Simulation of Ridesourcing Using Agent-Based Demand and Supply Regional Models: Potential Market Demand for First-Mile Transit Travel and Reduction in Vehicle Miles Traveled in the San Francisco Bay Area

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EXECUTIVE SUMMARY

In this study, we use existing modeling tools and data from the San Francisco Bay Area (California) to understand the potential market demand for a "first" mile transit access service and possible reductions in vehicle miles traveled (VMT) (and thus GHGs) at both the regional and station level. We develop a project scenario that targets commuters who drive alone but could take rail (Bay Area Rapid Transit, or BART) to work. We use travel time, cost, and distance data from San Francisco Bay Area travel models, Google and BART APIs, and TNC fares to explore the magnitude of change in overall travel time and cost for travelers who switch from driving alone to using TNC and BART to travel to work. The analysis indicates that 31% of the identified drive-alone trips could reduce generalized costs (travel time and monetary costs) by switching to TNC and BART. If all travelers who could benefit from traveling by TNC and BART, did in fact switch from drive-alone travel, about 40 thousand new BART trips could be generated and over a half a million miles of VMT avoided during the morning commute period. Most of these trips experienced relatively high levels of cost and VMT savings, which may be more likely to motivate behavioral change. Examination of cost savings by income level and vehicle availability suggests that the new service is more likely to benefit lower income households with fewer vehicles. Sensitivity analyses indicate that even with increased TNC fares and waiting times, there is still a relatively large number of trips that could benefit from switching from driving to TNC and BART. Tests of a shared TNC BART access service suggest cost savings and VMT reductions even when travel time costs increase by 60%. Analysis of benefits by station indicate locations with relatively high market potential (i.e., trips and cost saving) and environmental benefits (VMT reduction) for early pilot implementation. These results can be used to estimate potential TNC fare subsidies to increase performance by station to achieve project objectives, such as equitable access, increased BART ridership, and reduced VMT.

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 6:30am). Moreover parking structures are expensive to construct and large parking lots can increase the walking distance 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 (GHG) emissions.

The rise of transportation network companies (TNCs), such as Uber and Lyft, presents a new opportunity for transit agencies to bridge the first- and last-mile to high quality transit. Within the last year, transit agencies have piloted limited projects to test the concept in at least nine cities across the U.S., including Sacramento and Santa Clara, CA; Pinellas Park and Altamonte, FL; Denver, CO; Atlanta, GA; Philadelphia, PA; and Bloomington, IL. Most of these pilots use more flexible state and local funds, but in the spring of 2016, the Federal Transit Administration released a request for proposals (Mobility on Demand Sandbox or MOD) to fund expanded testing of public partnerships with TNCs. Almost eight million in Federal transit funds were awarded to transit agencies in California, Washington State, Oregon, Florida, Illinois, Texas, and Arizona to test different public-private models to increase access to transit.

The goal of current and proposed pilot programs is most frequently 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 GHG emissions are also common goals. However, to date, there is almost no research that actually 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 TNCs and transit agencies have been difficult to negotiate due to concerns by TNCs about competitive injury. However, Lyft reports that a large share of their Lyft rides start or end near a transit station, 30% in Boston and 37% in New York City (Lyft et al., 2016). Surveys of TNC users in San Francisco indicate that where high quality transit service is available, TNCs are a complement to transit (Rayle et al., 2014).

In this study, we use existing modeling tools and data in the San Francisco Bay Area to understand the potential market demand for a "first" mile transit access service and possible reductions in vehicle miles traveled (VMT) and GHGs at both the regional and station level. We develop a project scenario that targets commuters who drive alone but could take rail (Bay Area Rapid Transit, or BART) to work. We use travel time, cost, and distance data from San Francisco Bay Area travel models, Google and BART APIs, and TNC pricing structures to explore the magnitude of change in overall travel time and cost for travelers who switch from driving

alone to using TNC and BART. Equity effects are also explored by examining results by household income and auto availability categories. The study also demonstrates how these tools can be used by planners to evaluate promising early pilot locations and gain insight into the best way to target subsidies by groups and locations given project objectives.

Methods

As described above, there is very little data and research available on TNC use for transit access. However, travel survey data is available that captures typical daily travel patterns of individuals and households, as well as estimates of willingness-to-pay, to endure waiting, travel time, and monetary costs. In addition, we have the theoretical tools (activity-based travel demand models [ABMs] and dynamic assignment models [DTAs]), which use detailed travel activity data and transportation networks to replicate current and predict future traffic behavior. Importantly, DTA models also allow us to test the use of vehicle services with distinct operating characteristics, including those of TNC services, by travelers given observed travel needs, socioeconomic attributes, and preferences (including the individual value of time and willingness-to-pay). In this study, we demonstrate how available modeling tools and data can be used to evaluate TNC transit access programs. We integrate the MATSim DTM with the San Francisco Bay Area Metropolitan Transportation Commission's (MTC) ABM. We develop programs that collect data from Google and BART APIs, then this data is integrated to understand the potential market, cost savings, and VMT reductions from the TNC and BART access services.

Activity Based Travel Model

Activity-based microsimulation travel demand models (ABMs) simulate individual travel as derived from the need to participate in activities in specific space and time contexts. The sequence by which individuals participate in activities and travel is based on time-use decisions over time (24 hours or longer). Individuals' socio-economic attributes and travel environment (i.e., quality by mode of travel to different destinations) are typically represented at a high level of resolution. The probability of an individual traveler selecting a given alternative is a function of his or her socioeconomic characteristics and the relative attractiveness of the alternative. As a result, these models are better able to simulate the effect of changes in travel time and cost from the introduction of demand management strategies.

