IMPACTS OF SHARED AUTOMATED VEHICLES ON AIRPORT ACCESS AND OPERATIONS, WITH OPPORTUNITIES FOR REVENUE RECOVERY: CASE STUDY OF AUSTIN, TEXAS

Krishna Murthy Gurumurthy, Ph.D.
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
gkmurthy10@utexas.edu

Kara M. Kockelman, Ph.D., P.E.*
Professor and Dewitt Greer Centennial Professor of Transportation Engineering
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin – 6.9 E. Cockrell Jr. Hall
Austin, TX 78712-1076
kkockelm@mail.utexas.edu

Research in Transportation Economics Vol. 90, 101128

ABSTRACT

With rising use of ridesourcing apps and, eventually, self-driving vehicles, demands for airport parking spaces, rental cars, and, ultimately, airline service and availability are expected to fall everywhere, relative to background trends. This study uses publicly available ridesourcing demand data for the Austin, Texas area to pursue simulations of a futuristic fleet of shared autonomous vehicles or "SAVs", and quantify airport-revenue and -operations impacts. Results for a pandemic-free world suggest that dynamic ride-sharing (DRS) of centrally-dispatched vehicles across strangers (with current airport-related travel patterns) may reduce airport-related ground travel by up to 30% while reducing airport revenues by 46%, assuming ridesourcing permits continue to be charged $2 per trip. A time-varying zone-based toll around the airport can help offset lost parking and car-rental (but not seat-mile) revenues and potentially double present-day airport-access revenues. Such policies can come at the cost of adding non-revenue ridesourcing and SAV miles to the rest of the network, when incentivizing SAVs to leave the airport zone after a dropoff, in order to avoid curbside congestion. A combination of DRS among strangers and use of access fees on all commercial vehicles dropping off or picking up travelers can achieve a healthy middle ground.

Keywords: *Airport operations, airport parking, airport revenues, shared autonomous vehicles, dynamic ride-sharing, time-varying zone-based tolls*

BACKGROUND

Civil aviation is an important backbone of local, regional and national economies, and U.S. aviation accounts for over $1 trillion of annual gross domestic product (Federal Aviation Administration, 2017). Airports are key to such contributions, and generally function as self-supporting entities, run by counties, cities, municipalities, and other forms of governance, typically termed airport authorities, reliant on airline fees and local concessions, including parking, car-rental, and access fees. U.S. airline-related revenue earned by airports is regulated by the Federal

* Corresponding author

Aviation Administration (FAA), while car- rental fees, parking charges, and taxi-access fees comprise about 40% of all other U.S. airport revenues (Ibarcena, 2017). More recently, airports have begun charging access fees to ridesourcing companies as well. Out of the 40%, parking and car-rental fees form the bulk of the revenue stream and vary based on airport, airport size, vehicle ownership, and public transit service levels in the city. It may be that larger airports tend to generate more parking revenue, and popular tourist destinations may see more rental-car revenue. Airports in transit-centric cities like New York City may have relatively low rental-car revenue, whereas auto-centric cities like the Texas Triangle in Texas are likely to have higher parking-related revenue.

The use of smartphones, and consequent emergence of disruptive technologies, like ridesourcing applications run by transportation network companies (TNCs) such as Uber and Lyft, tends to lower the traditional revenue streams (Zmud et al., 2017). Studies have seen that parking revenue is no longer an indicator for airport passenger growth, and that it has been declining over the past few years (Henao et al., 2018). Airports report that TNC use is rising substantially, every year, and TNC permits to access major airports are regularly renegotiated to adapt to this evolution (Box et al., 2017). These permits fall into two broad categories: an annual fee versus a per-trip fee. Box et al. (2017) found that annual fees, typically assessed at small-hub airports, generate revenues of just $2,000 per year per company. However, Ibarcena (2017) states that fleet-size dependent fees in Georgia, at $300,000 per year for permitting more than 1,000 vehicles, may be the largest with growing usage. In medium to large hub airports, per-trip fees are common, and those total revenues can range from $2M to $5M USD per year (Box et al., 2017), on average, with a maximum of about $20M a year in the U.S.. Some environmentally conscientious airports, like the Seattle-Tacoma International Airport in Washington State, maintain an independent log of emission standards on all TNC vehicles that serve the airport (Schwanz, 2016). Most airports, however, rely on data that the TNCs themselves provide, based on rides made to those airports. A study in Washington DC showed that the lack of designated pickup and dropoff locations for TNCs at airports can quickly add congestion to the arrival and departure curbs (District Department of Transportation, 2018). Hermawan and Regan (2018) also corroborated that TNCs are exacerbating curbside congestion with a net increase in single-occupant travel after accounting for mode shifts. Shared fully-automated vehicles (SAVs) and other new auto modes will do the same.

SAVs are expected to provide a convenient and cost-competitive alternative to driving oneself or buying a self-driving vehicle in the future (Kockelman et al., 2016). Personal AVs and SAVs are expected to shift Americans' and others' long-distance travel patterns and mode choices (Perrine et al., 2018; Huang and Kockelman, 2019), impacting highways, airline revenues and airport operations significantly (RSG, Inc. et al., 2019). This is more likely to be true for trips shorter than 500 miles. For example, LaMondia et al. (2016) predicted a 20-30% shift in U.S. long-distance mode choices from airlines to AVs for distances under 500 miles (one-way) using Michigan's long-distance travel survey data. Similarly, Perrine et al. (2018) estimated that airline revenues for domestic travel within the U.S. may fall by 53% from the use of personal and shared AVs. Huang and Kockelman (2019) estimate 30% to 50% more vehicle-miles travelled (VMT) on Texas roadways and highways, due to new trip-makers, longer trips, and fewer airline trips, everything else constant. While household-owned AVs will have important impacts, they are expected to be expensive and difficult to own and use initially, with added costs over $25,000 or more, in early release years (IHS Automotive, 2014) and even $100,000 or more with how the technology is developing (Fagnant and Kockelman, 2015). In the future, SAVs operating as a smart and driverless TNC service, like Lyft, Didi and Uber, is expected based on a fleet evolution study (Quarles et al., 2020), and will change how people will travel in cities and regions. Studies have shown that without adequate policy in place, local, regional, and national VMT can increase, further congesting urban and rural networks (Simoni et al., 2019; Huang and Kockelman, 2019).

