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Exploration of Potential for Reduction in Vehicle Miles Traveled

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It is widely recognized that new vehicle and fuel technologies are necessary but not sufficient to meet deep greenhouse gas reduction goals in the United States. Demand management strategies, such as land use, transit, and auto pricing policies, are also needed. These measures, however, have historically faced political challenges and have been difficult to implement. Emerging ridesharing systems now suggest the possibility of a new demand management strategy that may be more politically palatable and reduce the number of vehicle miles traveled (VMT). To date, however, little research has evaluated their potential travel effects, especially on a regional scale. This study used the San Francisco, California, Bay Area activity-based travel demand model to simulate business-as-usual, transit-oriented development, and auto pricing scenarios with and without high, medium, and low ridesharing participation levels. The analysis suggests that relatively large VMT reductions are possible from moderate and high participation levels, but at low participation levels, VMT reductions are negligible. Moderate dynamic ridesharing alone compares favorably, with a 9% reduction in VMT, to transit-oriented development and auto pricing scenarios. The analysis also suggests a potentially promising policy combination: a moderately used regional dynamic ridesharing system with a 10- to 30-cent increase in the per mile cost of auto travel, which together may reduce VMT on the order of 11% to 19%.

New vehicle and fuel technologies are widely recognized to be necessary but not sufficient to meet deep greenhouse gas (GHG) reduction goals in the United States. Demand management strategies that reduce the number of passenger vehicle miles traveled (VMT) and related GHG emissions are also needed. These strategies typically include land use, transit, and auto pricing policies. Studies indicate that compact development that supports transit investments has a relatively modest impact on the number of VMT and GHG emissions (reductions on the order of 1.3% to 3.2% relative to the number of VMT and GHG emissions under business-as-usual scenarios) (*1*). Auto pricing policies at high per mile price levels should be significantly more effective. However, both measures have faced political challenges and have been difficult to implement. Emerging ridesharing systems now suggest the possibility of a new demand management strategy that may be more politically palatable and reduce the number of VMT and GHG emissions. Little, however, is known about the potential magnitude of this reduction, especially at regional scales.

The wider practical application of activity-based microsimulation travel demand models (ABMs) by metropolitan planning organizations not only allows the more complete simulation of land use, transit, and pricing policies (relative to that achievable with traditional four-step models) but also enables analysis of dynamic ridesharing services (DRSs). Unlike the traditional trip-based four-step travel models, ABMs track individual and household activities and travel throughout a typical day. This information makes it possible to identify trip start and end times by location, purpose, and mode. This information can then be used to identify by attributes the number of individuals and trips that could feasibly use dynamic ridesharing and, thus, the potential magnitude of avoided VMT.

The current study uses the ABM of the Metropolitan Transportation Commission (MTC) of the San Francisco Bay Area, California, to examine the potential magnitude of the market for and VMT reduction from DRSs with and without land use, transit, and auto pricing policies. The study begins with a discussion of what is known about the market and travel effects of DRSs. Next, the MTC ABM is described. This is followed by a detailed discussion of the simulated scenarios and the postprocessing models developed to estimate the travel effects of DRSs. The results of the model simulation of business-as-usual (base case), transit-oriented development (TOD), and auto pricing (VMT fee) scenarios with and without high, medium, and low DRS participation rates are presented. The study concludes with a summary of key results, policy implications, and future research.

BACKGROUND

Overview

DRSs automatically match drivers and riders with similar spatial and temporal constraints (i.e., trip origin–destination locations and departure and arrival times) and communicate matches upon request, in advance, or on demand in real time. Smartphone applications are provided to users to request rides, 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 (*2*).

Two common service models exist under the general category of DRSs: peer-to-peer ridesharing and taxisharing. In peer-to-peer ridesharing, drivers are independent service participants and riders reimburse drivers for some trip-related costs (e.g., fuel, tolls, and service fee). Drivers' ability to share rides is limited by the spatial and temporal constraints of their own travel. In the United States, peer-to-peer ridesharing companies (e.g., Zimride and Carma) operate in five U.S. cities (Austin, Texas; San Francisco, California; Washington,

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D.C.; Los Angeles, California; and New York City) (*2*). In taxisharing services, drivers may be licensed taxi drivers or independent contractors [in a transportation network company (TNC), such as Uber or Lyft]. Drivers are dispatched to maximize vehicle passengers and minimize passenger costs (e.g., travel time, wait time, and fares), given the spatial and temporal travel demand of users. In the future, automated vehicles may eliminate the drivers' role and significantly lower participant costs. Examples of taxisharing services in the United States are UberPool and Lyft Line (*2*).