The San Francisco Bay Area MTC's ABM belongs to the Coordinated Travel Regional Activity Modeling Platform (CT-RAMP) family of ABMs developed by Parsons Brinkerhoff. The activities or day patterns driving individuals' need to make travel-related choices are based on MTC's 2000 Bay Area Travel Behavior Survey. The data from this survey include 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 on intra-household travel. Originally, we planned to use the Sacramento Regional Travel Demand model for this case study; however, we discovered that this model did not represent intra-household travel, which was important for the proposed analysis. Thus, we decided to use the San Francisco Bay Area model instead of the Sacramento model for the current project. All individuals and their socioeconomic characteristics in the MTC study area are generated through a process known as a population synthesis, which uses statistical methods to expand survey samples (i.e., 2000 Public Use Microdata Sample and 2010 Census data) to represent the entire population. Demographic and employment categories include households by four income quartiles, population by five age categories, population by four income categories, high school and grade school enrollment, and employment by six North American Industry Classification System categories.

Like all other ABMs, tour and trip lists are generated for each individual in the MTC activity based model. 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 TNC service, we integrated the MATSim dynamic traffic assignment model with the MTC ABM.

Dynamic Assignment Model

To our knowledge, MATsim is the only DTA capable of using detailed travel activity patterns for large scale regional simulations. In Toronto, Canada, the MATsim DTA model was successfully integrated with a regional ABM to simulate the effectiveness of various policy interventions to meet climate changes goals by 2031 (Hatzopoulou et al., 2011). MATsim has also been integrated with ABMs in Dallas-Fort Worth, TX (Ziemke, et al., 2015), and Tel Aviv, Israel (Bekhor, 2011), and four step models in Austin, TX (Fagnant and Kockelman, 2015), and Los Angeles, CA (Goulias, et al., 2012). To avoid long computational times, MATsim uses a spatial queue model, rather than simulating car-following and lane-changing details, for significantly faster computational speeds. This makes the MATSim framework practical for a regional application.

The integration of MATSim with the MTC ABM required conversion of the MTC ABM roadway network and population trip list into the MATSim format. Python scripts were developed to automate the conversion of the MTC network and 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 log is 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.

Google and BART API Data

In order to test the demand and VMT effects of a first- and last-mile automated vehicle service in the Bay Area, we identified travelers who drive alone to work, live five miles from the closest BART station, and work within a half mile of a BART station. GIS was used to identify zones and centroids within the specified buffers. Reverse geocoding (using the BART API) was used to identify the BART station closest to the home and work zones within the buffers. Next, we queried the MATSim output data to identify the travelers who met our criteria. Table 1, below, describes the data sources and methods of calculation for the travel time and travel costs variables. For drive alone travel, MATSim provided data on the specific route taken by each traveler and thus we calculated travel time, travel distance, and route tolls by time of day. Parking costs and variable costs of travel were obtained from the MTC ABM. For TNC and BART travel, the Google API was used to calculate travel time and cost from the zone centroid to the BART station using the traveler's home location and departure time. With the estimated arrival time at the origin BART station and knowledge of the destination BART station, we use the BART API to calculate BART wait times, in-BART travel times, and BART fares. We assume the TNC wait time is five minutes. We also assume that walking from the destination parking lot and BART stations are approximately equal and thus do not include these travel times in the analysis. To calculate generalized cost, we use individual travelers (i) value of time to convert travel time minutes into dollars. Costs are in $2000. See equation 1 below.

(1) Generalized Cost$_i$ = (Travel Time$_i$ x Value of Time$_i$) + (Travel Cost$_i$)

Table 1. Time and Cost Variables for Generalized Cost Equations

	Variables	Calculation	Data Source
Drive Alone			
Travel Time	Auto Travel Time	Location Based Departure and Arrival Time	MATSim
Travel Cost	Parking	8 Hour Long Term Parking Cost by Zone	MTC ABM
	Toll	Current Toll on Route	MATSim Toll Route by Time of Day
	Per Mile Cost of Driving	Distance x Variable per Mile Cost	MATSim Distance MTC ABM per Variable Mile Cost
TNC and BART			
Travel Time	TNC wait time	None	5 minutes
	TNC travel time to BART	Auto Travel Time from Zone centroid to BART station	Google API
	BART wait time	Home Location and BART Departure Time	BART API
	In-BART travel time	BART Departure and Arrival Time	BART API
Travel Cost	TNC Cost	Base Fare ($2) + (Travel Minutes x $0.22) + (Travel Mile x $1.15) + Service Fee ($1.55) or Minimum Fare if Cost is Less than $6.55	Uber Cost Function with Google API Time and Distance
	BART Fare	Fare from Origin and Destination Station	BART API

Results

The analysis indicates that 31% of the identified drive-alone trips could reduce their generalized costs (travel time and monetary costs) by switching to taking TNC and BART to work. Table 2 shows the total and average daily results for the four hour morning peak. If all travelers who could benefit from traveling by TNC and BART did in fact switch from drive-alone travel, this could generate about 40 thousand new BART trips and avoid over a half million miles of vehicle travel. Average per trip reduction in VMT is about 15 miles and generalized costs is about $8. The total reduction in total morning peak period VMT is only about 2% and thus induced travel effects should not significantly offset VMT reduction.

Savings in generalized costs are driven largely by monetary savings in parking, tolls, and perceived vehicle operations costs. Parking costs in San Francisco are relatively high, as are tolls on bridges leading to San Francisco. Almost all the trips that reduce generalized costs also reduce monetary costs, while only 11% reduced travel time costs. As a result, there are total and average increases in Table 2 for travel time.

