

# 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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A Research Report from the National Center  
for Sustainable Transportation

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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

## Abstract

In much 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 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. Second, we simulate the effects of the introduction of an automated taxi service on conventional personal vehicle and transit travel in the San Francisco Bay Area region and use new research on the costs of automated vehicles to represent plausible per mile automated taxi fares. We use an integrated model for the San Francisco Bay Area that includes the MTC-ABM combined with the agent-based MATSim model customized for the region. This model set uses baseline travel demand data from the region's official activity-based travel model and dynamically assigns vehicles on road and transit networks by the time of day. 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 the 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 the same way that the automobile disrupted horse and cart transportation in the 20<sup>th</sup> century, automated vehicles hold the potential to disrupt our current system of transportation and the fabric of our built environment in the 21<sup>st</sup> century. Experts predict that vehicles could be fully automated by as early as 2025 or as late as 2035 (Underwood, 2014). 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 we integrate automated vehicle systems 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 adapt 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. Also, 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 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 mode choice, congestion, and VMT effects. The study is unique in that it articulates the size and direction of change on travel for a wide range of automated vehicles scenarios. Based on our review of the literature, we defined the following scenarios for simulation:

- **Highway Capacity Doubled:** Safety improvements 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.
- **25% Reduction in the Value of Driving Time:** Passengers would be free to use in-vehicle travel time to work and “play” in their vehicle.
- **20% Reduction in Operating Costs:** Safety improvements should reduce insurance costs. Optimal vehicle flow and reduced vehicle weight could also reduce fuel use.
- **New Drivers:** Full automation could increase mobility for older adults, people with disabilities, young people without driver’s licenses, and people living in poverty. To model this effect, we relaxed the age restriction for driving from 16 to 13 and the auto insufficiency restriction for those households who have fewer vehicles available than workers.
- **Combined Effects:** This scenario combines all the effects described above.
- **Road Pricing and Combined Effects:** The per mile operated cost is doubled (to 36 cents per mile) in the combined effects scenario

We summarize the results of the scenarios simulated with the MTC-ABM model in the table below. Because of the time constraints of the study, we took a conservative approach to the representation of induced travel in the operation of the MTC-ABM. Future research will include a more complete representation of induced travel for these scenarios. However, this conservative analysis indicates that vehicle miles travel increase across all scenarios except for the scenario that includes road pricing. Vehicle hours of delay decrease when highway capacity expands and with an auto pricing policy. Reduced value of drive time, lower vehicle operating costs, and new drivers tend to reduce the number of transit, walk, and bike trips and increase auto trips. The addition of road pricing increases transit, walk, and bike trips.

**Table ES-1. 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 Highway Capacity (100%)	4%	-78%	0%	0%	1%	-2%
Reduce Value of Drive Time (25%)	3%	7%	1%	1%	-5%	-4%
Reduce Operating Vehicle Costs (20%)	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 transit and conventional personal single occupant vehicles, given the introduction of an AT service with plausible low per mile fares. Fulton and Compostella (2018) 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. When transit travel varies, the new AT service has a significant impact on transit use (reducing it by more than half), vehicle miles of travel (increase by 18%), and congestion (24% increase in average AT travel time). ATs tend to out compete transit travel in the outer areas of the region and, as a result, there are more and longer vehicles trips on roadways (including deadhead travel), which tends to increase area congestion. AT use is highest when it is offered at a lower cost. This is also true with an increase in parking and per mile operational costs of conventional vehicles. The results of this research represent a conservative estimate of the traffic effects of AT services because of its limited representation of induced travel effects. Notably, this research highlights the significant threat of low cost AT services to suburban transit providers and efforts to reduce vehicle miles travel and traffic congestion.

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 behavioral parameters are used to estimate the plausible high-end of those travelers who may switch to BART from all modes, if the first-mile service to the traveler's nearest BART station improves 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% 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), the share of travelers benefiting from the service 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 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 these services used automated vehicle technology, the single passenger home-based pick up ride-hailing service increased benefits for almost 20% more trips.

# 1. Introduction

In much the same way that the automobile disrupted horse and cart transportation in the 20<sup>th</sup> 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, 2014). 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 we integrate automated vehicle systems 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 adapt 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. Also, 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 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.

In section three, we simulate the effects of the introduction of an automated taxi service on conventional personal vehicle and transit travel in the San Francisco Bay Area region and use

new research on the costs of automated vehicles to represent plausible per mile automated taxi fares. 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 use an integrated model for the San Francisco Bay Area that includes the MTC-ABM combined with the agent-based MATSim model customized for the region. This model set uses baseline travel demand data from the region's official activity-based travel model and dynamically assigns vehicles on road and transit networks by the time of day.

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 behavioral parameters are used to estimate the plausible high-end of those travelers who may switch to BART from all modes, if the first-mile service to the traveler's nearest BART station improves 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. 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.

