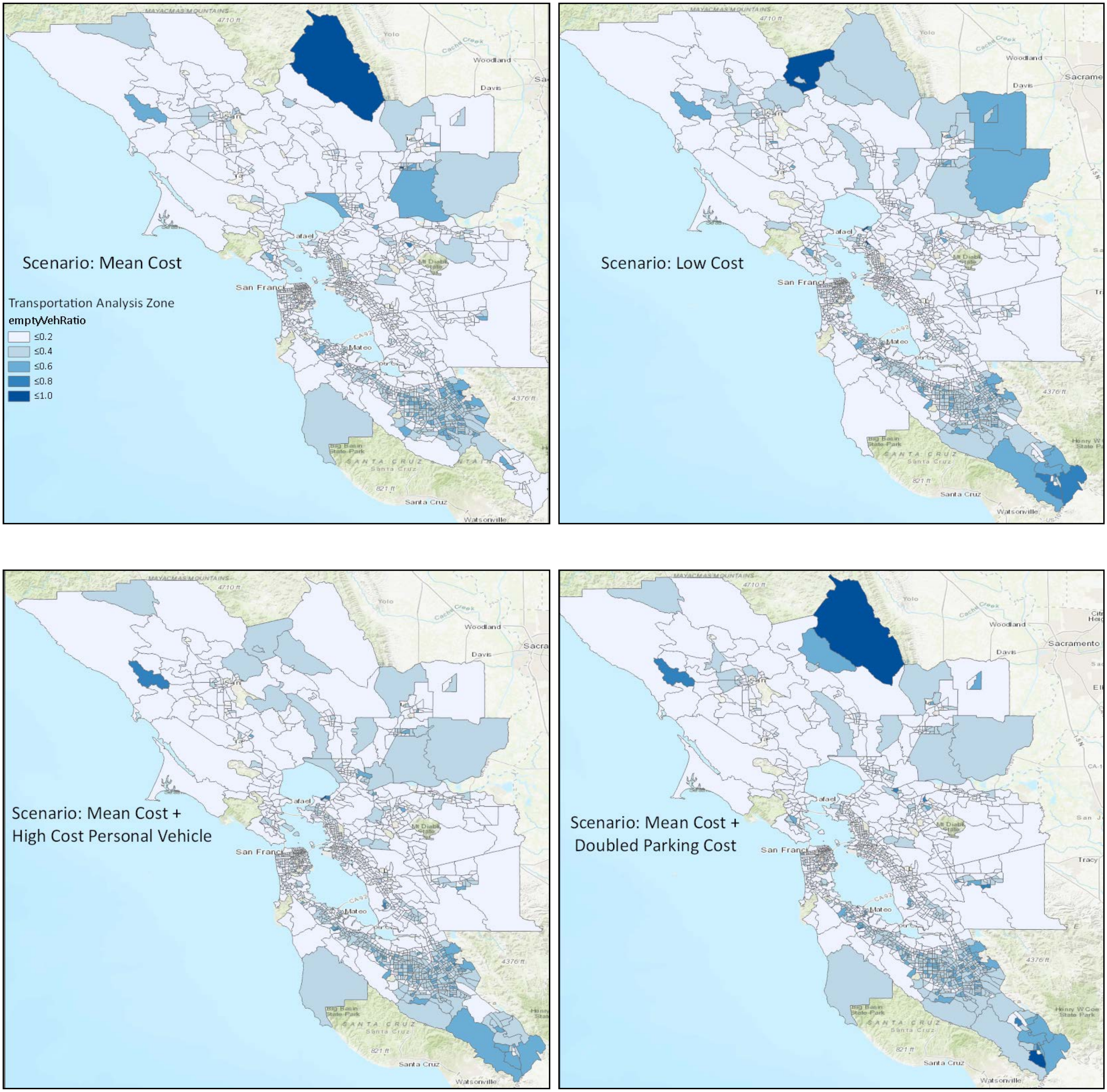


Figure 3.3 Spatial distribution of the ratio of empty vehicle distance (emptyVehRatio).