Table 2. Total and Average Daily Change (4 hour AM peak) in Trips, VMT, and Costs for Commuters Who Could Reduce Generalized Travel Costs (Both Time and Monetary Out-of-Pocket Costs)

	Total	Average
Transit Trips	39,990	0.31
VMT (miles)	-614,992	-15.41
Travel Time Costs	5,014 (hours)	7.54 (minutes)
Monetary Costs ($2000)	-$363,514	-$9.11
Generalized Costs ($2000)	-$320.925	-$8.04

Because travelers do not always have perfect knowledge and have individual values and preferences beyond costs and benefits that influence decision making, we describe the share of total trips that could cost less (as measured by generalized costs) by percentage change in costs, if travelers decided to make these trips by TNC and BART, rather than driving alone (Figures 1-3). The percentage change in costs is 50% or more for 43% of trips for time, 65% for money, and 27% for both time and money (generalized costs). Thus, a relatively large share of these trips experience large (and, perhaps, more evident) travel time and/or cost savings.
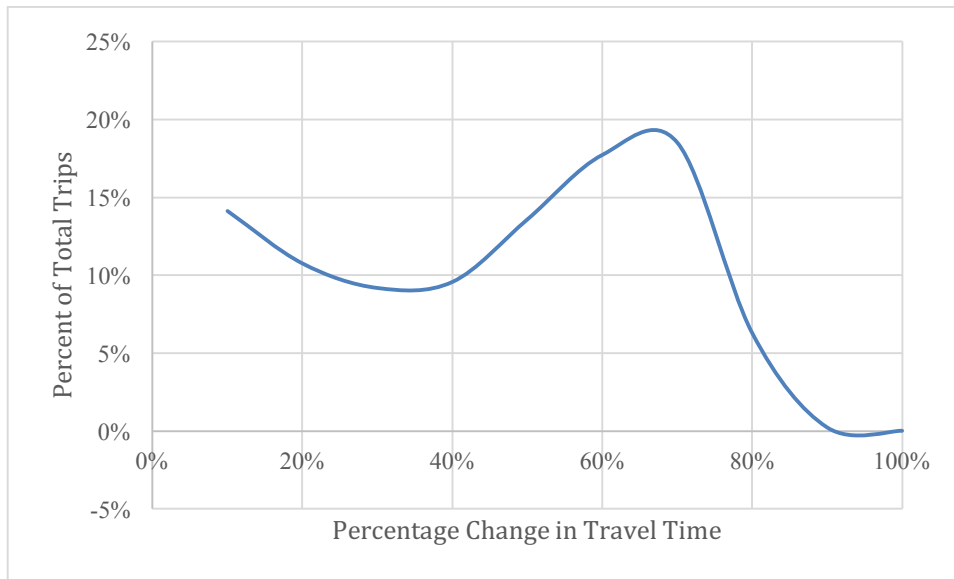

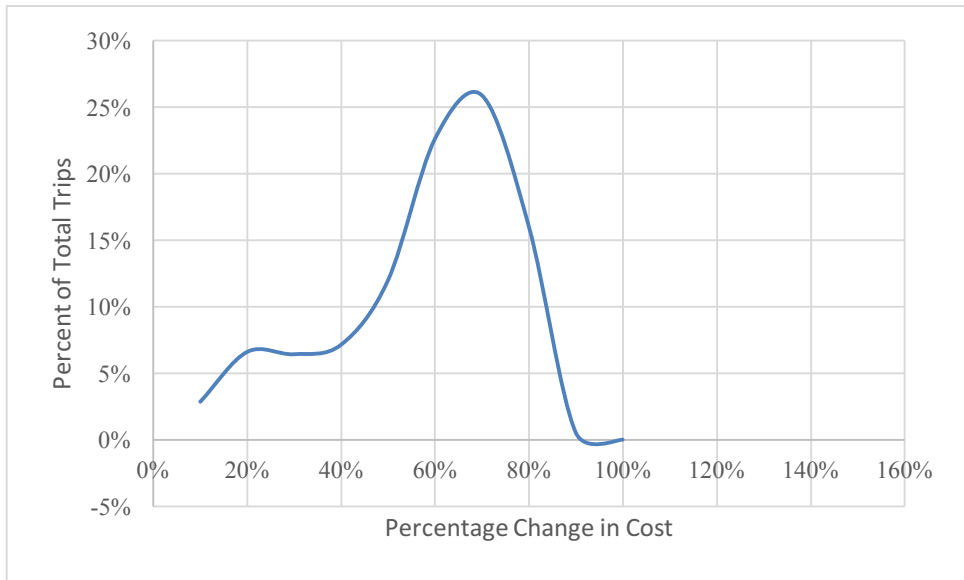**Figure 1. Trips with Reduced Travel Times**

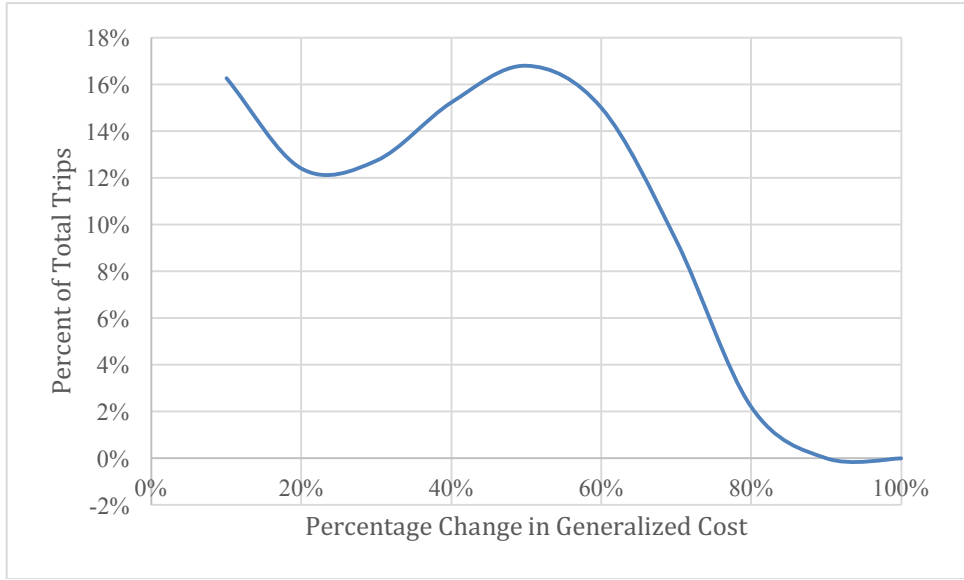**Figure 2. Trips with Reduced Monetary or Out-of-Pocket Costs**