## 2. The 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.

### 2.2. Literature Review

In this section, we summarize the modeling studies on personal automated vehicle technology with 100% market penetration, which capture the 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. We describe these studies and their results 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, the 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 three percentage points and transit mode share declines by three 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 the 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 increases with

and without a 65% reduction in the 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 in the value of time applies to all individuals with lower parking costs and expanded roadway capacity, then 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, change in VMT and delay may be 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%, then VMT increases by 0.4% and 2% and average vehicle travel time is reduced by about 2% to 5%. The combination of reduced values of travel times, 25% and 75%, and market penetration rates, 20% and 70%, produces greater VMT (about 1% to 19%) and average vehicle trip time (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. An activity and agent-based model (SimMobility) that makes use of local travel survey data, roadway and transit networks, and local taxi data simulate the policies. 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 three percentage point increase in transit mode share, and a one 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
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.

## 2.3. 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 draw from 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. 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, generates data that represent all individuals and their socioeconomic characteristics in the MTC study area. 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 10 AM), 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 operates with an iterative process. At each iteration, the model generates tour and trip lists for all individuals within the sample. Selection of choices at each stage of the model depends on an individuals' socioeconomic characteristics and the relative choice attractiveness. The generated individual trips are aggregated as the 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 model calculates the updated network variables, such as traffic volume and speeds and later, stored as average loaded network files, and used in the next iteration. These new network values are used to derive zonal skims (e.g., in-vehicle travel time and wait time), and are 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. Because of the time constraints of the study and the significant time to run multiple iterations, we limited the number of scenario iterations to three. Future research will expand the number of iterations and better represent the induced travel effects in the analysis.

## 2.4. 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. We simulate scenarios that examine plausible changes enabled by automated vehicle technology, including roadway capacity, the 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. Headways are reduced from two seconds to one half a second for conventional vehicles, on an abstract four by four gridded network (with 24 road links that are 120 meters long and two lanes in each direction). They report that the capacity of the network potentially triples with 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.

**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, and they may have a lower burden of in-vehicle travel time. 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<sup>1</sup> 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

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<sup>1</sup> 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.

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 shows that passenger value of travel time is 67% that of driver value of travel time; however, when adjusted for income, it is 82% (Fosgerau et al., 2007 cited in Ian Wallis Associates, 2014). This study did not detect significant differences in the value of travel time by trip purpose. The results of revealed<sup>2</sup> 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 increased by 0.95 percentage points and shared ride mode share increases by 1.08 percentage points. However, one online 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 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

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<sup>2</sup> Revealed preference surveys ask respondents questions about actual situations they experience

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 a 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, 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 declines 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 online 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 the availability of a fully automated vehicle would eliminate four of these reasons: too busy, disability, lack of driving knowledge, and legal issues. If respondents indicate one of those reasons, then they assume respondents would travel in a fully automated vehicle. They estimate the increase in total vehicle users 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 in 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%. The 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 the value of time for driving, and allowed for new drivers.

## 2.5. Results

We present the mode choice results in Table 2.2, which describe the percentage change in total trips by mode, respectively. Table 2.3 shows the roadway network results, which includes percentage changes in total VMT, vehicle trip volume, and vehicle hours of delay. Change in VMT approximates the effect on GHG emissions. In a model set that does not represent any change in the use of different vehicle types, the two are closely related. We describe all results in terms of change relative to the base case scenario.

The doubling of roadway capacity increase in VMT and trip volumes. VMT is increased by 6% in the peak period, 1% in the off-peak, and 4% for an average 24-hour daily period. Overall reductions in VHD are 78%. Increased roadway capacity and roadway speeds also increase the number of motorized trips (drive alone by 1% and transit by 1%) during the peak period; however, walk and bike trips decline by 3% in the peak and 2% in the off-peak.

The 25% reduction of the 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 we reduce operating costs for autos by about 20% (or 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 an automated vehicle even if the number of vehicles 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 are 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. Except for 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%	0%	1%	-3%
	Off-Peak	0%	0%	0%	-2%
	Total	0%	0%	1%	-2%
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), vehicle volumes (VOL), and vehicle hours of delay (VHD) for peak and off-peak periods for the automated vehicle scenarios.**

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	6%	0%	-70%
	Off-Peak	1%	0%	-83%
	Total	4%	0%	-78%
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%

## 2.6. 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 11%, 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. Relative Demand for Automated Taxis and Personal Vehicles Using Agent-Based Demand and Supply Models in the San Francisco Bay Area**