3.6 Conclusions

In this section, we evaluate the potential to reduce the demand for personal automated vehicles given the introduction of an automated taxis service with realistic, but low, per mile service costs. We also evaluate how further reducing the per mile price of an automated vehicle taxi service, reducing the per mile operational costs of personal vehicles, and increasing the pricing of parking could influence market potential for an automated taxi service as well as regional VMT and greenhouse gas emissions. The results indicate a relatively modest market potential (4% to 6% for the automated taxi mode share) concentrated in the inner-city areas of the region, but one that expands outward as the relative cost of the automated taxi service decline. Similarly, average empty-vehicle travel time and distance is estimated to be relatively low for the region; however, as relative costs of the automated taxis service decline, these regional averages increase. Empty-vehicle distances in the outer areas of the region can be up to approximately ten times higher than inner city distances. The current study simulates a short-term time horizon and thus the increase in VMT is modest (about 1%) and CO_2 is estimated to be reduced due to improved vehicle flows from automated vehicle technology. As discussed in section two, over the longer run increases in VMT may be larger and reductions in GHG emissions from traffic flow improvements may be off-set by induced travel.

4.0 Comparison of Automated First Mile Access Modes to Heavy Rail

4.1 Introduction

It is well known that, on average, travelers will not walk more than a quarter mile to a transit station and that bus service to the nearest transit station is often too costly to provide and too slow to ride. Parking at transit stations is typically an expensive short-term fix because, over-time, parking lots fill up with commuters early in the morning (sometimes as early at 6:30 am). Moreover, parking structures are expensive to construct, and large parking lots can increase the distance to walk to transit. Both use valuable land that could be converted to residential and business uses, which in turn, could generate increased transit ridership. The failure to optimally use transit undermines sustainable operating revenue and increases both congestion and greenhouse gas emissions.

The rise of new mobility services, such as ride-hailing (e.g., Uber and Lyft) and ridesharing (e.g., UberPool, Lyft Line, and Via) presents a new opportunity for transit agencies to bridge the first and last mile to high quality transit. Within the last few years, transit agencies have piloted numerous projects throughout the U.S. to test this concept. The goal of these projects is commonly the cost-effective improvement of access to and ridership of high quality transit, particularly for disadvantaged populations. In areas with significant congestion, reductions in vehicle travel and greenhouse gas emissions (GHGs) are also common goals. However, to date, there is limited research that evaluates these potential impacts. This includes both modeling to anticipate potential benefits and empirical analysis using observed data from actual implemented pilot programs. Data sharing agreements between ride-hailing and transit agencies have been difficult to negotiate due to concerns about competitive injury. However, four recent public opinion surveys suggest that between 3% to 9% of respondents use ride-hailing and ridesharing services as access and egress modes to transit (see literature review below).

In this study, we use the San Francisco Bay Area Metropolitan Transportation Commission's activity-based model (MTC-ABM) and the MATSim dynamic assignment model to understand the potential market demand for "first" mile transit access service. First, the MTC-ABM model and its behavioral parameters are used to estimate the plausible high-end of those who may switch to BART from all modes, if first mile service to the traveler's nearest BART station was significantly improved during the AM peak period. Second, we use the MTC-ABM to estimate demand to simulate the travel time and cost benefits for each traveler (and their value of time) of different ride-hailing (Uber and Lyft) and ridesharing services (Uber Pool/Lyft Line and Via) with the MATSim model. User cost of the ride-hailing and ridesharing services are estimated for services that use conventional vehicles with a driver and automated vehicles. The results provide insight into relative benefits of each service and automated vehicle technology, the potential market for these services, and the relative magnitude of individual and system-wide costs and benefits.

4.2 Literature Review

The fours studies examine the magnitude of the complementary effects of ride-hailing and ridesharing on transit. These studies are summarized in Table 4.1 and described in more detail below.

Ride-hailing among residents in urban and suburban neighborhoods in seven metropolitan areas, Boston, Chicago, Los Angeles, New York, San Francisco/Bay Area, Seattle, and Washington, D.C., is analyzed with the results of an on-line survey conducted between August 2015 and January 2016 (Clewlow and Misha, 2017). The survey employed density (housing and population) and metropolitan area demographic (age, income, and gender) sampling targets from the 2011-2015 ACS. The data was weighted to match these demographic distributions. The final sample size is not reported and the response rate for this survey is not available. Clewlow and Mishra (2017) find that, since using ride-hailing, survey respondents use heavy rail transit (3%) more frequently and use bus and light rail less frequently (6% and 3%, respectively).