Figure 3. Trips with Reduced Generalized Costs (Time and Money)

In Figure 4, we examine the share of trips by percentage reduction in VMT and see that 79% of trips reduced their VMT by a percentage change of more than 50%. Thus, mode switching that does not occur for small changes in cost savings may result in less than proportional reductions in VMT.
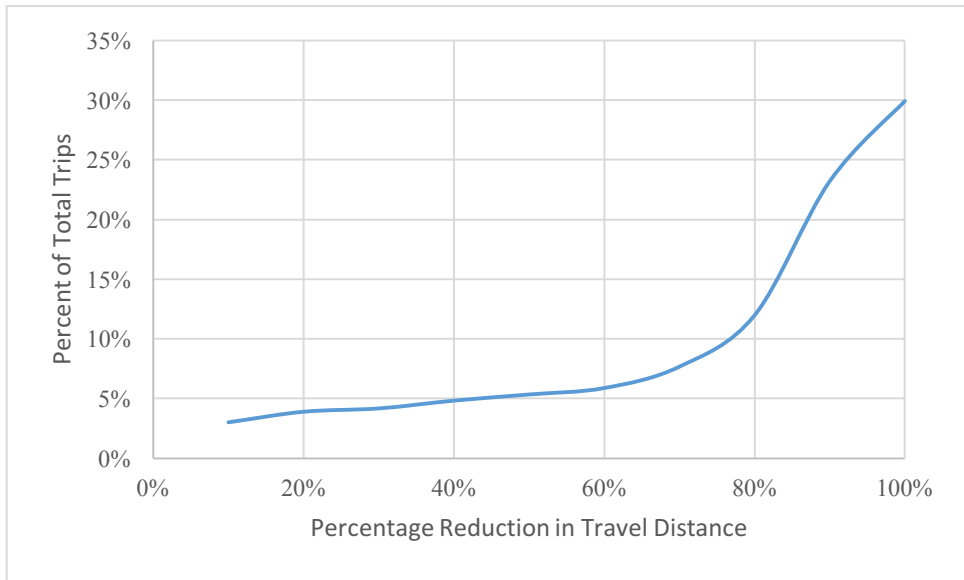
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Figure 4. Trips with Reduced Travel Distance

In Table 3, we examine the ratio of the number of trips with reduced generalized cost to the number of trips with increased or no change in generalized costs by household income class and vehicle ownership. We can see that those in the lowest income category are somewhat more likely to benefit relative to the mean. Monetary savings are valued relatively higher for lower income than higher income travelers. Those in households with one vehicle are also more likely (relative to the mean) to benefit and those with three or more vehicles are less likely to benefit. The ability to keep a vehicle available for other household members is more valuable when a household has fewer rather than more vehicles. It appears that this program would tend to assist lower income households with fewer vehicles.

Table 3. Ratio of Trips with Reduced Generalized Costs and Trips with No Change or Higher Generalized Costs by Household Income Group and by Number of Household Vehicles

	Ratio
Total Trips	0.46
Household Income	
0-20K	0.47
20-50K	0.46
50-100K	0.45
100K+	0.46
Household Vehicles	
1	0.54
2	0.46
3+	0.41