#### **3.1. Introduction**

At the end of 2017, Waymo, Google’s autonomous vehicle spinoff, announced the launch of its ride-hailing service. Since then, it has been testing its “Early Rider” service with its autonomous vehicles, without backup drivers, in Phoenix, Arizona (U.S.), areas. In this paper, we simulate the effects of the introduction of a similar service on conventional personal vehicle and transit travel in the San Francisco Bay Area region. We call this service “automated taxis” and use new research on the costs of automated vehicles from Fulton and Compostella (2018a and 2018b) to represent plausible per mile automated taxi (AT) fares. The simulation of alternative automated taxi scenarios uses a regionally calibrated agent-based model using the MATSim (Multi-Agent Transport Simulation) framework. This model uses baseline travel demand data from the region’s official activity-based travel model and dynamically assigns vehicles on road and transit networks by the time of day. This study differs from previous studies in its policy focus, that is, it studies the effect of automated taxi services on conventional personal vehicle and transit travel and resulting systemwide VMT and congestion. It is also unique in its use of realistic travel demand, and roadway and transit travel times that vary by time of day in a large metropolitan region.

#### **3.2. Literature Review**

In this section, we review studies that simulate automated vehicle taxis or AT services with methods similar to those employed in this study. Fagnant and Kockelman (2014) simulate an AT fleet in a small downtown of the Austin-like city. They use randomly generated travel demand 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 area without a physical representation of roadway networks. As a result, they simulate ATs 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 the base and AT scenarios and show reductions in energy use by 12% and GHGs by 6%.

Later studies (Fagnant et al., 2015 and Fagnant 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 AT fleet 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 AT (multiple paying passengers) ranged from 17% to 52% of the increase for the AT scenario.

Chen et al. (2016) simulate an electric AT 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 dynamic assignment route choice with vehicle repositioning. In these scenarios, they reduce the value of AT travel time to 25%, 35%, and 50% of current value of travel time and per mile charges are 75 cents, 85 cents, and one dollar. As the value of automated vehicle travel time and average per mile cost increases, average trip length decreases. When the electric AT service costs 85 cents per mile, average trip distance increases by 20 to 29 percent at 25% and 35% values of automated vehicle travel time but declines somewhat (4%) at 50% value of automated vehicle travel time. At 35% value of automated vehicle 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.

Studies simulated ATs and shared ATs (multiple paying passengers) in Berlin, Germany with the MATSim modeling framework, which includes a dynamic assignment model with vehicle relocation capabilities (Bischoff and Maciejewski, 2016; Bischoff et al., 2017; Maciejewski and Bischoff 2016, 2017). The model uses local travel behavior data to schedule automated vehicle fleets for an average weekday dynamically. The authors (Bischoff, Maciejewski, and Nagel, 2017) simulate different levels of market penetrations for ATs (20% to 100%). They find that the share of empty drive time to total drive time ranges from 17% to 19%. When examining the share of empty rides per zones from an AT 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%) (Bischoff and Maciejewski, 2016).

Another study (de Almeida Correia et al., 2016) examines the effects of a fully automated personal vehicle fleet (not ATs) 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 Arentze and Molin (2013). This study 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. They find 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%) with area-wide parking charges. 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% to 31%, 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) used a static assignment route choice model with a rule-based mode choice model (using proximity and trip length) to simulate AT and shared AT services with and without transit. The model uses population attributes and travel demand data from a local travel survey. It also uses travel times based on hourly updated link speeds from a roadway network. However, ATs and shared ATs with and without transit see increases in VMT (88% and 43%, respectively) due to empty vehicle travel and the elimination of bus routes.

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 ATs with a fare that is 40% of the conventional taxi fare. They simulate the policy with activity and agent-based model (SimMobility) that makes use of local travel survey data, road and transit networks, and local taxi data. The model represents trip, destination, time-of-day, mode, and route choice. They find a shared AT to vehicle replacement rate of 1 to 4 and a 29% increase in the daily shared AT mode share, a 3% increase in transit mode share, and a 1% increase in both the taxi and walk mode share.

In sum, most studies of ATs to date simulate route choice and empty vehicle repositioning impacts, with and without hypothetical demand data and fixed vehicle speeds. Three studies add mode choice effects to the simulation. One examines ATs but use fixed vehicle speeds and a rule-based mode choice model (Martinez and Crist, 2015). Another study simulates ATs using fixed speeds (Chen et al., 2016). The final study (de Almeida Correia et al., 2016) focuses on personal automated vehicles, rather than ATs, and simulates all secondary effects in a geographically limited area (the CBD) and only reports mode choice effects. In contrast, the current study simulates empty vehicle repositioning travel, route choice, and mode choice effects of ATs using individual travel activity data from an official regional activity-based model and represents vehicle travel speeds by time of day (5 time periods) in a larger metropolitan area with both suburban and urban areas. We report a wide range of travel effects along with a discussion of the potential effects of not representing changes in trip-making, destinations, and travel time of day.