SAVs will be less expensive to access, thanks to avoidance of high purchase costs and without driver-related labor costs (Loeb and Kockelman, 2019), which form 60-80% of TNC and taxi revenues (Walker and Johnson, 2016; Grover, 2019). Low-cost SAVs at a $1 per mile or less fare (Fagnant and Kockelman, 2018; Bösch et al., 2018; Loeb and Kockelman, 2019; Becker et al., 2020) are expected to induce new and longer travel demands, while encouraging more single-occupant travel. From an airport operation's perspective, single-use SAVs circulating at airports (for passenger pickups and dropoffs) will exacerbate congestion along many sections of airport networks. Some may argue that advanced automation technology will ensure some congestion mitigation during travel by optimizing braking and accelerating, ideally in coordination with other vehicles on the road segment. While this may be the case, there is bound to be congestion at the limited curbspace available at airports. SAVs, regardless of automation sophistication, will need to stop at the curb to pickup and dropoff travelers accessing and egressing the airport. Although fees levied on SAVs will generate revenue for the airport, they may not be successful in curbing congestion. Tscharaktschiew and Evangelinos (2019) highlight how congestion is expected to worsen in light of automation available to users, even when there is road pricing thanks to complications in welfare impacts when drivers are able to switch between driving and being driven. The change in a traveler's value of travel time is important to take into account, especially for higher value airport access trips. This is expected to lead to lower sensitivities making it difficult to mitigate congestion at the curb. Policies to optimally moderate such induced demand merit investigation. Such impacts can be avoided if more travelers are bundled into fewer cars, with SAV systems pooling travelers so that trips are shared through dynamic ride-sharing (DRS). DRS has been shown to reduce needed vehicle fleets by 60-95% (Spieser et al., 2014; Burghout et al., 2015; Martinez and Viegas, 2017; Alonso-Mora et al., 2017; Fagnant and Kockelman, 2018; Gurumurthy and Kockelman, 2018). Another option is to price travel entering and exiting the airport using a zone-based toll that is time-varying, similar to the policy applied at the city level in Simoni et al. (2019) and Gurumurthy et al. (2019), but focused within the airport zone. This can help discourage large numbers of SAVs from waiting near the airport for new trips and can help keep traffic flowing across the airport's roadways and curb spaces. Some airports currently use a staging area for TNCs to aid in better flow at the flight arrival curbspace. However, these lots have capacity issues at peak times (Davol, 2017) and may not be generally viable for medium to large hub airports.

In this study, the multi-agent transport simulation tool MATSim is used along with a TNC's paid-trips dataset from Austin, Texas to quantify the impact of SAVs on airport operations in terms of both revenue and curbside congestion. The Austin-Bergstrom International Airport (ABIA) had an annual passenger traffic of about 15.8 M people in 2018[†], and this is rapidly increasing. It is well connected by transit, and provides short-term and long-term parking options. TNC access for drop-offs and pickups are regulated by the airport with a per-trip fee of $2. Data availability for ABIA and the airport's characteristics makes it a suitable case study. Data set descriptions are provided in the next section to provide some background on the TNC service. This is then followed

[†]Obtained from http://www.austintexas.gov/news/december-2018-passenger-cargo-traffic-austin-bergstrom

by simulation methods used, results and inference, along with conclusions and recommendations for airport managers.

RIDEAUSTIN DATASET

Ridesourcing companies currently operate similar to how a future fleet of SAVs may operate, minus the added human factor that may bring down compliance and optimality in SAV operations. Ridesourcing data are largely unavailable for large, for-profit corporations like Uber and Lyft. However, the Austin-based non-profit TNC RideAustin released its data (https://data.world/ride-austin) in 2017 for trips made through their smartphone application between June 2016 and April 2017. A total of nearly 1.5 M trips were logged in that period, with numbers quickly rising to a daily average of about 7,000 paid trips across the City of Austin.

RideAustin was created when TNCs lost a vote on drivers being required to undergo fingerprint-based background checks to operate in Austin, and immediately stopped operations (Dockterman, 2016). This meant that RideAustin operated without competition for almost a year before the two major TNCs returned. Origins and destinations for airport trips by RideAustin users, who are potential users/more likely adopters of SAVs (Lavieri et al., 2017; Stoiber et al., 2019), add value to this simulation. All dataset trips are geotagged with coordinates truncated up to 3 decimal places to ensure privacy, with anonymous but consistent/permanent driver and rider IDs provided throughout the 1-year period. Trips performed by riders are captured and can be synthetically recreated to use with MATSim (described below). Figure 1 shows the total trips that started or ended at the airport for every day in the dataset. After RideAustin usage stabilized, a daily average of about 700 trips were observed either starting at or ending near the airport. A noticeable peak is seen in March, 2017, from higher airport usage during Austin's annual and internationally known South by Southwest (SxSW) event. One 24-hour period from 00:00 to 23:59 hours on 7th April 2017 was chosen to provide a stable share of trips that does not appear affected by any notable random events.