Next, we examine the percent of total trips by BART station (where trips would originate) to identify the stations that may have the best potential for early implementation. Figure 5 shows the BART stations that ranked in the top ten for total new BART trips, reduced generalized costs, and/or avoided VMT. BART stations south of San Francisco (Balboa Park, Glen Park, 24th Street, 16th Street, and Civic Center) show significant early potential with the possibility of expansion to stations further south to Millbrae (Daly City, Colma, South San Francisco, San Bruno, and Millbrae). Other potential high impact stations could include Ashby, Rockridge, Lake Merritt, Concord, and Fruitvale. If this were a feasibility study for a TNC pilot, a more detailed station-based analysis would be required, including an examination of equity benefits. In addition, a more detailed examination of the change in overall costs for passengers at all the BART stations could provide insight into the effect of subsidies (and magnitude) in the form of reduced TNC fares on accessibility for disadvantaged groups, overall increase in BART revenue, and reduced VMT.
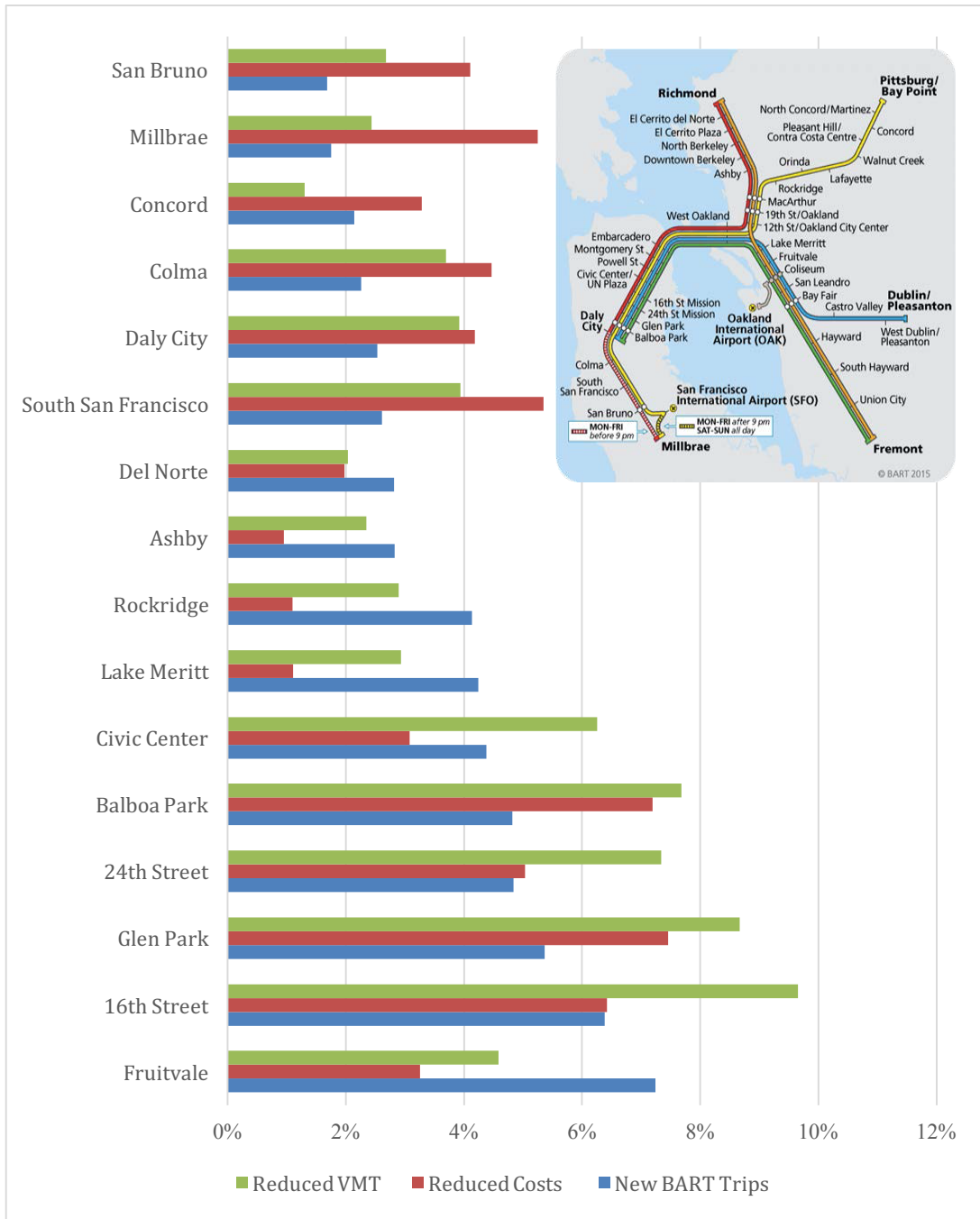
Figure 5. BART Stations Ranking in the Top Ten for New BART Trips and/or Reduced VMT and Generalized Costs

Sensitivity analyses were conducted to understand the effect of changes in TNC user costs, wait times, and travel times on transit trips, generalized costs, and VMT. In Figure 6, we see that a 10%, 30%, and 50% increase in TNC user costs (compared to the baseline scenario) reduce transit trips and increase generalized costs and VMT by about 6-7%, 15-17%, and 21-26% respectively. In Figure 7, TNC wait times are increased from five minutes to 10, 15, and 40

minutes, and reduce transit trips and increase generalized costs and VMT by 13-17%, 18-25%, and 22-33%, respectively. Finally, to examine the effect of a shared TNC transit access service, TNC user costs are reduced by half and travel time is increased by 30% and 60%. As shown in Figure 8, the scenario that reduces user costs by 50% and increases travel time by 30%, relative to the baseline, increases transit trips by 53% and increases generalized costs and VMT by 20% and 29%, respectively. When travel time is increased by 60%, there is still an increase in transit trips (by 39%) and reductions in generalized costs and VMT compared to the baseline scenario (by 11%).
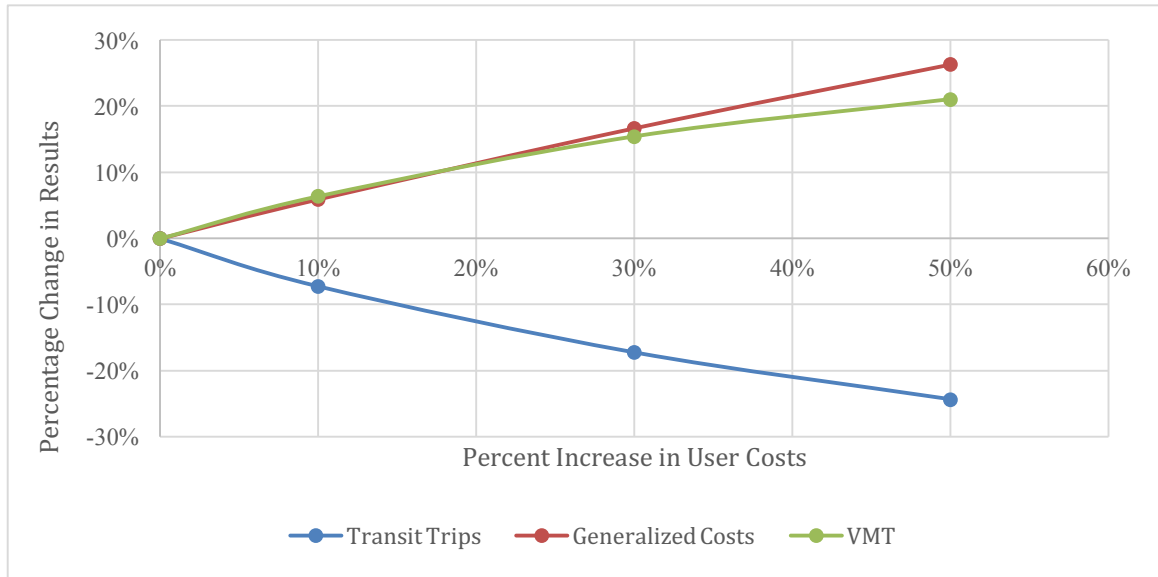