Potential Travel Effects

DRSs provide a new mode of travel at new travel time and cost price points to many destinations and service areas. Ubiquitous DRSs may result in a series of complex and interrelated 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 users, which would tend to reduce auto travel distance and time. However, in the long term, these benefits may be offset, to some degree, by induced travel. With improved first and last mile access to transit stations, these services (particularly taxisharing) could increase transit use and lead to some reduction in congestion and auto travel, depending on the travel effects that are induced.

DRSs may also provide fares that are lower and travel times that are shorter than those of the forms of transit travel available and may thus increase auto travel and congestion. Individuals without access to a private vehicle or transit may travel more by auto. This increased auto travel would not increase VMT in the peer-to-peer model but could do so in the taxisharing model. A reliable and affordable alternative to private vehicles may reduce auto ownership among participants, which would tend to reduce auto travel and encourage transit use, walking, and bike use. Lower auto ownership levels may increase demand for more centralized residential locations with high-quality multimodal access to destinations. In areas with pent-up travel demand, congestion may not be significantly reduced. However, overall efficiency (person throughput) and equity (greater access to transportation) could be significantly improved. Table 1 provides a summary of some possible outcomes of DRSs and their effects on VMT and GHG emissions.

Policies such as TOD can reduce the spatial distribution of trip origins and destinations and thus increase the probability of ridesharing. In addition, expansion of access to transit, walking, and biking increases the probability of ridesharing for one or more segments of a daily tour when it reduces the probability that trip segments within the same tour can be accomplished only by driving alone. Improved transit, walking, and biking modes, however, may provide cheaper and more timely access than ridesharing for some travelers and their destinations.

Auto pricing policies, such as VMT fees, increase the incentive to share rides by reducing travel costs for drivers and passengers. The higher costs of auto travel would tend to encourage shorter travel distances between residential and employment locations and more development around high-quality transit and thus further increase the feasibility of ridesharing. Again, higher auto pricing costs could also make transit use, walking, and bike use more cost-effective than ridesharing for some travelers and their destinations.

Literature Review

The authors are not aware of any available study that systematically evaluates the travel effects of operational DRSs. However, some recent studies of similar services are of relevance. Rayle et al. surveyed taxi and TNC (e.g., Uber and Lyft) users in San Francisco and found that the majority of TNC rides would have taken significantly

TABLE 1 Dynamic Ridesharing Services: Potential Outcomes and Effects on VMT and GHG Emissions

Category	Possible Outcomes: If DRS . . .	Effects on VMT and GHG Emissions
Auto ownership	Provides access to necessary destinations at a lower overall cost (time and money) than private vehicles, then auto ownership declines and use of non-SOV modes increases.	–VMT/GHG[a]
Trip generation	Is affordable and access to a car and transit is limited, then new auto trips may be induced.	+VMT/GHG[a]
Mode choice	Costs (time and money) are less than those of SOVs, then mode share increases for DRS and decreases for SOVs.	–VMT/GHG[a]
	Costs (time and money) are less than transit, then mode share increases for DRS and decreases for transit.	+VMT/GHG[a]
	Costs (time and money) for first and last mile transit access and use are less than those by travel by SOVs, then mode share for DRS and transit increases and decreases for SOV.	–VMT/GHG[a]
Destination choice	Contributes to lower overall travel time and costs to central areas relative to outlying areas, then travel to central areas is more likely.	–VMT/GHG
	Contributes to lower overall travel time and costs to outlying areas than to central areas, then travel to outlying areas is more likely.	+VMT/GHG
Route choice	Involves additional travel to pick up and drop off passengers, then a longer overall vehicle travel distance will be required for trips.	+VMT/GHG
	Contributes to more overall congestion, then longer routes are possible to avoid congestion and minimize travel time and there could be more stop-and-start travel.	+VMT/GHG
	Contributes to less overall congestion, then shorter, more direct routes are possible and there could be more stop-and-start travel.	–VMT/GHG
Urban form	Contributes to lower overall travel time and costs to central areas than to outlying areas, then demand for residential and employment space may be greater in central areas.	–VMT/GHG
	Contributes to lower overall travel time and costs to outlying areas than to central areas, then demand for residential and employment space may be greater in outlying areas.	+VMT/GHG

NOTE: SOV = single-occupancy vehicle; – = reduced VMT and GHG emissions; + = increased VMT and GHG emissions.
[a] Mediated by induced travel.

longer by transit (*3*). Overall, passengers take taxis and TNCs to travel to and from transit stations and to access destinations faster than it is possible when they take transit (*3*). A preliminary evaluation of peer-to-peer carsharing services in Portland, Oregon, indicated that a significant number of trips made by the service would not have been made if the service had not been available and that the service frequently substituted for transit (*4*).