Two studies examine the use of ride-hailing by California millennials (age 18 to 34) and Generation Xers (age 35 to 50) in California, in urban, suburban, and rural areas, with the results of an on-line survey administered in the fall of 2015 (Alemi et al., 2017a and Alemi et al., 2017b). A quota method was used to collect samples from the different regions in California and urban, suburban, and rural neighborhoods. In addition, recruitment targets, included gender, age, household income, race and ethnicity, and presence of children. The final sample was weighted to these targets, plus student/employment status, from the 2014 ACS (1-year estimate) with neighborhood classifications from Salon (2015). The final dataset included 1,731 samples, which represent 36% of those invited to complete the survey. 26% of the sample had used ride-hailing in the past (N=483) and 10% of the sample used it at least once per month (N=209) (Alemi et al., 2017a). Alemi et al. (2017) report that ride-hailing increases access and egress use of transit by 9%.

Another study reports on a survey of ride-hailing users in central San Francisco. The survey was administered at locations and times of the day where high concentrations of ride-hailing users were observed in the spring of 2014 (Rayle et al., 2016). This survey likely oversamples recreational trips and underestimates other types of trips and it is not a representative sample of ride-hailing users. Approximately half of those invited to take the survey did so. 17% of survey respondents were intercepted after exiting a ride-hailing vehicle and were then asked to report on the ride-hailing trip they had just completed. 83% were asked to complete the survey, if they had used ride-sourcing within the last two weeks. Both samples completed the same survey. The total sample size is 380 adults. Rayle et al. (2016) show that 5% of survey respondents use ride-hailing to access a specific public transit station.

In another study in Denver (Colorado), the author served as a ride-hailing driver and administered a survey to passengers that explored their use of ride-hailing services. In addition, the author collected data on the productivity of ride-hailing travel (i.e., share of time and distance a driver is not transporting a passenger relative to total driver time and distance traveled) by recording driving time, distance, and locations with and without a passenger (Henao, 2017). The author collected data on 416 rides and 311 passengers completed the survey. This is a 75% response rate. Henao (2017) reports that 5.5% of his riders were connecting to transit and 20.5% of respondents indicated that they had at some point used ride-hailing to connect to transit.

Table 4.1. Description of stated response surveys about ride-hail and rideshare travel.

Author(s)	Location(s)	Method (date collected)	Sample	Representative
Alemi et al. (2017a)	California (urban, suburban, and rural)	On-line survey (2015)	1,731 adults 18 to 50 (483 ride-hail users; 209 at least 1x per month)	Age, income, gender, race and ethnicity, presence of children, geographic area and neighborhood types (urban, suburban, rural)
Clewlow and Mishra (2017)	Urban and suburban Boston, Chicago, Los Angeles, New York, San Francisco/Bay Area, Seattle and Washington, D.C.	On-line survey (2015-2016)	Not reported.	Metro area age, income, gender; screened to systematically varied on population and housing density
Rayle (2016)	Central San Francisco at high demand locations and time of day	Intercept survey (2014)	380 ride-hail users (83% within last 2 weeks & 17% just completed trip)	No
Henao (2017)	Denver	UberX/Lyft driver reported activity and passenger use; self-administered passenger survey (2015)	416 passenger rides; 311 passenger surveys	No

4.3 Methods

In this study, we demonstrate, how available modeling tools and data can be used to evaluate new first mile transit access services. We integrate the MATSim dynamic traffic assignment model (DTM) with the San Francisco Bay Area Metropolitan Transportation Commission's (MTC's) ABM. Like all other activity-based models, tour and trip lists are generated for all travelers in MTC activity-based model area. The individual and joint trips are later aggregated into the origin and destination matrices and are assigned into the network by mode and by time of the day. In the process, there is no way to link traveler attributes with the vehicles and modes they occupy. In order to continue this link and understand how drivers' perception of time and money costs could change their behavior in the presence of a new ride-hailing or ridesharing service, we integrated the MATSim dynamic traffic assignment model with the MTC-ABM.