### **3.3. Methods**

This study integrates the San Francisco Bay Area activity-based travel demand model (MTC-ABM) with an application of the MATSim framework that includes a dynamic traffic assignment (DTA) model to simulate the choice to use a personal auto or an AT based on individuals' value of time and the per mile cost of each mode. This is the official model of the San Francisco Bay Area Metropolitan Transportation Commission (MTC), which is the region's transportation planning organization. ABMs typically use static traffic assignment models to circumvent the

long computational times required to simulate real urban networks in DTAs. In static assignment models, the detailed output from ABMs, including 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). This approach is not feasible when simulating the effects of automated vehicle fleets, as the additional mileage of deadheading vehicles and the effects of waiting times is not feasible in static models.

### **3.3.1. Simulation framework**

To avoid long computational times MATSim uses a queue model on links, 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.

MATSim 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. The basic, iterative approach of a MATSim simulation may be described as follows (Horni et al., 2016):

- i. Initial demand: All agents have an initial daily plan, which serves as a starting point in the iterative improvement process.
- ii. Mobility simulation: Plans of all agents are executed concurrently, to allow estimation of the influence of agents plans on each other. This step typically uses a queue simulation to simulate car traffic, which gives estimates of congested travel time.
- iii. Scoring: The information from the simulation is used to estimate the score of each plan. This typically takes the form of travel times and time spent performing activities. The experienced utility is used to update the score associated with the plan.
- iv. Re-planning: Then, some 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 iterate until the system reaches a stable state. Typical re-planning 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 demonstrates robust results that include automated vehicle simulations (Bischoff and Maciejewski, 2016; de Almeida Correia et al., 2016).

### 3.3.2. *Simulation of automated taxi fleets in MATSim*

MATSim includes a module that simulates the effects of automated taxi fleets. This MATSim automated vehicle extension<sup>3</sup> dispatches 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. A fleet-wide optimization approach handles vehicle dispatch for large fleets with reasonable computational times. The dispatch algorithm follows a simple, but efficient, heuristic which can be described by two states. First, in times of oversupply (i.e., during off-peak periods), the closest vehicle is dispatched to a new ride request. 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 ATs will need to travel empty in between customers, additional vehicle miles will be traveled. It is possible to evaluate mode choice with several pricing schemes for AT service. Various fare structures can be represented, including subscription, flag fall, distance, and time-based fares, and analyzed on a detailed spatial and 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 (e.g., smaller gaps between vehicles and improved interaction at intersections). Recent studies (Maciejewski and Bischoff, 2017; Maciejewski et al., 2017) 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 may consume 1.5 to 2.0 times less of the nominal flow capacity, measured in passenger cars per hour, compared to conventionally driven vehicles of the same size, though they both occupy the same amount of space on the road.

We illustrate the logic of the mixed vehicular traffic module as follows. If 1,200 vehicles per hour are allowed to leave a link, and all of them are conventionally driven vehicles, then everything remains the same. If automated vehicles only require half the amount of flow capacity of conventionally driven vehicles, then 800 automated vehicles traveling 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, then the effective capacity would increase to 2,400 vehicles. Maciejewski and Bischoff (2017) first use the methodology.

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<sup>3</sup> Available via <http://matsim.org/extensions>

### 3.3.3. Model Conversion and Adaptation

The integration of MATSim with the MTC-ABM required conversion of the MTC-ABM population trip lists (or individual travel activity data) into a synthetic MATSim population. Python scripts were developed to automate the conversion of the MTC trip list (travel activity by person/household attribute) to the MATSim format. The trips list conversion required the refinement of trip departure time by an hour to the minute. We used the 2000 Bay Area Transportation Survey 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 were randomly selected and then assigned departure times within the hour based on weighting factors developed from this distribution. To the trip list, we added the Individual value of time. These estimates are available from the MTC-ABM and based on a stated preference survey conducted in the San Francisco Bay Area and included in the MTC-ABM. Value of time is log-normally distributed and segmented by four income groups (low, medium, high, and very high). We used the individual value of time to estimate the generalized cost function of each person in the MATSim model. The MTC-ABM is multi-modal and, besides single occupant passenger vehicle travel, it includes public transit, multi-occupant vehicle travel, and bike and walk travel. Due to the age of the model, it does not represent transportation network companies (TNC) or ride-hailing travel. The resulting MATSim model was re-calibrated to explicitly represent the choice to use single-occupant conventional vehicles (SOV), automated taxis (ATs), and/or transit modes, depending on the scenario as described below. We used standard MATSim calibration practices (see chapters 3 and 4 in Maciejewski et al., 2017).

The roadway network was generated using OpenStreetMap data. This is the standard approach in most MATSim model development projects and allows a reasonably depiction of link speeds, capacities, and the number of available lanes. We converted transit schedules from General Transit Feed Specification (GTFS) by combining available transit feeds from more than 30 different agencies operating in the area.