Two studies used survey data to examine the potential demand for DRSs in a university context, in Berkeley, California, and Cambridge, Massachusetts. They estimated that 20% to 30% of commuters who drive alone to campuses could use a DRS (*5, 6*). Amey estimated that reductions in VMT could range from 9% to 27% for daily university commute travel, but the analysis did not account for induced travel (*6*).

Several simulation modeling studies evaluated peer-to-peer ridesharing services. Agatz et al. developed an optimization model with fixed morning commute data (i.e., the quantity of travel did not change if travel time and cost changed) from the Atlanta, Georgia, regional travel model that matched riders and drivers (with similar temporal and special constraints and fixed travel times) while minimizing system VMT and travel costs and maximizing driver revenues (*7*). They found that, even with relative low participation rates and a time flexibility of 20 min, the peer-to-peer ridesharing matching rate was 70%, VMT was reduced by 25%, and travel costs were reduced by 29%. Di Febbraro et al. developed a discrete event, dynamic pickup and delivery model to optimally match drivers, riders, and network paths to minimize access and egress times in the morning and afternoon peak periods in Genoa, Italy (*8*). They found that only 13% and 15% of matches were refused because of excessive delays. Xu et al. combined two equilibrium models, a market pricing model and a traditional static assignment model, to simulate the hypothetical effect of congestion and ridesharing price on the decision of a given number of drivers and passengers to share rides (*9*). Dubernet et al. used the MATSim model to simulate the feasibility of ridesharing in Switzerland and found that between 47% and 87% of all trips made on a daily basis could be matched into two-person carpools (*10*).

Two studies used actual taxi record data to simulate the effects of taxisharing services. Santi et al. developed a graph-theoretic model that estimated the trade-off between the time and monetary benefits and costs of the use of the service with data on 150 million taxi trips in New York City in 2011 (*11*). They found a significant potential for reduced vehicle travel (40%) at relatively low levels of discomfort with reduced service and passenger costs. In that study, activity data were fixed, and thus induced travel effects were not represented. Martinez et al. used an agent-based model that matched taxis to clients while meeting the spatial and temporal requirements of clients' trips given a maximum wait time in Lisbon, Portugal (*12*). A microsimulation traffic model simulated taxi trips using fixed activity data from taxi records that included origin and destination information and start time information for each trip. They found a possible average reduction in passenger fares of 9% in the taxisharing service compared with the fares for a traditional taxi service.

Fagnant et al. used travel activity data from Austin's regional travel demand model (a trip-based model) with MATSim to simulate an automated ridesharing system (*13*). In that study, shared autonomous vehicles (SAVs) service the travel needs of the entire population in the region (one SAV for 10 private autos). Travelers participate in DRS when doing so adds no more than 10% of their trip travel time. Relocation methods were also tested and compared. SAVs generated 10% more VMT without DRS and 10% less VMT with DRS than a comparable non-SAV system. That study used fixed activity data from a regional travel model. In another study, Fagnant and Kockelman conducted sensitivity analyses of SAVs without dynamic ridesharing that provided some insights into how congestion and VMT effects may be mediated in a simulation in which travel activity or demand is not fixed (*14*). These sensitivity analyses allowed trip generation, destination choice, and land use patterns to vary. The results indicated that low congestion levels in centralized urban areas are key to reduced induced travel from SAVs (*14*).

In sum, a limited number of studies have quantified 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 or 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 on the basis of DRS fees and travel time delays.

METHODS

The ABM of the MTC of the San Francisco Bay Area belongs to the Coordinated Travel–Regional Activity Modeling Platform family of ABMs developed by Parsons Brinckerhoff. The activities or day patterns that drive individuals' need to make travel-related choices in time and space are based on the MTC's 2000 Bay Area Travel Behavior Survey. The data from this survey include data from 2-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 nonmandatory tours (escort, shop, other maintenance, social or recreational, eat out, and other discretionary). A more advanced feature of the Coordinated Travel–Regional Activity Modeling Platform family of models is the representation of interactions among household members.