To identify the number of travelers who might switch to a first mile service to the traveler's closest heavy rail station, if accessibility was significantly improved by this service, we used the MTC-ABM and modified three parameters in its mode choice model. The MTC-ABM mode choice model is based on a nested logit structure with utility functions consisting of traveler, purpose, and mode specific variables and skims. The mode choice model predicts travel by one of 18 different travel modes, which includes drive to heavy rail. Several modifications were made in its utility function to simulate improved first mile accessibility to the heavy rail station. The minimum age to use this mode was decreased to 13 years old, so that the mode was made available to those who are under the legal driving age. The constraint of owning at least one auto was relaxed so that persons living in households without a car can to drive to transit. Drive time and cost were multiplied by several values of “S” (between 0 and 1) to determine the variable change thresholds that can produce a significant shift to this mode, to reflect the increased convenience and lower cost of accessing transit via ridesharing. The final value of “S” in this study is 0.9. A scenario was run in which long-term choices (work and school location choice, auto ownership, and daily activity pattern type for each individual) from a baseline 2010 alternative were held constant. This enabled the identification of individuals whose mode changed because of the modification in the utility of the drive to heavy rail mode. The results show a 34.1% increase in the number of drive to BART heavy rail transit trips for the AM peak period. The increase in the drive to BART mode share was derived from the following mode share reductions: 4% from drive alone, 6% from shared-ride, 7% from walk transit (local bus, light rail or ferry, BART, express bus, and commuter rail), and 7% from drive transit (local bus, light rail or ferry, express bus, and commuter rail). 2% of trips switched from the AM peak to another time-period. In sum, the MTC-ABM model and its estimated behavioral parameters were used to estimate the plausible high-end of those who may switch to BART from all modes, if first mile service to the traveler’s nearest BART station was significantly improved during the AM peak period.

Python scripts were applied to convert the trip list (travel activity by person/household attribute) to the format required by MATSim. The conversion of the trips list required the refinement of trip departure time by hour to minute. The 2000 Bay Area Transportation Survey was used to estimate the distribution of trip departure time by 15-minute intervals by hour within each time period and by county. Trips within each hour from the model are then randomly selected and then assigned departure times within the hour based on weighting factors developed from this distribution. Individual value of time was included in the trip list. These estimates are available from the MTC ABM and are based on a stated preference survey conducted in the San Francisco Bay Area. Value of time is log normally distributed and segmented by four income groups (low, med, high, and very high). This variable is important in estimating the generalized cost function for each person.

4.4 Scenarios

The MATSim model was used to simulate a base case scenario in which the 83,804 individuals who used the drive to BART mode (as describe in the methods section above) use a conventional personal vehicle to the closest BART station. The per mile operational cost to drive this vehicle is about 18 cents per mile and it costs the driver $3 to park at the BART station. Parking capacity constraints were not included to the model, as the base case is meant to depict very optimistic conditions for drivers (See Table 4.1)

Three alternative first mile services are simulated with the MATSim model. In the first scenario, all these agents are modeled using a single-passenger ride-hailing service, such as Uber and Lyft. In the second scenario, eight-seat vehicles are deployed to provide a home-based pick up ridesharing service. In the third scenario, the same eight-seat vehicles provide a ridesharing service that picks up riders who walk to the service collection point from their home. This service is comparable to Via.

In the MATSim model, vehicle dispatch is handled by using a fleet-wide optimization approach. On the passenger side, an agent calls for a vehicle the moment he wishes to depart. The assignment then takes place based on insertion heuristics. Some certain service criteria can be specified to limit the detour a passenger experiences when riding with a ridesharing vehicle. These are characterized by a maximum travel time which is defined by a trip specific detour (as a factor of the direct travel time) plus a constant. In addition to this, a certain maximum waiting time (which is considered part of the travel time) cannot be exceeded. If no vehicle can be dispatched to the customer, the ride will not be fulfilled. A more detailed description of the algorithms is available (Bischoff et al, 2017).

Operational costs for each of these services are estimated assuming that there is a human driver or an automated vehicle. All the services drop passengers off at the BART station and thus we assume no BART parking costs. Thee estimated average fare of 48 cents per mile based on research conducted by Fulton and Compostella (2018a and 2018b) is used for the automated vehicle ride-hailing service. As discussed previously, this figure includes the amortized vehicle purchase cost over 100,000 miles of driving, fuel cost, insurance, maintenance, and cleaning for an automated vehicle with an internal combustion engine. The fare for the shared automated vehicle services is estimated to be an average of 26 cents per mile, which adjusts the Fulton and Compostella (2018a and 2018b) figure with the number of riders in the shared vehicles. The fare for the ride-hailing service is assumed to be the same as the current Uber service in the Bay Area, which is approximately $2.00 per mile. We assume that the shared ride services with a driver would split the per mile cost between two passengers and thus the per mile cost is reduced to 75 cents.