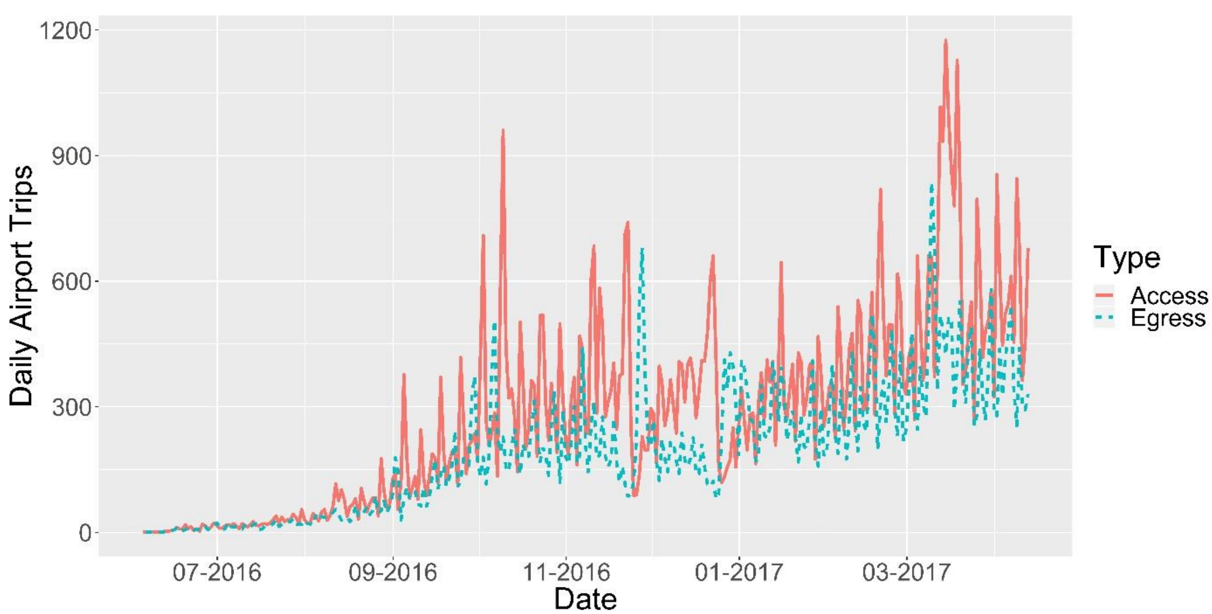

Figure 1 Number of RideAustin trips starting (egress) and ending (access) at ABIA airport each day

Figure 2 shows the access and egress trips by time of day and Figure 3 illustrates the spatial variation of all airport trips in the dataset across Austin, Texas. It is clear from the Figures that many travelers in Austin choose to fly in the early afternoon hours with 30 plus access trip requests logged for the chosen date in the RideAustin dataset. Arrival at ABIA is typically in the early evenings to later in the night. Geographically, travelers in TAZs downtown and the core of the City are seen to frequent the airport using ridesourcing. There is some demand all the way south from San Marcos to access the airport, but no egress trips were logged for the same in the dataset. Travelers living in the outer suburbs are Austin may be opting into driving their personal vehicles and choosing parking options at the airport, owing to RideAustin not being popular in those neighborhoods.