Figure 6. Percent Increase in User Costs and Percentage Change in Transit Trips, Generalized Costs, and VMT Compared to Baseline Scenario
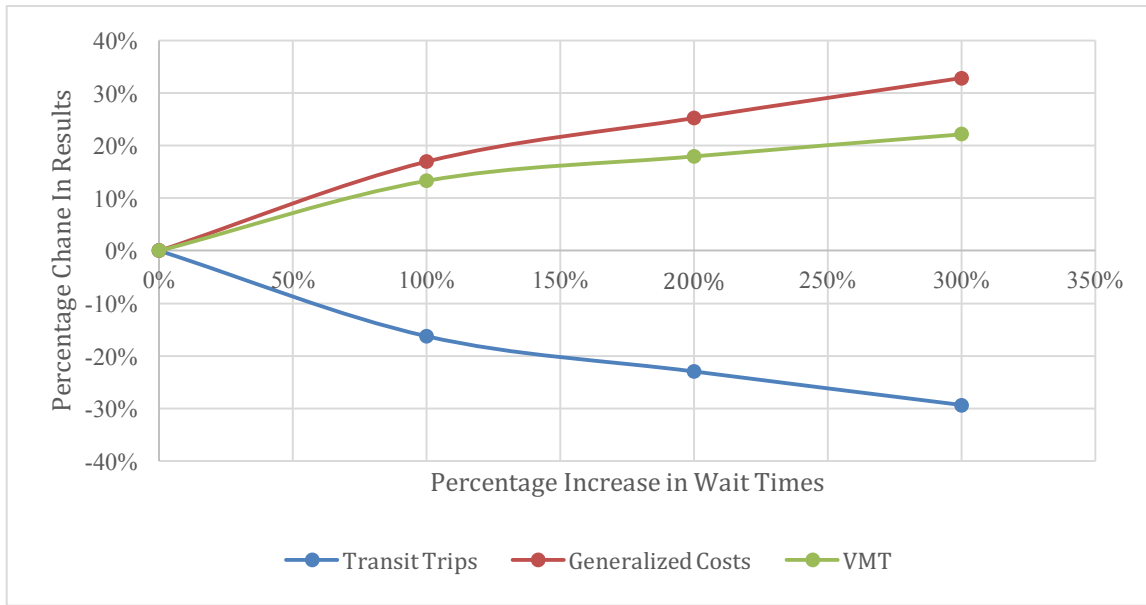
Figure 7. Percent Change in User Costs and Percentage Change Wait Times and Transit Trips, Generalized Costs, and VMT Compared to Baseline Scenario
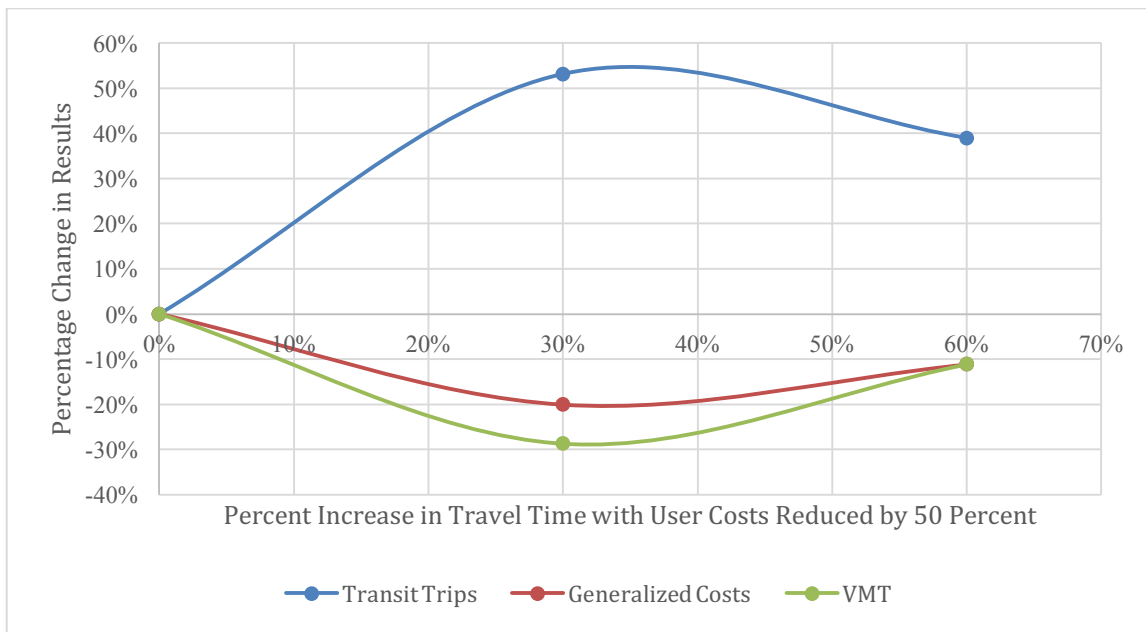
Figure 8. 50% Reduction in User Cost and Percent Increase in Travel Time and Percentage Change in Transit Trips, Generalized Costs, and VMT Compared in Baseline Scenario

In sum, we see that even with increased TNC user costs and waiting times, there is still a relatively large number of trips that could benefit (via reduced generalized costs) from switching from driving alone to using TNC and BART to travel to work during the morning

commute and thus reducing VMT. The results of the shared TNC service is also promising. We see potential baseline benefits are exceeded even when travel time costs increase by 60%.