Table 4.2. Scenario description.

Scenario	**Vehicle**	**Paying Occupants**	**Pick-Up Location**	**Costs**	
				Human Driven Vehicle	Automated Vehicle
Base Case	Personal	Single	Home	$0.18	NA
Scenario 1	Shared Ride	Multiple	Home	$0.75 per mile	$0.26
Scenario 2	Shared Ride	Multiple	Common Point Near Home	$0.75 per mile	$0.26
Scenario 3	Shared	Single	Home	$1.50 per mile	$0.48

4.3. Results

The scenario results are described in Table 4.3 below. Compared to the base case scenario, scenario 1, the shared-ride home pick-up (Uber Pool and Lyft Line type services), shows generalized cost savings for 33% of trips with drivers and 73% of trips with driverless vehicles. The average gain is $1.50 (with a standard deviation of $3.18) and $2.00 (with a standard deviation of $2.88), respectively for human driven and automated vehicles. The total system benefit for the human driver scenario is about 39 thousand dollars and the total loss is about 180 thousand dollars. For the driverless vehicles, the total benefit is much higher due to lower per mile operating costs (about 114 thousand dollars) and the total loss is significantly lower (about 54 thousand dollars).

The additional travel time required to access the shared-ride vehicle at the common pick-up location in scenario 2 appears to significant erode the likely market demand for the service and its benefits. For human driven vehicles, only 16% of trips benefit from the service with an average benefit of about $1.50, with a standard deviation of about $3, and a total benefit of 18 thousand dollars. Again, the service that uses the automated vehicles, performs better due to lower user fares. For this service, gains are estimated for 36% of trips, with an average gain of $1.31 per trip (with a standard deviation of $2.51), and a total gain of $36 thousand dollars.

In scenario 3, the single passenger ride-hailing service with home pick-up locations was the worst performing scenario when human driven vehicles were used, but performed better than the automated vehicle shared-ride common pick-up location service because of superior travel times. The share of trips that gained benefits was 12% in the human driven vehicle service and 55% in the automated vehicle service. The average benefit was about $1.24 (standard deviation $3.24) and $1.56 (standard deviation $2.26), respectively for the human driven and automated vehicles. Total benefits were $11 thousand and $67 thousand, respectively for the driver and driverless vehicles.

Table 4.3. Change in generalized costs from the base case to the alternative scenarios during the AM peak period.

Generalized Cost: Change from Base Case	**Scenario 1: Shared-Ride Home Pick-Up**		**Scenario 2: Shared-Ride Common Location Pick-Up**		**Scenario 3: Shared-Vehicle Home Pick-Up Location**	
	Driver	AV	Driver	AV	Driver	AV
% Trips Gain	33%	73%	16%	36%	12%	55%
Average	$1.52	$2.03	$1.49	$1.31	$1.24	$1.56
Standard Deviation	$3.18	$2.88	$3.17	$2.51	$3.24	$2.36
Total	$38,979.15	$114,827.78	$18,847.62	$36,611.97	$11,035.11	$66,479.51
% Trips Loss	67%	27%	84%	64%	88%	45%
Average	-$3.49	-$2.62	-$11.22	-$6.50	-$8.80	-$6.93
Standard Deviation	$3.46	$2.98	$21.74	$13.64	$13.17	$15.63
Total	-$179,529.53	-$53,778.84	-$722,632.90	-$319,286.67	-$599,922.76	-$238,917.55

AV=Automated Vehicles

4.4 Conclusions

In this study, we use the San Francisco Bay Area Metropolitan Transportation Commission's activity-based model (MTC-ABM) and the MATSim dynamic assignment model to understand the potential market demand for "first" mile transit access service. First, the MTC-ABM model and its estimated behavioral parameters are used to estimate the plausible high-end of those who may switch to BART from all modes, if first mile service to the traveler's nearest BART station was significantly improved during the AM peak period. Second, we use the MTC-ABM estimated demand to simulate the travel time and cost benefits for each traveler (and their value of time) of different ride-hailing (Uber and Lyft) and ridesharing services (Uber Pool/Lyft Line and Via) with the MATSim model.