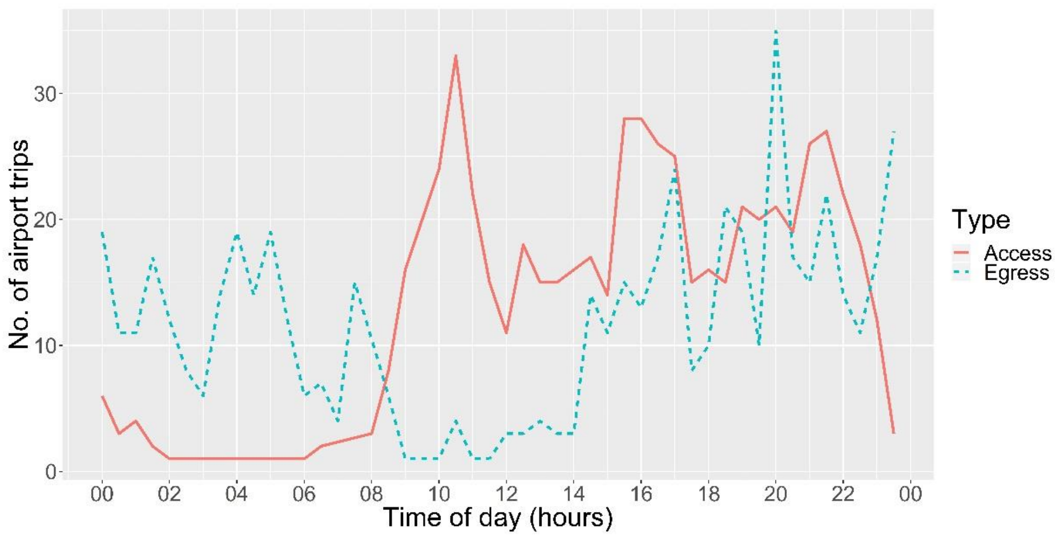

Figure 2 Access and egress trips made by time of day for chosen date

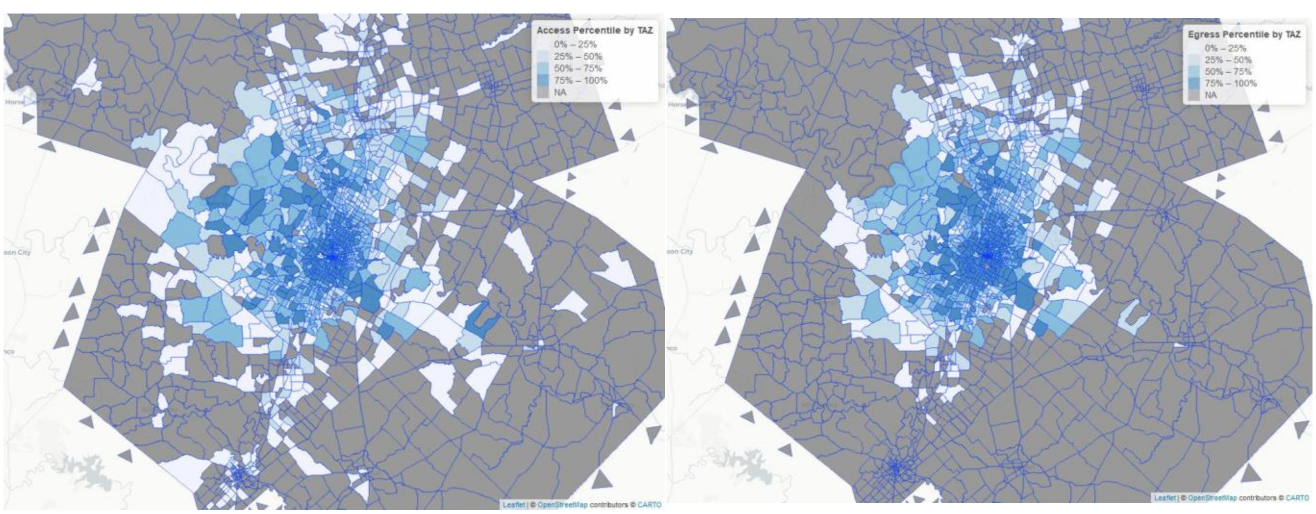

Figure 3 Spatial distribution of airport access and egress trips

Data for this summary reveals that each of these 635 TNC vehicles served almost 1.82 ± 1.28 trips per day, on average. Fares were assessed as a fixed (start-up) fare of \$1.50, a time-dependent fare of \$0.25/min, and distance-dependent fare of \$0.99/mi. RideAustin also uses a surge factor applied based on experienced delays and driver availability throughout the day. Fares also rise with larger vehicles chosen (to handle larger travel-party sizes or lots of luggage, for example). On average, RideAustin's airport-based (at origin or destination) trips during this 24-hour period costed \$1.90/mi. For a clear analysis of TNC trips in the Austin area encompassing the entire dataset, please refer to Zuniga-Garcia et al. (2020).

METHODOLOGY

An agent-based simulation of airport access and egress trips was performed using MATSim (Horni et al., 2016) to microscopically (i.e., at the link and person levels) observe the future impact of SAVs at, and around, the airport. The use of a simulation framework adds flexibility in analyzing different policies and a fleet's operational characteristics that are not currently observed from revealed data. Conducting this at the agent level helps modelers keep track of individual trip-makers' behavior throughout the simulation timeframe for all cases tested. Figure 4 shows the MATSim loop that is comprised of a mobility simulation, replanning module to innovate agents' daily plans, and scoring to estimate feasibility, in each iteration. A dynamic traffic assignment algorithm governs the mobility simulation which essentially models a vehicle's movement from link-to-link and within the link using a queue-based traffic model. The replanning module uses a co-evolutionary iterative in order to choose modes which conform to a logit structure for choice. The scoring of an agent's progress in the simulation is done based on value of productive time and value of travel time to compare how travelers are reacting to a new mode being available, or to a new policy being incorporated in the simulation. Ultimately, the replanning and scoring module ensures that a convergent set of trip itineraries are produced for the agents being simulated. The results of the mobility simulation provide link-level statistics of travel times and congestion, and can be used to observe effects near the airport.

In MATSim, all traveler demand stays constant while the replanning module attempts to find better utility for each agent by changing mode, departure time, and route. For airport trips, the replanning module in this study is specifically focused on route choice and departure-time choice in lieu of competing modes. Additionally, agents' reactions to future policies implemented within the simulation framework are also captured, and these policies are explained later. With the focus of this analysis being the comparison of present-day TNC operation to future low-cost SAVs with DRS, assuming a fixed demand helps us focus on the operational differences between these scenarios. Several studies allude to shared mobility being the norm in the future (Fagnant and Kockelman, 2015; Shaheen and Cohen, 2019; K.M. Gurumurthy et al., 2019; Narayanan et al., 2020), so demand is likely only to increase compared to our assumption and results from this study, thus, can provide a suitable argument for airport ground operations reform. Person-level scoring is important to realize how current-day TNCs compare to future operation of SAVs, especially while considering changes in fare structure and operations. This is derived using the scoring schema that is present within MATSim. Parameter assumptions for this schema in order to capture the differences in operation are discussed below.

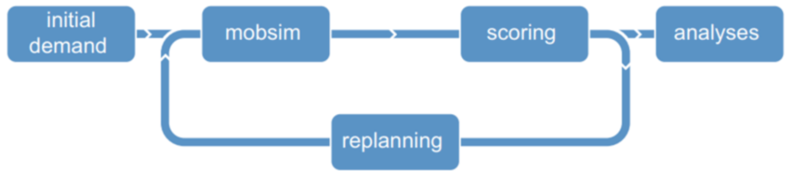

Figure 4 MATSim's multi-agent transport simulation loop (Horni et al., 2016)

Trip data from the RideAustin dataset (spanning 24-hr for the chosen day) were filtered for airport trips and post-processed to obtain a suitable input for MATSim. Trip itineraries in MATSim consist of tours of activities and legs. That is, an agent starts at an activity location where the agent is assumed to be productive, and the trip between activity locations is called a leg, where the agent is using a preferred mode for travel. Since the simulation focuses on airport trips, two activity locations are assumed here – home and airport, i.e., the travelers in these simulations are always at home or at the airport. All legs, as stated earlier, are assumed to be TNC/SAV legs to understand airport access and egress using the current services like Uber and Lyft, and future services like those of SAVs. Trip data used here are available with distinct origin and destination coordinates up to the third decimal place owing to privacy concerns. However, even with three decimal places, home locations are spread throughout the region with a fair representation of actual geographic trip distribution.