### 3.3.4. Adaption of the MATSim scoring function

As described above, scoring of plans is one of the core functionalities in MATSim. The scoring function that is described by default in *formula 1* below, can be easily customized to take additional constraints into account (Horni et al., 2016).

$$S = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)} \quad (1)$$

Where  $S$  is the score of the plan that the agent has performed,  $q$  is the specific activity performed,  $N$  is the number of all activities.  $S_{act,q}$  describes the score for performing the activity, and  $S_{trav,mode(q)}$  is the score for traveling to the activity, which is usually negative.

In this paper,  $S_{trav,mode(q)}$  was adapted to include the additional generalized cost of parking according to the destination zone  $q$ , if an agent selects the conventional single-occupant vehicle mode. When performing an activity, the person-specific value of time is used to calculate  $S_{act,q}$ .

### 3.4. Simulation Scenarios

We simulate the relative demand for ATs and SOVs with the automated taxi module in MATSim. The AT mode uses an estimated average fare of 48 cents per mile based on research conducted by Fulton and Compostella (2018). This figure includes the amortized vehicle purchase cost over 100,000 miles of driving, fuel costs, insurance, maintenance, and cleaning for an automated vehicle with an internal combustion engine. We simulate SOV travel in MATSim using the base case per mile operational cost from the MTC-ABM, which is about 20 cents per mile in the year equivalent to Fulton and Compostella's estimate. SOVs are conventionally driven based on the assumption that automated vehicles will initially be made available by fleet operators who are well positioned to maintain vehicles to minimize accident risks.

Both the ATs and SOVs are charged bridge tolls as represented in the MTC-ABM. SOVs still park and incur the average zonal parking charges, as represented in the MTC-ABM, and walk time penalties (up to 15 minutes per trip). ATs do not pay parking charges or experience the walk time penalty. As discussed above, the model includes the value of time for each potential agent of the synthetic population. All five scenarios, as described in Table 3.1, hold multi-occupant personal vehicle travel, walk, and bike travel demand constant. Four scenarios hold transit demand constant and thus the choice to drive SOVs or use ATs is based on trade-offs between the total time (roadway travel time, parking walk time penalty, and waiting times) and cost (per mile, parking, and tolls) and the individual's value of time. The fifth allows transit mode share to vary. In this scenario, we model use of ATs and SOVs based on transit travel time, in-vehicle travel time, transit access and egress, transfers, and wait, and transit fares.

For the vehicle flow of ATs, we assume an improvement factor of 1.5. All scenarios hold the AT fleet constant at a high level of 30,000 vehicles. As the simulation is down-scaled to 5% of demand, the fleet size allows every agent to use the AT mode whenever required. We ran a total of 50 iterations for each scenario. Given the limited choice set (only change of mode and small adaptations to departure time and route allowed), this is enough to reach a new equilibrium stage, as described previously.



**Table 3.1. Summary of Scenarios**

Scenario	Per Mile AT <sup>a</sup> Fare	Per Mile SOV <sup>b</sup> Cost	Choice dimensions	Average Zonal Parking Costs
Base Case	No AT	20 cents	SOV, AT	MTC-ABM values
1) Mean AT Cost	48 cents	20 cents	SOV, AT	
2) Low AT Cost	36 cents	20 cents	SOV, AT	
3) Mean AT Cost + High Cost Personal Vehicle	48 cents	23 cents	SOV, AT	
4) Mean AT Cost + Doubled Parking Costs	48 cents	20 cents	SOV, AT	Double MTC-ABM Values
5) Low AT cost + Shift from Transit	36 cents	20 cents	Public transit, SOV, AT	MTC-ABM values

<sup>a</sup> Conventional single-occupant vehicle; <sup>b</sup> Automated Taxi; <sup>c</sup> multi-passenger vehicles, walk, and bike

### 3.5. Simulation Results

All scenarios result in different mode shares, distribution of use, traffic flow conditions, and vehicle miles traveled. We discuss these results in detail in the following sections.

#### 3.5.1. Changes in Mode Share

We show the mode shares for each scenario in Table 3.2. In all scenarios, AT use is between 4% and 6%. As discussed above, in the first four alternatives to the base case, in which the transit and other modes, including multi-passenger modes, are held constant, only SOVs can switch to ATs. Use of AT is highest when offered at a lower cost. This is true even when parking and per mile operational costs of SOVs increase relative to the base case.

In the fifth alternative, we model transit travel explicitly with low AT costs. Significantly, total transit mode share declines by more than half. ATs out-compete bus transit travel in the outer areas of the region. Longer total vehicle trips, including empty vehicle AT (deadhead travel), significantly increase congestion, as explained in more detail below. The relatively small reduction in the SOV mode share results from increased congestion in this scenario. As discussed above, the MATSim model largely holds each travelers’ trip making, destinations, and departure time choice constant because it uses fixed trip schedules. As congestion makes it harder for travelers to meet these basic travel arrival time requirements, additional wait times and savings in parking costs become less important to the traveler. As a result, the model likely underpredicts the SOV mode shift to ATs. The same logic applies to the transit mode share. More travelers may switch to ATs from transit if they could change their trip-making, destinations, and departure time choices. We note likely overestimated congestion in the scenario results due to the lack of explicit representation of these factors in the model.