User costs of the ride-hailing and ridesharing services are estimated for services that use conventional vehicles with a driver and automated vehicles. Human driver first mile access services may benefit as many as one third or as few as about 12 percent of travelers who choose to travel by BART during the am peak period. Not surprisingly, when these services use automated vehicles (with significant labor cost reductions) these shares more than triple. Our results also suggest that it may be more challenging to provide travel time savings, relative to driving a personal vehicle and parking, with shared-ride services that have a common pick-up location rather than a home location. Many of those using the transit access modes live further away from BART stations and it may be harder to find a time-efficient pick up locations in these areas. However, this scenario did garner benefits for 4% more trips than did the human driven ride-hailing service. On the other hand, when automated vehicle technology was used for these services, the single passenger home-based pick up ride-hailing service increased benefits for almost 20% more trips.

REFERENCES

Factors Limiting and/or Encouraging Their Use and Impacts on Other Travel Modes among Millennials and Gen Xers in California". To be presented in *TRB 97th Annual meeting* and to be submitted to Transport Policy (forthcoming). 2017a.

Alemi, Farzad, Giovanni Circella, Patricia Mokhtarian and Susan Handy (forthcoming) "On-demand Ride Services in California: Investigating the Factors Affecting the Frequency of Use of Uber/Lyft". To be presented in *TRB 97th Annual meeting* and to be submitted to Transportation Research Part C (forthcoming). 2017b.

Ambühl, Lukas, Francesco Ciari, and Monica Menendez. "What about space? A simulation based assessment of AVs impact on road space in urban areas." In *16th Swiss Transport Research Conference (STRC 2016),(Swiss Transport Research Conference (STRC))*. 2016.

Auld, Joshua, Dominik Karbowskia, and Vadim Sokolova. "Assessing the regional energy impact of connected vehicle deployment." (2017).

Arentze, Theo A., and Eric JE Molin. "Travelers' preferences in multimodal networks: design and results of a comprehensive series of choice experiments." *Transportation Research Part A: Policy and Practice* 58 (2013): 15-28.

Azevedo, Carlos Lima, Katarzyna Marczuk, Sebastián Raveau, Harold Soh, Muhammad Adnan, Kakali Basak, Harish Loganathan et al. "Microsimulation of demand and supply of autonomous mobility on demand." *Transportation Research Record: Journal of the Transportation Research Board* 2564 (2016): 21-30.

Bansal, Prateek, Kara M. Kockelman, and Amit Singh. "Assessing public opinions of and interest in new vehicle technologies: an Austin perspective." *Transportation Research Part C: Emerging Technologies* 67 (2016): 1-14.

Batley, R., Mackie, P., Bates, J., Fowkes, T., Hess, S., de Jong, G., Wardman, M., Fosgerau, M., 2010. Updating Appraisal Values for Travel Time Savings. Report to the Department for Transport, UK.

Bischoff, Joschka, and Michal Maciejewski. "Simulation of city-wide replacement of private cars with autonomous taxis in Berlin." *Procedia computer science* 83 (2016a): 237-244.

Bischoff, Joschka, and Michal Maciejewski. "Autonomous taxicabs in Berlin–a spatiotemporal analysis of service performance." *Transportation Research Procedia* 19 (2016b): 176-186.

Bischoff, J. M. Maciejewski and K. Nagel, "City-wide shared taxis: A simulation study in Berlin," *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, Yokohama, 2017, pp. 275-280. doi: 10.1109/ITSC.2017.8317926

Brown, Austin, Jeffrey Gonder, and Brittany Repac. "An analysis of possible energy impacts of automated vehicle." In *Road vehicle automation*, pp. 137-153. Springer International Publishing, 2014.

Burns, L. D., W. Jordan and B. Scarborough. Transforming personal mobility. 21 *Technical Report*, The Earth Institute, Columbia University, New York, 2013. 22

Chen, T. Donna, and Kara M. Kockelman. "Management of a Shared Autonomous Electric Vehicle Fleet: Implications of Pricing Schemes." *Transportation Research Record: Journal of the Transportation Research Board* 2572 (2016): 37-46.

Chen, T. Donna, Kara M. Kockelman, and Josiah P. Hanna. "Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions." *Transportation Research Part A: Policy and Practice* 94 (2016): 243-254.