Average trip scores assessed before and after changes in policy will help infer how traveler utility was impacted. In order to standardize inferences on current and future trip-making behavior, travel parameters within the simulation are adapted from Simoni et al. (2019) for the present-day and future scenarios that involve SAVs. MATSim maximizes the net utility across all trips and activities for each agent using a genetic algorithm where activity-related utilities are obtained using a logarithmic function based on base travel time (Charypar and Nagel, 2005). The value of travel time savings can be set using the first equation in (1) based on an activity's experienced duration and SAV travel time disutility (normalized to 1). The marginal utility of money is set at 0.79, consistent with Simoni et al. (2019), to reflect the value of travel time (VOTT) of $18/hr within MATSim. SAV travel in mode choice studies in MATSim for Austin, Texas has previously assumed a 50% lower VOTT (Simoni et al., 2019; Gurumurthy et al., 2019). The VOTT assumption remains at $18/hr for this analysis since travelers are expected enjoy time in an SAV similar to being chauffeured in a TNC vehicle. This is not a concern as it does not impact mode choice, but is useful when comparing traveler utility before and after the policy implementation. The data used to synthesize the travelers used in this study come from the RideAustin trip dataset as discussed earlier. These travelers used a TNC vehicle to go to or leave the airport from their origin or destination, respectively. With an inexpensive service provided by SAVs (through fare reductions from no driver-related costs) and further discounts from choosing to share rides, it is unlikely that travelers will change their mode to a conventional mode. It is possible that they may choose to use a personal AV, but since this study targets a future where the bulk of travelers will not have access to a personal AV thanks to high upfront add-on costs for the automation technology, all travelers are assumed to choose to travel in an SAV. The alternative specific constants, required by MATSim for every mode, are set to 0 as a result. While current day TNC operations are roughly about $2/mi, studies anticipate SAV fares lower than $1/mi (see, for e.g., Bösch et al., 2018; Fagnant and Kockelman, 2018; Loeb and Kockelman, 2019). Solo travel in an SAV is charged $1/mi in this study. Changes in traveler utility with fares lower than currently observed will also show propensity for SAV travel. Traveler utility in this study is comprised mainly of the disutility from fares and travel time as shown in equation 1. Without mode choice, the absolute value of traveler utility is not as useful as the relative change in utility between scenarios. Therefore, the percentage change in utility is reported in the results.

$$\mathrm{VTTS} = (\beta_{act} - \beta_{mode}) / \beta_{cost}$$
$$U_{TNC/SAV} = -\text{ Travel Time } - 0.79 \times \text{Fare}_{\ TNC/SAV,\ DRS/no\text{-}DRS} \tag{1}$$

Table 1 Scoring Parameters for Current and Future Services

The agent-based simulation framework, MATSim, described above is used here to compare current-day airport access and egress to that by future modes that differ in fares and utility. These changes in behavior are studied in conjunction with some operational policies that are expected in SAVs to curb congestion. These policies and their associated modules are discussed next.

Policy 1: Dynamic Ride-Sharing and Fleet-Sizing

Using up empty seats in traditional 4-seat passenger vehicles can be an effective policy to reduce congestion and has been studied for several years (e.g., Agatz et al., 2011; Martinez and Viegas, 2017; Fagnant and Kockelman, 2018; Gurumurthy and Kockelman, 2018; Gurumurthy et al., 2019). Just like Uber Pool and Lyft Shared allow better seat usage presently, SAVs are likely to be assigned multiple travelers that have similar origins and destinations so as to increase revenue earned per mile and to reduce congestion. This en route vehicle-to-request matching is termed as dynamic ride-sharing (DRS). Willingness to share rides is only slowly improving now (Gurumurthy and Kockelman, 2019) but is widely expected in the future (Krueger et al., 2016), and can potentially impact airport trips the most since they are strong attractors and generators of trips.

In this study, and similar to Gurumurthy et al. (2019), DRS is implemented using Hörl's (2017) contribution to MATSim. Matching is done through the simulation day with no prior knowledge of trip start time, origin and destination. To maintain realistic and acceptable matching, a maximum waiting threshold of 30-min is used so that travelers are able to access an SAV during the day. The utility maximization through iterations ensures that the accepted waiting time is as low as possible for each traveler. This waiting threshold time includes vehicle-to-request assignment, as well as response time taken by the vehicle to reach the request. When DRS is enabled, vehicle assignment refers to an SAV being assigned to as many trip requests as possible after trip requests are aggregated for a short amount of time. These aggregations are performed based on request origins and destinations and on a rolling 5-min window so that occupancy is maximized while also accounting for added delays from detours. All seats in this traditional 4-seat vehicle are available for DRS since there is no driver associated with an SAV. Further, fare incentives are typically needed to encourage sharing, and shared rides are expected to cost less than a solo ride. A 50% discount in the $1/mi fare is assumed for shared rides so that travelers perceive a higher utility of lower fares when sharing. Detours impose an inherent disutility as travel times would be longer than on a solo ride. As the heuristic does not match optimally to begin with, several iterations of the simulation are used to identify maximum traveler utility so that matches and delays are acceptable.

As previously seen in this type of methodological setup, the extent of DRS was found to be dependent on fleet size, assuming that all travelers are willing to participate in DRS. To understand how DRS works for these airport trips, the total number of TNC drivers that served the requests in the dataset is used as a reference for maximum fleet size. The operation of that fleet is compared to reduced fleet sizes where one SAV serves every 5 and 10 requests. The average vehicle occupancy (AVO) per revenue trip for different fleet sizes provides information about how effective the reduced fleet is, relative to the larger fleet. This means that a single-occupant service would by default have an AVO of 1.0. Distance-weighted AVO, on the other hand, would take into account deadheading (TNC case) or empty (SAV case) miles and lead to an AVO less than 1.0 but is not reported here. AVO, along with the average response times observed, helps quantify how the fleet is operating. Another metric of interest from this policy is the change in overall VMT that is achieved with DRS, which is an indicator of congestion at the airport.

Policy 2: Time-Varying Zone-Based Tolling

Airports today charge TNCs either annually or on a trip-by-trip basis. This generates a steady source of revenue, but may not be effective with low-cost SAVs in terms of reducing the number of SAVs crowding airport curbsides and creating congestion. A time-varying charge is tested in this study and levied on SAVs once they enter the airport area demarcated by a zone or geofence. The charge is based on the amount of time spent within the geofence while picking up or dropping off a traveler. The time-varying aspect attempts to curtail curbside congestion by incentivizing SAVs to leave the geofence once the trip is completed. All times spent by SAVs within the geofence are tracked realtime in the simulation. Although other modes are not simulated, this charge is expected to be applied only on SAVs, and not on personal vehicles, using sensors on-board that can uniquely identify these vehicles. In practice, these SAVs would simply need to log how many times they crossed a geofence - and when, and report this to the airport. Airports may additionally use a smart counter to verify the number of SAVs that are within the zone based on license plate reading.