All individuals and their socioeconomic characteristics in the MTC study area are generated through a statistical process known as a population synthesis, which expands survey samples (i.e., 2000 Public Use Microdata Sample and 2010 census data) of households to represent the entire population. 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.

Transportation supply is represented by the transportation analysis zone system (geographic units of analysis) and roadway and transit networks. The following modes are represented in the MTC ABM: drive alone free and paid, shared ride free and paid, walk, bike, and transit (with walk, bike, and drive access and egress modes). The 2010 zone system includes 1,454 zones. Network assignment is for the following time periods: the early off-peak period (3 to 6 a.m.), the morning peak period (6 to 10 a.m.), midday (10 a.m. to 3 p.m.), the p.m. peak (3 to 7 p.m.), and off-peak late (7 p.m. to 3 a.m.). Traffic is assigned to the network by the use of static assignment processes.

In this study, induced travel is represented through the application of elasticities from the literature as opposed to the complete travel time convergence process used in the MTC ABM. Postprocess coding for DRS by use of the convergence process would have been much more complex and computer run times for each scenario would have been significantly longer (a fully iterated run takes at least 3 days, and postprocessing for DRS scenarios can take from 6 to 24 h). As a result, the fully converged 2010 base case scenario was used and the policy scenarios (the TOD and VMT fee scenarios) were simulated with one additional model run. This approach allowed multiple scenarios to be run for each policy type and numerous sensitivity analyses that address the uncertainties around the travel effects of DRSs to be conducted. The DRS scenarios required postprocessing of the base case, VMT fee, and TOD model output files (as described below). For the scenarios that would result in a change in the average number of VMT per hour (i.e., VMT fee, TOD, and DRS), the long-run elasticity of VMT with respect to the average number of VMT per hour (0.64) was used to represent induced travel (*15*). The elasticity was applied to the change in the average number of VMT per hour in each of the five time periods in the model, and the resulting change in VMT for each time period was summed for each scenario. Change is always relative to the 2010 base case.

Although no direct empirical evidence of the effect of ridesharing on induced travel is available to date, solid empirical evidence shows that reduced congestion lowers the cost of driving and increases the quantity of vehicle travel (*16*).

SCENARIOS

The analysis included the business-as-usual (base case), TOD, and auto pricing (VMT fee) scenarios with and without high, medium, and low DRS participation rates. In the TOD scenario, residential densities around transit stations were increased by 10%, 20%, and 50% by the random selection of households from the least-dense to the most-dense zones in the region. Density was calculated with a quarter-mile buffer at the traffic analysis zone level. In the VMT fee scenario, the per mile auto operating cost for passenger vehicle travel in the MTC ABM (17.9 cents) was increased by 10, 30, and 50 cents (in 2000 U.S. dollars).

A postprocessing program was developed in C to estimate the potential market and travel effects of DRS, as illustrated in Figure 1. In Stage 1 of the postprocessing program, the relevant MTC ABM files are read into the program. These include the following files:

- Household and individual characteristics from the population synthesis,

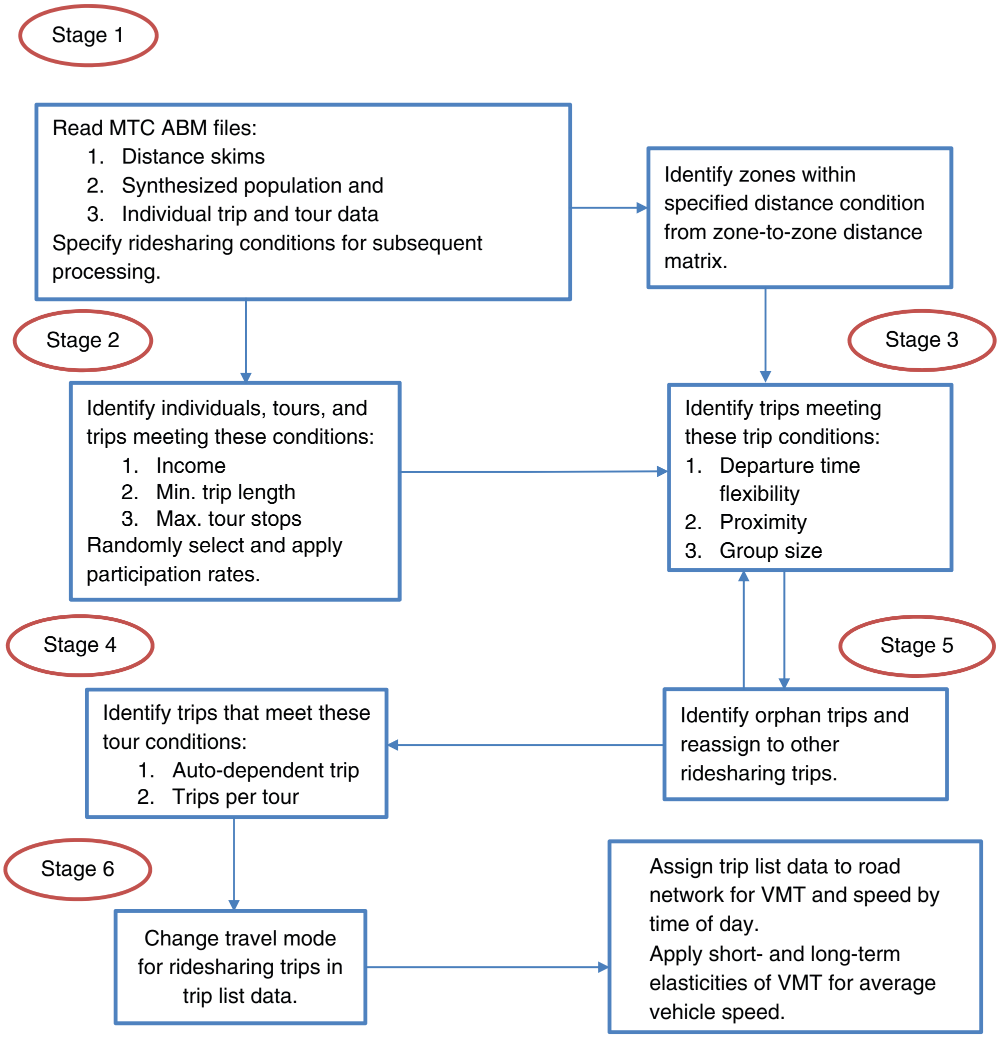

FIGURE 1 ABM postprocessing for DRS scenarios.

TABLE 2 Sensitivity Analyses and Average Elasticities of Travel for Condition Values

Variable	Value	Ride-Sharable Trips	Weighted Average Speed	VMT (LR)[a]
Maximum income	\$50,000, \$100,000, \$150,000 and \$500,000	0.0342	0.0014	–0.0040
Maximum participation	20%, 40%, 60%, and 100%	1.7011	0.0135	–0.0322
Minimum trip length	5, 10, 20, and 30 mi	–60.0523	–0.0360	0.0924
Maximum proximity	5 and 10 mi	–0.0211	–0.0011	–0.0013
Maximum flexibility	15 and 30 min	0.1069	0.0046	–0.0152

[a] VMT (LR) = long-run elasticity of VMT with respect to vehicle speed.

- Data on tour- and trip-level daily travel by households and individuals, and
- Zonal network distance estimates.

At this stage, the program specifies the following global conditions for ridesharing:

1. The minimum and maximum number of travelers allowed in a ridesharing trip (group size),
2. The presence of one driver for each ridesharing trip,
3. The maximum number of minutes that a traveler is willing to wait to share a ride (maximum departure time flexibility),
4. The minimum trip distance for a traveler to share a ride (minimum trip length),
5. The maximum percentage of ride-sharable trips within a tour required for a traveler to share a ride (maximum ride-sharable trips per tour),
6. Maximum number of stops allowed in a tour to participate in a ridesharing trip (maximum tour stops),
7. Maximum individual income level required for an individual to participate in ridesharing,
8. The rate at which people will share a ride given the ability to share a ride (participation rate), and
9. The maximum number of miles between trip origin zones of potential ride shares (proximity).