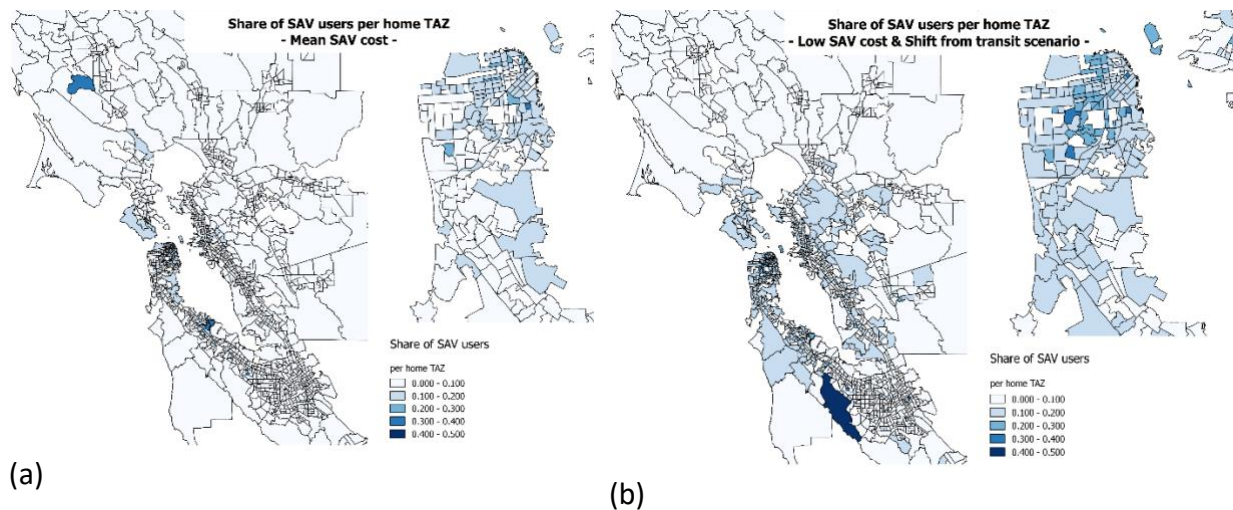
**Table 3.2. Mode Share Change**

Scenario	SOV <sup>a</sup>	AT <sup>b</sup>	Transit	Other <sup>c</sup>
Base case	48.9 %	-	7.3 %	43.8 %
1) Mean AT Cost	44.7 %	4.1 %	7.3 %	43.8 %
2) Low AT Cost	42.7 %	6.2 %	7.3 %	43.8 %
3) Mean AT Cost + High Cost Personal Vehicle	43.5 %	5.4 %	7.3 %	43.8 %
4) Mean AT Cost + Doubled Parking Costs	43.9 %	5.0 %	7.3 %	43.8 %
5) Mean AT cost + Shift from Transit	47.1 %	6.1 %	3.0 %	43.8 %

<sup>a</sup> Conventional single-occupant vehicle; <sup>b</sup> Automated taxi; <sup>c</sup> multi-passenger vehicles, walk, and bike

### 3.5.2. Affected Users

In the mean AT cost scenario, the transportation analysis zones (TAZs) with the highest share of travelers who switch from SOVs to ATs are in central business areas, such as central San Francisco, as Figure 3.1(a) shows. In many of these areas, at least 10% to 20% of travelers are now traveling in ATs. The figures for the scenarios 2 to 4 are similar to Figure 3.1 (a). However, in the low AT cost + shift from transit scenario, a much larger share of ATs users reside in the outer areas of the region and formerly used transit (see Figure 3.1(b)).



**Figure 3.1. Relative Share of AT Users per Home TAZ**

### 3.5.3. Travel Time Changes

Passenger wait time for ATs results in higher overall average travel time for ATs compared to SOVs. See Table 3.3 below. Transit travel times are significantly higher across all the alternatives to the base case. As a result, when public transit travelers can use ATs (scenario 5), as described above, there is a significant shift from transit travel to AT travel, particularly in the outer areas of the region.

Except for the fifth scenario, average SOV travel times are lower than in the base case scenario. This can be explained by two factors. First, as discussed above, travelers in more central and congested business areas are more likely to switch from SOVs to ATs and thus travelers in less congested areas with lower initial travel times are more likely to continue using SOVs. Second, as discussed above, ATs occupy less roadway capacity relative to SOVs, and thus there is a small overall increase in roadway capacity. In the fifth scenario, more vehicles travel longer distances on roadways due to large shifts from transit to ATs in more outlying areas of the region and relatively small shifts from SOVs to ATs. As a result, this scenario shows significantly higher average travel times across all modes compared to all other scenarios and the base case.