Figure 5 shows the geofence that is a two-mile perimeter around the airport. It is bounded by the U.S. route 183 and state route 71 in the north, and the airport perimeter in the south. Advanced positioning and navigation that are expected in SAVs will make it considerably easy to track and enforce time-varying tolls. SAVs in the geofenced area are charged 10¢, 25¢ and 50¢ for every minute spent inside the area to obtain the resulting sensitivity. These tolls are similar to a time-varying toll applied throughout the City of Austin in Gurumurthy et al. (2019). Ideally, this toll is adjusted based on prevalent access and egress times across all modes at an airport. However, the link-level rates used in Gurumurthy et al. (2019) are updated to match the airport area under consideration with some variations to test sensitivities. Revenue generated from such a toll is compared to revenue for the same number of vehicles at the current per-trip average rate of $2/trip (Box et al., 2017). Although SAVs are expected to leave the airport area immediately to avoid tolls, this may increase the fleet’s VMT from leaving the airport after dropoff and can increase response times for consecutive pickups that start at the airport. This added VMT and increased response time are reported in the results for all time-varying zone-based tolling scenarios to understand the policy’s viability.

Policy Interactions

The future is uncertain and it is difficult to know what people will prefer while traveling in an SAV to a high degree of accuracy. A combination of policies mentioned above are also tested in this research. The use of DRS by SAVs to serve these trips is enabled and these vehicles are charged the time-varying zone-based toll to ensure that they do not crowd the curbside. The use of DRS here would mean that a smaller fleet can serve the same number of trips with acceptable response times and low fares, thereby lowering revenues if only per-trip charges are continued to be levied. However, the use of the time-varying toll can help recover some of the lost revenue.

Additionally, some airports have begun the use of a staging area, where vehicles wait instead of roaming airport roads to avoid pickup on airport road segments during ground egress. This ensures that travelers accessing the airport are not delayed by being dropped at the curbside, while simultaneously freeing up the pickup curbside for personal vehicles and transit lines. Deadheading and unoccupied vehicle miles that do not accrue revenue may decrease as requests are assigned to vehicles closer to the terminal. Since Austin's ABIA has a staging area to hold TNC vehicles, a vehicle lot less than a mile away has been included in this study to understand the impact of these lots. Although ABIA has transformed a nearby parking garage (about a quarter mi away) to use as an egress zone in addition to holding TNC vehicles in a lot, this study assumes that travelers continue to be picked up at the curb, but SAVs spend no time waiting at the curbside for the traveler since they are requested on arrival at the curb. The fleet effects of this staging area are compared to added miles imposed by Policy 2 since it incentivizes SAVs to leave the airport area and not roam the airport without a rider until a new request has been assigned. To ensure that SAVs are close by and to lower response times, the size of the geofence is shrunk to a radius of one mile. This shrinkage inherently means that SAVs will spend less time within the geofence and lower revenue, but this may be outweighed by lower response times.

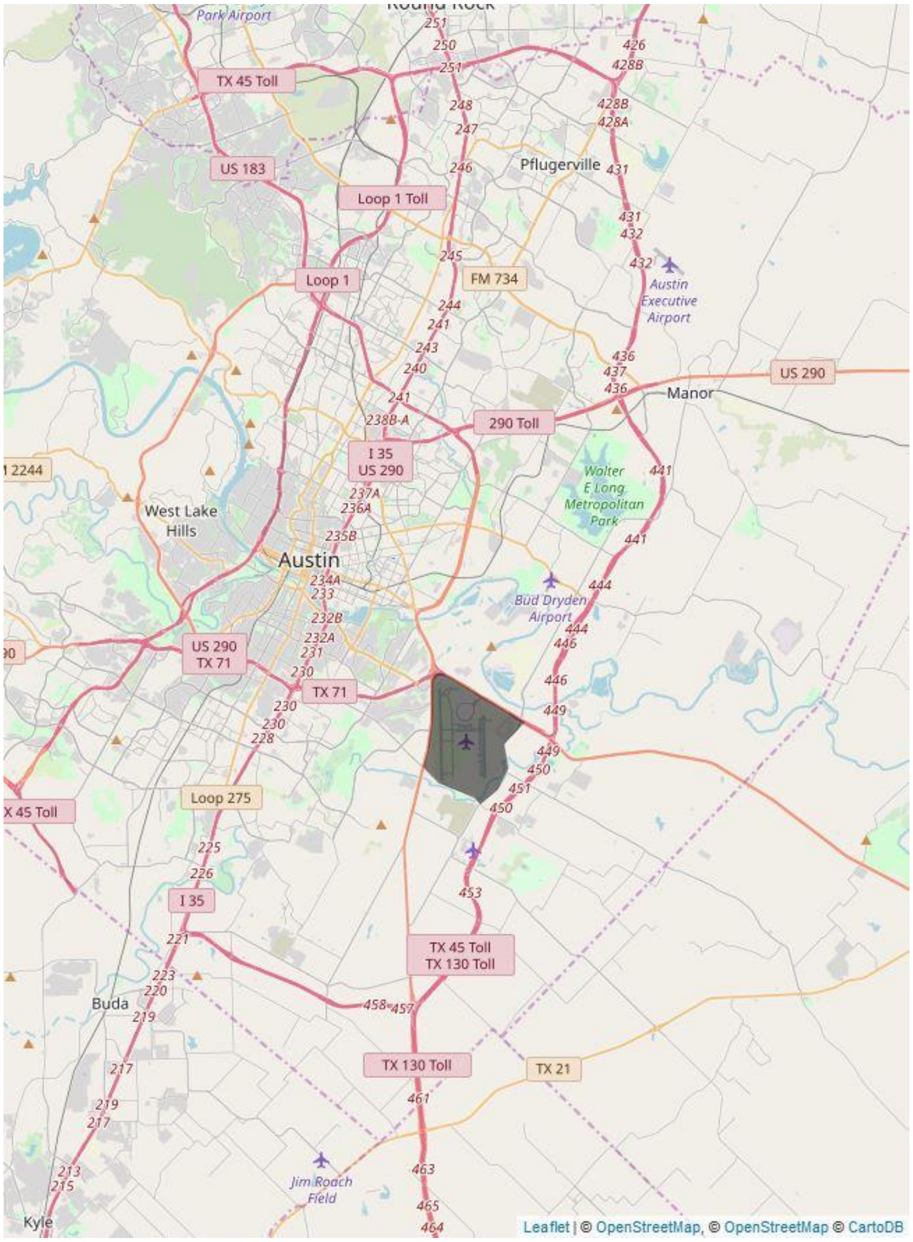

Figure 5 Austin's ABIA airport area geofenced for time-varying tolling is shown as the shaded area