Stage 2 identifies individuals with tours and trips that meet the maximum income, minimum trip length, and maximum tour stop conditions. These individuals are then randomly selected to share a ride on the basis of specified participation rates. In Stage 3, the trips identified in Stage 2 are evaluated to identify those who meet departure time flexibility, proximity, group size, and driver conditions. The MTC ABM currently uses 1-h departure time windows. The 2000 Bay Area Travel Survey is used to estimate the distribution of trip departures by 15-min intervals per hour within each time period and by county. Trips within each hour from the model are then randomly selected and assigned departure times within the hour on the basis of the weighting factors developed from the estimated distribution. In Stage 4, the resulting trips are then evaluated against tour-level conditions, including auto-dependent trip (i.e., one or more trips within a tour can be satisfied only by the auto mode) and the number of trips per tour, to further refine ride-sharable trips. In Stage 5, the program identifies ridesharing trips that lost a ridesharing group (orphan trips) between Stage 3 and Stage 4. The program reassigns these orphan trips to new ridesharing groups on the basis of an iterative process among Stage 3, Stage 4, and Stage 5. In Stage 6, travel modes for ridesharing trips are changed in the original input trip list. Finally, the revised trip list is assigned to the roadway network to estimate VMT and speed (in miles per hour) by time of day, which are adjusted with elasticities from the literature, as described above, to represent long elasticities.

In the current study, the following conditions were fixed across all scenarios: the maximum income was \$375,000, the group size ranged from two to five, a maximum of 50% of tour trips had to be ride sharable, and the maximum number of tour stops was six. Sensitivity analyses of income, participation rates, trip lengths, origin proximity, and travel time flexibility were conducted. The study did not include trips that could be matched along a route. As the literature review pointed out, evidence of the effect of these variables on the willingness to participate in DRSs is limited. The results of the sensitivity tests indicated that ride-sharable trips were elastic with respect to participation rates and length of trips (Table 2). However, all other travel results were inelastic with respect to variation of the other condition variables.

Three DRS scenarios in which DRS parameters were varied to represent minimum use, moderate use, and maximum use of the service were created. Variable conditions in the dynamic ridesharing scenarios (maximum, moderate, and minimum use) included the following: departure time, participation rate, and proximity. These scenarios were simulated alone and in combination with the VMT fee and TOD scenarios. The parameters selected for these scenarios are described in Table 3. Income was not varied because the results of the sensitivity test indicated that participation and VMT were relatively less sensitive to this variable than the other variables (with the exception of proximity). Because proximity would be affected by the TOD scenario, the authors decided to include this in the scenario, despite the relatively low elasticity values. The scenarios with high and low DRS participation rates were designed to be scenarios of extreme use, and the scenario with a moderate DRS participation rate was likely a conservative estimate of the use of a DRS with high-quality regionwide service and affordable use costs.

RESULTS

The share of the ride-sharable trips relative to the total number of trips in each scenario is presented in Table 4. At maximum levels of ridesharing use, 32% to 41% of all trips were ride sharable (or trips that

TABLE 3 Minimum, Moderate, and Maximum DRS Use Values

Variable	Minimum	Moderate	Maximum
Maximum participation (%)	20	50	100
Minimum trip length [mi (km)]	30 (48.3)	10 (16.1)	5 (8)
Maximum proximity [mi (km)]	1 (1.6)	5 (8)	15 (24.1)
Maximum flexibility (min)	15	30	60

TABLE 4 Share of Ride-Sharable Trips Relative to Total Trips by Scenario

Scenario	Ridesharing (%) Maximum	Moderate	Minimum
Base case	40.54	9.56	0.11
10% TOD	40.33	9.48	0.11
20% TOD	40.24	9.46	0.10
50% TOD	40.03	9.40	0.10
VMT fee (10 cents)	38.07	8.85	0.09
VMT fee (30 cents)	34.49	7.90	0.07
VMT fee (50 cents)	31.92	7.26	0.06

TABLE 6 Percentage Change in Long-Run VMT Relative to Base Case Without Ridesharing for Policy Scenarios With and Without Ridesharing

Scenario	With Ridesharing (%) Maximum	Moderate	Minimum	Without Ridesharing (%)
Base case	−23.1	−8.7	0.0	0.0
10% TOD	−23.3	−8.9	−0.3	−0.2
20% TOD	−23.4	−9.0	−0.4	−0.3
50% TOD	−23.5	−9.3	−0.7	−0.6
VMT fee (10 cents)	−24.6	−11.3	−3.3	−3.2
VMT fee (30 cents)	−26.8	−15.6	−8.7	−8.5
VMT fee (50 cents)	−28.5	−19.1	−13.1	−13.0

could be shared, given the specified conditions if a traveler decides to share it) across the policy scenarios. At minimum levels, less than 1% of all trips were ride sharable. At moderate levels, 7% to 10% were ride sharable. As discussed above, the scenarios with high and low DRS participation rates were designed to be scenarios of extreme use that bookend the more moderate ridesharing use scenario.