**Table 3.3. Average Travel Times (minutes:seconds)**

Scenario	SOV <sup>a</sup>	AT <sup>b</sup>	Public Transit
Base Case	19:51	/	36:59
1) Mean AT Cost	18:38	21:04	36:59
2) Low AT Cost	17:16	21:22	36:59
3) Mean AT Cost + High Cost Personal Vehicle	18:16	21:40	36:59
4) Mean AT Cost + Doubled Parking Costs	18:52	22:27	36:59
5) Mean AT cost+ Shift from Transit	20:54	26:27	40:45

<sup>a</sup> Conventional single-occupant vehicle; <sup>b</sup> Automated taxi

### 3.5.4. Vehicle Mileage

Increases in VMT is a frequently raised concern about automated vehicles. When transit was not allowed to vary in the first four alternative scenarios, there were small increases in VMT, which ranged from 0.9% to 1.5%. When transit travel varies and AT costs are relatively low, there is a significant increase in VMT: 18% compared to the base case scenario. See Table 3.4.

Another concern is that empty passenger ATs traveling from one customer’s drop-off destination to the next pickup location could compound the problem of increased VMT. In the first four AT scenarios, the share of empty VMT is between 5% and 6% of overall AT miles traveled. In the fifth scenario, this value increases to over 9%. Empty mileage is not evenly distributed throughout the network but is of most concern in less centrally located and densely populated areas.

As discussed above, the simulations do not represent all behavioral changes that may result from congestion, such as reduced trip making, selection of more local travel destinations, and changes to off-peak travel times. This would tend to overestimate the increase in VMT. On the other hand, VMT is likely underestimated in the simulations because the failure to represent these effects could underestimate shifts from SOVs and transit to ATs. Over and underestimation of VMT would also influence congestion and travel time estimates. Future research should include a broader range of behavioral effects. However, limited funding for travel model research and long computer run times for simulation of more behaviorally complex research makes this challenging. As the literature review illustrates, the authors are

aware of only one study published to date that represents all these effects, but in a much smaller geographic area (the central business district in Singapore) than the one used in this study, for shared AT scenarios (Azevedo et al., 2016). This study reports changes in mode share but not VMT.

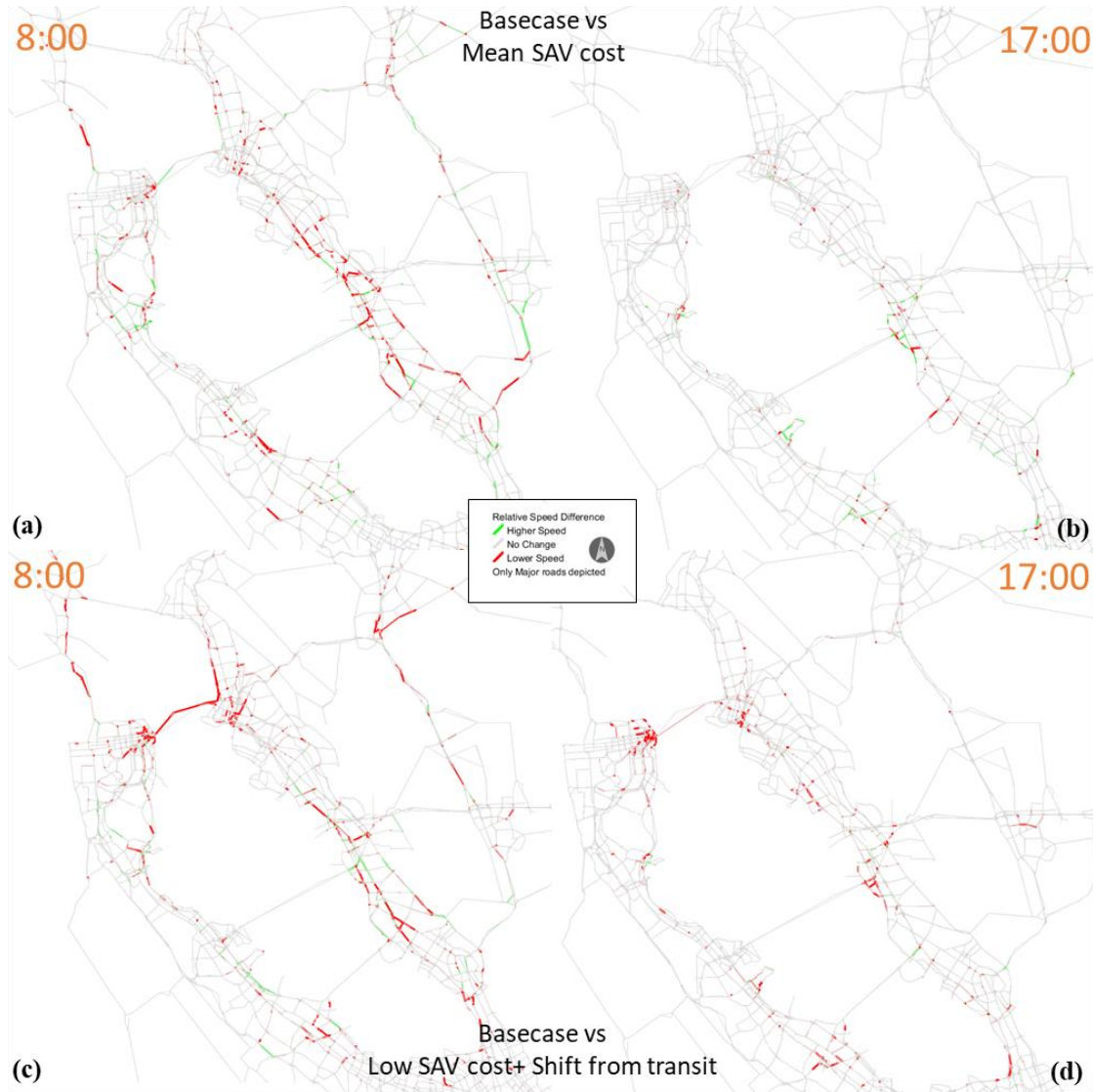
**Table 3.4. Daily VMT change (5 percent model)**