Conclusion

The analysis indicates that 31% of identified drive-alone trips could reduce their generalized costs (travel time and monetary costs) by switching to a TNC taxi and taking BART to work. If all travelers who could benefit from traveling by TNC and BART did in fact switch from drive-alone travel, about 40 thousand new BART trips could be generated and over a half a million miles of VMT avoided during the morning commute period. A significant share of trips experienced relatively high levels of cost and VMT savings and thus may be more likely to motivate behavioral change and provide environmental benefits. Examination of cost savings by income level and vehicle availability suggests that the new service is more likely to benefit low income households with fewer vehicles.

Sensitivity analyses indicate that even with increased TNC user costs and waiting times, there is still a relatively large number of trips that could benefit (via reduced generalized costs) from switching from driving to using TNC and BART to travel to work during the morning commute and thus reducing VMT. The results of the shared TNC service is also promising. These suggest potential baseline benefits are exceeded even when travel time costs increase by 60%.

Analysis of benefits by station identify locations with relatively high market potential (i.e., trips and cost saving) and environmental benefits (VMT reduction) for early pilot implementation. These results can be used to estimate potential TNC fare subsidies to increase performance by station to achieve project objectives, such as equitable access, increased BART ridership, and reduced VMT.

This initial analysis suggests the possibility of significant economic, equity, and environmental benefits from a TNC-BART access service and BART station locations that could serve as early pilots. Of course, a broader and more detailed analysis should be conducted to evaluate the feasibility of such pilot programs. The study, however, illustrates how existing models and data can be used to conduct a "first cut" evaluation of the potential for such programs and, perhaps, direct resources more effectively toward detailed site level analyses.

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Appendix A: Literature Review

Dynamic ridesharing services (DRSs) automatically match drivers and riders with similar spatial and temporal constraints (i.e., trip origin/destination locations and departure/arrival times) and communicate matches upon request, in advance, or on demand in real time (in as little as 30 to 90 seconds). Smart phone applications are provided to participants, which allow them to request a ride, evaluate and view ratings of drivers and riders, accept or reject matches, and pay drivers. Social networks and incentive systems may be used to expand service participants and use. Under the general category of DRSs, there are two common service models, peer-to-peer ridesharing and taxi-sharing. In peer-to-peer ridesharing, drivers are independent service participants and reimbursed for trip related costs (e.g., fuel, tolls, and service fee). Drivers' ability to provide shared rides is restricted by trip related spatial and temporal requirements. In the U.S., peer-to-peer ridesharing companies (e.g., Zimride and/or Carma) currently operate in five U.S. cities (Austin, TX; San Francisco, CA; Washington, D.C.; Los Angeles, CA; and New York City, NY) (Hallock and Inglis, 2015). In taxi-sharing services, drivers may be licensed taxi drivers or independent contractors (in a Transportation Network Company [TNC], such as Uber or Lyft), fees are established by service operators to compensate both the driver and service provider, and drivers are better able to conform to riders' spatial or temporal requirements. Drivers are dispatched to maximize vehicle passengers and minimize passenger costs (e.g., travel time, wait time, and fares). In the future, automated vehicles may eliminate the drivers' role and significantly lower participant costs. Examples of taxi-sharing services in the U.S. are UberPool and Lyft Line.

DRSs provide a new mode of travel at new travel time and cost price points to many destinations in service areas. Ubiquitous DRSs may result in a series of complex and inter-related behavioral and systems level effects, with both positive and negative impacts, on congestion, VMT, and GHG emissions. In the short term, fewer vehicles may be needed to meet the travel needs of service participants, which would tend to reduce auto travel distance and time. However, in the long term, these benefits may be off-set, to some degree, by induced travel. By improving first- and last-mile access to transit stations, these services (particularly taxi-sharing) could increase transit use and lead to some reduction in congestion and auto travel, depending on induced travel effects. DRS may also provide lower fares and/or travel times relative to available transit travel and thus may increase auto travel and congestion. Individuals without access to a private vehicle or transit may travel more by auto. This would not increase vehicle miles traveled in the peer-to-peer model, but could in the taxi-sharing model as mediated by taxi-sharing fees. A reliable and affordable alternative to private vehicles may reduce auto ownership among participants, which would tend to reduce auto travel and encourage transit, walk, and bike use. Lower auto ownership levels may increase demand for more centralized residential locations with high-quality multi-modal access to destinations. In areas with pent up travel demand, congestion may not be significantly reduced. On the other hand, overall efficiency (person throughput) and equity (greater access to transportation) could

be significantly improved. Table A-1 provides a summary of some possible outcomes of DRSs and effects on VMT and GHG emissions.