Childress, Suzanne, Brice Nichols, Billy Charlton, and Stefan Coe. "Using an activity-based model to explore the potential impacts of automated vehicles." *Transportation Research Record: Journal of the Transportation Research Board* 2493 (2015): 99-106.

Clewlow, Regina R., and Gouri Shankar Mishra. *Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States*. No. UCD-ITS-RR-17-07. Research Report–UCD-ITS-RR-17-07, Davis: University of California, 2017.

Circella, G., S. Handy, and M. Boarnet. "Impacts of Gas Price on Passenger Vehicle Use and Greenhouse Gas Emissions. 30 September 2014." (2014).

Cyganski, Rita, Eva Fraedrich, and Barbara Lenz. "Travel-time valuation for automated driving: A use-case-driven study." In *Proceedings of the 94th Annual Meeting of the TRB*. 2015.

de Almeida Correia, Gonçalo Homem, and Bart van Arem. "Solving the User Optimum Privately Owned Automated Vehicles Assignment Problem (UO-POAVAP): A model to explore the impacts of self-driving vehicles on urban mobility." *Transportation Research Part B: Methodological* 87 (2016): 64-88.

Englund, Cristofer, Lei Chen, and Alexey Voronov. "Cooperative speed harmonization for efficient road utilization." In *Communication Technologies for Vehicles (Nets4Cars-Fall), 2014 7th International Workshop on*, pp. 19-23. IEEE, 2014.

Fagnant, Daniel J., and Kara M. Kockelman. "The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios." *Transportation Research Part C: Emerging Technologies* 40 (2014): 1-13.

Fagnant, Daniel J., Kara M. Kockelman, and Prateek Bansal. "Operations of shared autonomous vehicle fleet for austin, texas, market." *Transportation Research Record: Journal of the Transportation Research Board* 2536 (2015): 98-106.

Fagnant, Daniel J., and Kara M. Kockelman. "Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas." *Transportation* (2016): 1-16.

Fosgerau, M, K Hjorth and SV Lyk-Jensen (2007) The Danish value of time study – final report. *Danish Transport Research Institute report 5*. 48pp.

Goodwin, Phil B. "Empirical evidence on induced traffic." *Transportation* 23, no. 1 (1996): 35-54.

Gucwa, Michael. "Mobility and energy impacts of automated cars." In *Proceedings of the Automated Vehicles Symposium, San Francisco*. 2014.

Hague Consulting Group (HCG) with Accent Marketing and Research (1999) *The value of travel time on UK roads – 1994.* Report for Department of Transport Environment and the Regions. 377pp.

Handy, Susan, and Marlon G. Boarnet. "Impact of Highway Capacity and Induced Travel on Passenger Vehicle Use and Greenhouse Gas Emissions." *California Environmental Protection Agency, Air Resources Board, Retrieved August* 28 (2014): 2015.

Harper, Corey D., Chris T. Hendrickson, Sonia Mangones, and Constantine Samaras. "Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions." *Transportation research part C: emerging technologies* 72 (2016): 1-9.

Henao, Alejandro. "Impacts of Ridesourcing-Lyft and Uber-on Transportation Including VMT, Mode Replacement, Parking, and Travel Behavior." PhD diss., University of Colorado at Denver, 2017.

Hensher, DA (1984) Full information maximum likelihood estimation of a nested logit mode choice model. *Working paper no. 13.* Macquarie University, Transport Research Centre, School of Economic and Financial Studies. 32pp.

Horni, Andreas, Kai Nagel, and Kay W. Axhausen, eds. *The multi-agent transport simulation MATSim*. London: Ubiquity Press, 2016.

Ian Wallis Associates Ltd. “Car passenger valuations of quantity and quality of time savings.” NZ Transport Agency research report 551. Wellington, New Zealand (2014).

Le Vine, Scott, Alireza Zolfaghari, and John Polak. "The tension between autonomous cars’ impacts on intersection level-of-service and their occupants’ use of travel time for leisurely or economically-productive activities." In *Proceedings of the 94th Annual Meeting of the Transportation Research Board, January 2015*. 2015.

Lioris, Jennie, Ramtin Pedarsani, Fatma Yildiz Tascikaraoglu, and Pravin Varaiya. "Platoons of connected vehicles can double throughput in urban roads." *Transportation Research Part C: Emerging Technologies* 77 (2017): 292-305.