RESULTS

A 100-iteration simulation of each policy described above was conducted using MATSim on a supercomputer. These simulations were compared with different fleet sizes to determine whether smaller fleet sizes managed to service trips with the same response time as larger fleet sizes. The base case refers to the simulation of the RideAustin dataset for the 24-hour period. Results from this case were validated with the dataset available to ensure that trip costs, travel times, response times and average trips executed per vehicle were well within range of each other. Table 1 shows the changes in permit revenue received by the airport and changes in fleet characteristics that indicate curbside congestion expected at the airport.

With DRS enabled, smaller fleets are able to serve the same number of trips, but with marginally higher response times. With fares expected to be lower, the added delay from pooling rides is perceived as acceptable indicated by the nearly 100% increase in traveler utility. These large changes in utility are also a byproduct of simulating a small sample (i.e., only airport trips). As expected, the VMT of these fleets are up to 30% lower than before due to better empty seat usage. Smaller fleets find it harder to match trips within acceptable margins of delays, therefore, a smaller change in VMT is observed. However, larger fleets also go unused for most parts of the day, so they may add congestion if found idling in the airport area for new trips. Idling on the network when the SAV is not in use was not explicitly modeled here. An AVO of approximately 1.20 shows that fewer SAVs are accessing the airport during the day, which translates to a reduction in revenue of up to 47% compared to how much a fleet serving single trips might contribute to the airport.

Time-varying zone-based tolling is seen to alleviate some of the losses arising from SAVs with DRS enabled. However, the choice of charge levied for the time-varying toll is crucial. Fleets of size similar to present-day TNCs show a 21% decrease in revenue for a 10¢/min toll, but a 100-300% increase in revenue for higher charges. Since the tolling is time-varying, SAVs tend to leave the airport after a dropoff, as expected, and, therefore, a higher response time is observed likely owing to subsequent pickup. This added VMT by the fleet, which is more than 2 times the VMT from the observed data, may add congestion outside of the airport network due to travel without a passenger. However, this will free up the infrastructure for airport ground access and egress. It is interesting to see that the magnitude of toll does not have an impact on the fleet's performance. Since the policy incentivizes SAVs to leave the airport, the magnitude can be adjusted to obtain appropriate revenue. Tolls being passed on to travelers will be the only concern. The change in traveler utility is lower than when served with DRS, but higher than the base case. This could be arising from long response times when smaller fleets are offered without DRS.

A combination of the two policies was also tested since DRS reduced airport revenue while time-varying tolling increased it, but had the opposite effects in terms of congestion at the airport. Since DRS would be enabled, a smaller fleet of 1 SAV serving 5 requests was chosen and simulated with time-varying tolling. The increase in airport revenue was lower since fewer SAVs were accessing airports but still dropping off the same number of passengers because of an AVO of 1.19. Response times dramatically increased because SAVs were not available for airport egress trips, and delay from trip-matching for airport access may also have contributed to the smaller change in utility.

Table 1 Airport Permit Revenue and Curbside Congestion by Policy

Scenario	**SAVs/TNCs Available per x Request**	**%Change in Avg. Traveler Utility**	**AVO (Avg. Veh. Occ.)**	**%Change in Airport Revenues**	**% Change in SAV VMT**	**Average Response Time** (in min)	**Avg. #Trips per SAV per day**
Base Case with TNCs	1 : 2	-	1.00	-	-	1.3	1.8
Dynamic Ride-Sharing	1 : 2	91.1%	1.23	-47.6%	-29.7%	6.5	1.5
	1 : 5	90.9%	1.23	-43.7%	-27.2%	7.9	4.8

		1 : 10	79.7%	1.20	-36.2%	-17.7%	12.2	9.5
Time-varying Zone-based Toll	10 ¢/min	1 : 2	73.6%	1.00	-21.2%	101.6%	4.1	1.7
		1 : 5	68.1%	1.00	0.5%	153.5%	14.6	5.7
		1 : 10	69.7%	1.00	3.8%	178.2%	19.3	11.3
	25 ¢/min	1 : 2	73.6%	1.00	97.0%	101.6%	4.1	1.7
		1 : 5	70.6%	1.00	150.6%	154.1%	14.7	5.6
		1 : 10	69.7%	1.00	159.5%	178.2%	19.3	11.3
	50 ¢/min	1 : 2	73.6%	1.00	294.0%	101.6%	4.1	1.7
		1 : 5	85.1%	1.00	402.0%	153.6%	14.6	5.7
		1 : 10	69.7%	1.00	419.0%	178.2%	19.3	11.3
DRS + Time-varying Zone-based Toll	10 ¢/min	1 : 2	70.5%	1.20	-17.5%	84.6%	17.7	1.5
		1 : 5	46.4%	1.20	-38.5%	64.3%	23.1	4.7
		1 : 10	67.5%	1.19	-38.4%	72.6%	26.2	9.4
	25 ¢/min	1 : 2	73.0%	1.20	97.6%	81.8%	17.7	1.5
		1 : 5	46.8%	1.21	54.1%	65.6%	23.4	4.7
		1 : 10	42.6%	1.20	52.1%	70.1%	26.4	9.4

Table 2 shows the impact of policies described and tested, but with the addition of a staging area for a smaller tolled-zone. The use of a vehicle cuts the average response time in half as observed when SAVs are incentivized to leave the area and marginally improves trip matching for DRS. A smaller geofence to accommodate the lot translated to fewer dollars collected, and, therefore, the airport revenue was low. Under particular scenarios, like the use of the 50¢/min charge and the existing fleet size translated to an increase in revenue by about 63%. The size of fleet serving a fixed demand is expected to be lower thanks to DRS so the chances of this rise in revenue may be less likely. Overall, the improvement in service parameters for the fleet improved the traveler utility considerably and similarly to the scenario with only DRS and no tolls. This means that providing a staging area is key to making low-cost access and egress to airports more favorable, but it may come at the cost of a decrease in revenue.