TABLE A-1. Dynamic Ridesharing Services: Potential Outcomes and Effects on VMT/GHGs

Category	Possible Outcomes	Change Direction
Auto Ownership	If DRSs replace private auto for all travel needs at a lower cost, then auto ownership declines and use of non-single occupancy vehicle (SOV) modes increases.	- VMT/GHG*
Trip Generation	If access to a car and transit is limited and DRS is affordable, then new trips may be induced.	+ VMT/GHG*
Mode Choice	If travel time and costs are lower by DRS than SOVs, then DRS increases and SOVs decrease.	- VMT/GHG*
	If time and cost are lower by DRS than transit, then DRS increases and transit decreases.	+ VMT/GHG*
	If overall travel time and cost for DRS (first/last mile) and transit are lower than SOVs, then DRSs and transit increase and SOV decreases.	- VMT/GHG*
Destination Choice	If overall travel time and cost for all modes are reduced to central areas relative to outlying, then travel to central areas is more likely.	- VMT/GHG
	If overall travel time and cost for all modes are reduced to outlying areas relative to central, then travel to outlying areas is more likely.	+ VMT/GHG
Route Choice	DRS travel to pick-up and drop-off passengers and/or relocation miles.	+ VMT/GHG
	If congestion worsens, then longer routes are possible to avoid congestion and minimize travel time.	+ VMT/GHG
	Stop and start travel.	+ GHG
Build Form and Location Choice	If overall travel time and cost for all modes is reduced to central areas relative to outlying, then demand for residential and employment space may be greater in central areas.	- VMT/GHG
	If overall travel time and cost for all modes is reduced to outlying areas relative to central, then demand for residential and employment space may be greater in outlying areas.	+ VMT/GHG

* mediated by induced travel; single occupant vehicle (SOV); - = reduce; + = increase

Currently, the author is aware of no available study that systematically evaluates the travel effects of an operational DRS. However, some recent studies of similar services are of some relevance. Rayle et al. (2014) survey taxi and TNC services (e.g., Uber and Lyft) in San Francisco,

CA, and find that the majority of TNC rides would have taken significantly longer by transit. Overall, passengers take taxis and TNCs to travel to and from transit stations and to access destinations faster than possible by taking transit (Rayle et al., 2014). A preliminary evaluation of peer-to-peer carsharing services in Portland, OR, indicates that a significant number of trips made by the service would not have been made if the service were not available, and the service is frequently substituted for transit (Dill, 2015).

Two studies use survey data to examine the potential demand for DRSs in a university context in Berkeley, CA, and Cambridge, MA,. They estimate that 20-30% of drive-alone commuters to campuses could use a DRS (Deakin et al., 2010; Amey, 2011). Amey (2011) estimates that reductions in VMT could range from 9-27% of daily university commute travel, but the analysis does not account for induced travel.

Several simulation modeling studies evaluate peer-to-peer ridesharing services. Agatz et al. (2011) develop an optimization model with fixed morning commute data (i.e., the quantity of travel does not change if travel time and cost change) from the Atlanta regional travel model that matches riders and drivers (with similar temporal and special constraints and fixed travel times) while minimizing system VMT and travel costs and maximizing driver revenues. They find that, even with relative low participation rates (2%) and a time flexibility of 20 minutes, the peer-to-peer ridesharing matching rate is 70%, VMT is reduced by 25%, and travel costs are reduced by 29%. Di Febbraro et al. (2013) develop a discrete event, dynamic pickup and delivery model to optimally match drivers, riders, and network paths to minimize access and egress times in a DRS in the morning and afternoon peak period in Genoa, Italy. They find that only 13-15% of matches are refused due to excessive delays. Xu et al. (2014) combine two equilibrium models, a market pricing and traditional static assignment, to simulate the hypothetical effect of congestion and ride-sharing price on the decision of a given number of drivers and passengers to rideshare. Dubernet et al. (2012) use the MATsim model to simulate the feasibility of ridesharing in Switzerland and find that between 47% and 87% of all trips made on a daily basis could be matched into two-person carpools.

Two studies use actual taxi record data to simulate the effects of taxi-sharing services. Santi et al. (2014) develop a graph-theoretic model that estimates the trade-off between the time and monetary benefits and costs of using the service with data on 150 million taxi trips in New York City in 2011. They find significant potential for reduced vehicle travel (40%) at relatively low levels of discomfort with reduced service and passenger costs. In this study, activity data is fixed and thus induced travel effects are not represented. Martinez et al. (2014) use an agent based model that matches taxis to clients while meeting the spatial and temporal requirements of clients' trips given a maximum wait time in Lisbon, Portugal. A micro-simulation traffic model simulates taxi trips using fixed activity data from taxi records that include origin and destination and start time information for each trip. They find a possible average reduction in passenger fares of 9% in the taxi-sharing service compared to a traditional taxi service.

Fagnant and Kockelman (2015) use travel activity data from the Austin, TX, regional travel demand model (trip based model) with MATsim to simulate an automated ridesharing system. In this study, shared autonomous vehicles (SAVs) service the travel needs of the entire population in the region (1 SAV for 10 private autos). Travelers participating in DRS when doing so will add no more than 10% of their trip travel time. Relocation methods are also tested and compared. Relative to a comparable non-SAV system, SAVs generated 10% more VMT without DRS, and 10% less with DRS. This study uses fixed activity data from regional travel model.

In another study, Fagnant and Kockelman (2014) conduct sensitivity analyses of SAVs without dynamic ridesharing, which provide some insights into how congestion and VMT effects may be mediated in a simulation where travel activity or demand is not fixed. These sensitivity analyses allow trip generation, destination choice, and land use patterns to vary. The results indicate that low congestion levels in centralized urban areas are keys to reduced induced travel from SAVs.

In sum, there are a limited number of studies that quantify the effects of dynamic ridesharing systems in a real or theoretical urban environment. Most of these studies use one or more types of models: static or dynamic traffic/route assignment with and without optimization techniques. Traveler or vehicle demand characteristics are almost always fixed (or are not sensitive to changes in travel time and cost introduced by the DRS), including origin and destination locations, as well as departure and arrival times. Many studies test the effectiveness of different optimization techniques to match potential drivers and passengers. Other studies attempt to simulate the decision to share based on DRS fees and travel time delays.

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