Scenario	SOV <sup>a</sup> (1,000)	AT <sup>b</sup> (1,000)	Empty AT	Total (1,000)	Relative change <sup>c</sup>
Base case	7,250	0	n/a	7,250	-
1) Mean AT Cost	6,727	591	5.1 %	7,318	+ 0.9 %
2) Low AT Cost	6,359	1,005	6.7 %	7,364	+ 1.5 %
3) Mean AT Cost + High Cost Personal Vehicle	6,504	846	6.5 %	7,350	+ 1.4 %
4) Mean AT Cost + Doubled Parking Costs	6,574	773	6.5 %	7,347	+ 1.4 %
5) Low AT cost+ Shift from transit	7,154	1,298	9.6 %	8,452	+ 18.1 %

<sup>a</sup> Conventional single-occupant vehicle; <sup>b</sup> Automated taxi; <sup>c</sup> Compared to Base Case

### 3.5.5. Traffic Flow

In all the AT scenarios, the additional mileage generated by ATs compared to the base case leads to an increase in congestion and a reduction in average speeds. Figure 3.2 depicts the relative average speed differences between the base case and the mean AT cost, and the low AT cost + shift from transit scenario during both morning and afternoon peak hours in the major road network. In both scenarios, congestion is greater in the morning than in the afternoon because the morning peaks are already closer to their saturation point. For the mean AT cost scenario, speed decreases the morning (a) mostly affecting links on freeways and highways. In the afternoon (b), the effects are not as wide-spread. In the low AT cost + shift from transit scenario, speed changes from the base case in the morning (c) are far more drastic and affect almost all major roads leading into central business districts. During the afternoon (d), typical AT pick-up areas are most affected, including the San Francisco CBD and the downtown Oakland areas.



**Figure 3.2. Relative change in average network speeds during AM and PM peak hours**

### 3.6. Conclusion

In this paper, we evaluate the potential to reduce the demand for transit and conventional personal single occupant vehicles given the introduction of an AT service with plausible low per mile fares. When transit travel varies, the new AT service has a significant impact on transit use (reducing it by more than half), vehicle miles of travel (increase by 18%), and congestion (24% increase in average AT travel time). ATs out-compete transit travel in the outer areas of the region and, as a result, there are more and longer vehicles trips on roadways (including deadhead travel), which tends to increase area congestion. Use of the AT service is highest when offered at a lower cost. This is true even with an increase in parking and per mile operational costs of conventional vehicles are increased. The results of this research represent a conservative estimate of the traffic effects of AT services because of its limited representation

of induced travel effects, as described above. Notably, this research highlights the significant threat of low cost AT services to suburban transit providers and efforts to reduce vehicle miles travel and traffic congestion.

Behavioral research on automated vehicles and related services is still in its infancy. Future research should include explicit representation of personal vehicles with multiple occupants, walk, and bike modes and trip-making, destination, and departure time choice. However, inclusion of these effects significantly increases the computational for scenario simulation and thus the breadth of the analysis.

## 4. 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 four 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 online survey conducted between August 2015 and January 2016 (Clewlow and Misha, 2017). The survey employed density (housing and population) and metropolitan area demographics (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 online 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., the 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)
Clewwlow 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 4.2.)

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

#### 4.5. 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 significantly 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

## 4.6. 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) shares are more than tripled. 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.

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