Compared with the results obtained in the base case scenario, ride-sharable trips declined somewhat in the TOD and VMT fee scenarios with higher levels of TOD and VMT fees across all levels of ridesharing use. Transit, walk, and bike travel increased relative to auto travel in both the TOD and VMT fee scenarios. In the TOD scenario, as land uses intensified around transit stations, these modes were better able to compete with auto travel. In the VMT fee scenario, higher auto travel costs made the walk, bike, and transit modes more attractive than auto travel. As discussed above, improved transit, walk, and bike modes may provide cheaper and more timely access than ridesharing for some travelers and their destinations and the VMT fee could also make transit use, walking, and bike use more cost-effective than ridesharing for some travelers and their destinations. The share of the ride-sharable trips did not include induced travel effects and thus may be underestimated to some degree. Shorter auto travel times due to increased ridesharing (as described below) would tend to induce more auto trips.

As presented in Table 5, in the ridesharing scenarios, daily average weighted speed (in miles per hour) relative to that in the base case without ridesharing increased by about 8% for maximum use levels, 3% to 6% for moderate use levels, and 0% to 4% for minimum use levels. The variation in the results was greater across the VMT fee scenarios than the TOD scenarios. Again, induced travel was not represented in these data, and thus the reductions were likely overestimated (Table 5).

TABLE 5 Percentage Change in Daily Average Weighted Speed Relative to Base Case Without Ridesharing for Policy Scenarios With and Without Ridesharing

Scenario	With Ridesharing (%) Maximum	Moderate	Minimum	Without Ridesharing (%)
Base case	7.7	3.3	0.0	0.0
10% TOD	7.8	3.5	0.2	0.1
20% TOD	7.8	3.6	0.3	0.2
50% TOD	7.9	3.7	0.5	0.4
VMT fee (10 cents)	7.8	3.9	1.2	1.1
VMT fee (30 cents)	8.0	4.8	3.0	2.9
VMT fee (50 cents)	8.3	5.5	4.3	4.3

The VMT results, which included induced travel effects over the long run, are shown in Table 6. The reductions in VMT in the TOD scenarios relative to the VMT in the base case were relatively small, which is not surprising in the San Francisco Bay Area, which already has relatively high residential densities and high levels of transit use compared with those in other regions in California and the United States. The VMT reduction for the VMT fee scenarios, however, was comparatively large (ranging from 3% to 13% with induced travel over the long run). Addition of dynamic ridesharing to the base case, TOD, and VMT fee scenarios showed reductions in VMT on the order of 9% to 30%. The VMT fee and TOD policies could have been combined into one scenario. If so, it could have performed better than the TOD and VMT fee policies with minimum ridesharing but not with maximum and moderate ridesharing because of the large gap in effectiveness of the policies.

CONCLUSIONS

This study used the San Francisco Bay Area's (MTC) ABM to explore the potential reduction in VMT (and related GHG emissions) from a regional dynamic ridesharing system at different levels of use. The results indicate that relatively large VMT reductions are possible from moderate and high levels of use of ridesharing. At low levels of ridesharing, VMT reductions are negligible. The dynamic ridesharing scenario with a moderate level of use alone (added to the base case scenario) compares favorably, with a 9% reduction in VMT, with all TOD scenarios and the VMT fee scenarios in which the auto travel cost is increased by 10 and 30 cents without ridesharing. These findings are promising given the potential political challenges to the implementation of TOD and VMT fee policies. The results obtained with the combination of dynamic ridesharing with the TOD and VMT fee scenarios suggest that some policy combinations may be more effective than dynamic ridesharing alone but perhaps more politically palatable; for example, a moderately used regional DRS with a 10- to 30-cent increase in VMT fees may produce reductions in VMT on the order of 11% to 19%.

Future research should explore the factors associated with higher levels of dynamic ridesharing, including individual attributes, the characteristics of tours and trips, and time and cost benefits. In addition, the travel effects of dynamic ridesharing systems should be simulated explicitly, including auto ownership, mode choice, destination, and taxisharing pickup VMT. Future research should also explore how the market may expand if passengers could be picked up along a route by a ridesharing vehicle.

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All errors are those of the authors.

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