Lyons, G., Jan, J., Holley, D., 2007. The use of travel time by rail passengers in Great Britain. Transp. Res. Part A 41 (1), 107–120.

Maciejewski, M. in Horni, A.; Nagel, K. & Axhausen, K. W. *(Eds.),* Dynamic Transport Services, ch. 23, *The Multi-Agent Transport Simulation MATSim, Ubiquity, London,* **2016**

Maciejewski, Michal, and Joschka Bischoff. "Congestion effects of autonomous taxi fleets." *Transport* (2017): 1-10.

Maciejewski, Michal, Joschka Bischoff, Sebastian Hörl, and Kai Nagel. "Towards a testbed for dynamic vehicle routing algorithms." In International Conference on Practical Applications of Agents and Multi-Agent Systems, pp. 69-79. Springer, Cham, 2017.

MacKenzie, Donald, Stephen Zoepf, and John Heywood. "Determinants of US passenger car weight." *International Journal of Vehicle Design* 65, no. 1 (2014): 73-93.

Malokin, Aliaksandr, Giovanni Circella, and Patricia L. Mokhtarian. "How do activities conducted while commuting influence mode choice? Testing public transportation advantage and autonomous vehicle scenarios." In *Transportation Research Board 94th Annual Meeting*, no. 15-1179. 2015.

Martinez, Luis, and P. Crist. "Urban Mobility System Upgrade–How shared self-driving cars could change city traffic." In *International Transport Forum, Paris*. 2015.

Menon, Nikhil, Abdul R. Pinjari, Yu Zhang, and Linghong Zou. "Consumer Perception and Intended Adoption of Autonomous-Vehicle Technology: Findings from a University Population Survey." In *Transportation Research Board 95th Annual Meeting*, no. 16-5998. 2016.

Preston, John, and Oxford Univ. (United Kingdom). Transport Studies Unit;. *Transport Investment, Transport Intensity and Economic Growth*. University of Oxford, Transport Studies Unit, 1997.

Rayle, Lisa, Danielle Dai, Nelson Chan, Robert Cervero, and Susan Shaheen. "Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco." *Transport Policy* 45 (2016): 168-178.

Roman, C, R Espino and JC Martin (2007) Competition of high-speed train with air transport: the case of Madrid–Barcelona. *Journal of Air Transport Management 13*, no.5: 277–284.

Schoettle, B. and Sivak, M. (2014a) A survey of public opinion about autonomous and self-driving vehicles inthe US, the UK and Australia. Michigan: University of Michigan.

Schoettle, B. and Sivak, M. (2014b). The reasons for the recent decline in young driver licensing in the United States. Traffic Injury Prevention, 15, 6-9.

Schaller, Bruce. "Elasticities for taxicab fares and service availability." *Transportation* 26, no. 3 (1999): 283-297.

Shladover, Steven, Dongyan Su, and Xiao-Yun Lu. "Impacts of cooperative adaptive cruise control on freeway traffic flow." *Transportation Research Record: Journal of the Transportation Research Board* 2324 (2012): 63-70.

Thakur, Praveen, Robert Kinghorn, and Renan Grace. "Urban form and function in the autonomous era." In *Australasian Transport Research Forum (ATRF), 38th, 2016, Melbourne, Victoria, Australia*. 2016.

Underwood, Steven E. "Disruptive innovation on the path to sustainable mobility: creating a roadmap for road transportation in the United States." In *Road Vehicle Automation*, pp. 157-168. Springer International Publishing, 2014.

Wadud, Zia, Don MacKenzie, and Paul Leiby. "Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles." *Transportation Research Part A: Policy and Practice* 86 (2016): 1-18.

Zhang, Wenwen, Subhrajit Guhathakurta, Jinqi Fang, and Ge Zhang. "The Performance and Benefits of a Shared Autonomous Vehicles Based Dynamic Ridesharing System: An Agent-Based Simulation Approach." In *Transportation Research Board 94th Annual Meeting. Available at: htp://trid. trb. org/view. aspx*. 2015.

Zhang, Wenwen, and Subhrajit Guhathakurta. "Parking spaces in the age of shared autonomous vehicles: How much parking will we need and where." In *Transportation Research Board 96th Annual Meeting*. 2017.