Table 2 Airport Effects for a Staging Area

Scenario		SAVs/TNCs Available per x Request	%Change in Avg. Traveler Utility	AVO (Avg. Veh. Occ.)	%Change in Airport Revenues	% Change in SAV VMT	Average Response Time (in min)	Avg. #Trips per SAV per day
DRS + Time-varying Zone-based Toll	25 ¢/min	1 : 2	92.0%	1.23	-18.5%	27.0%	13.8	1.5
		1 : 5	71.4%	1.21	-57.8%	0.9%	14.7	4.7
		1 : 10	87.9%	1.21	-59.9%	0.8%	16.7	9.5
	50 ¢/min	1 : 2	75.9%	1.21	63.3%	26.9%	13.4	1.5
		1 : 5	68.2%	1.20	-12.3%	2.7%	14.1	4.8
		1 : 10	70.5%	1.20	-18.9%	2.1%	16.4	9.5

CONCLUSIONS

Airport and airline use continue to rise over time, along with population and incomes, but TNC applications and SAVs will impact such demands. This research explores how airport operations may be affected by the use of low-cost SAVs for airport access and egress. Airports are set to lose parking revenues from this reduction in demand. Dynamically shared rides (DRS) to access airports will further limit revenue earned through access fees as fewer vehicles can serve the same number of trip requests with comparable response times. Results of this work's agent-based simulation suggest that airports may lose 30-60% revenues from airport-access fees levied on TNCs in a future world of SAVs, where DRS reduce the number of SAVs serving airport with the same level of service. Further, these estimates may not depend on the per-trip fee charged since a smaller fleet serving the same demand would still apply.

DRS use is simulated to lower TNC-sourced revenues by up to 30% for a medium-hub airport like Austin's ABIA, even without taking into account losses in parking and car-rental revenues expected from a change in demand. Such shifts can impact some airports' financial viability, but planning ahead (to reduce investments in parking garages and applying different access fees) can help ensure airport solvency. A time-varying zone-based toll levied at 10¢, 25¢ and 50¢ per min helps decrease curbside congestion during peak times of day, and delivers large revenue gains, while still leaving SAVs operable with revenues earned at 50¢/mi for a shared trip. However, this would mean that egress from the airport may be affected with longer response times since SAVs are no longer within the airport area. The choice of the magnitude of toll is important to make up for falling revenues. However, this study does not control for other modes being utilized and may only prove useful in keeping commercial SAVs away from the curbside. A combination of the two policies may increase revenue, but may do so at the cost of excessively-long SAV response times, making air travel even less attractive in a world of AVs for long-distance travel. The use of a staging area helped cut average response times in half. Some airports already use such staging areas for quicker access to TNCs, but the decline in revenues observed from this behavior needs to be kept in mind, and an appropriate toll for such a case needs to be carefully assessed. The results of this study are arrived at with the assumption that all current-day TNC demand is expected to switch over to SAV use in the future. However, the reality is that SAVs will also be competing with other modes for daily trips made for other purposes. This means that there is expected to be a larger demand for SAV use which is expected to translate into more airport trips made by SAVs, thereby reinforcing the results.

Limitations and Future Work

Two broad limitations exist in this study: data- and simulation-related. TNC trip data from 2016-17 is used in this study for the specific case of Austin's medium-hub airport. The airport authority at ABIA has revised TNC egress recently, in 2019, in order to manage curbside congestion by moving pickup areas to a nearby garage parking lot. Although this supports the case for rising curbside congestion, the results from this study are based on TNCs and SAVs providing curb-to-curb convenient access and egress to airports without much of a walk. It is too soon to say how the added walking distance to egress impacts TNC use, but it can be assumed to not make much of a difference in terms of future demand with lower fares studied here. Several enhancements can still be made for more realistic airport access and egress simulations. For example, endogenous calculation of SAV access and egress times for SAV-demand feedback would be valuable. Data sets for other airports and future air travel conditions will be valuable. The analysis here is rigorously made for a medium-hub airport such as the ABIA, however, many large cities (like Chicago or New York City) may have more trips originating from or destined to common locations, such as a high-density downtown, providing for higher DRS use, but also lower airport revenues. Smaller airports charging annual fees may see smaller changes in revenue, if revenue from daily demand by SAVs does not exceed the annual fee. Another concern that may arise is from the lack of mode alternatives. The scenarios assume that all ride-hailing travelers in the dataset will continue to use SAVs but if operators pass on the bulk of all charges at the airport, there may be a shift in mode especially in times of day when the service is in demand and the airport is busy. These can be future avenues of research focused on integrated econometric analysis with simulation-based inputs to determine mode elasticities.

Regardless, the future holds many uncertainties for travel and for airports around the world. Still-rising demand for long-distance personal travel keeps many airports relatively busy much of the year, with many planning gate and runway expansions. This work helps airport managers call attention to parking and access and fee plans, to ensure more-optimal operations long term. Airport managers may then use policy studied here to maximize their revenue by mining into data that may have been collected for fees such as TNC vehicle, entry time, exit time, and purpose, to assess time-varying fees. Additionally, this may also serve as awareness to what associated factors need to be kept in mind while planning for a future of shared mobility. Future work can further incorporate a comparative analysis of alternative funding sources with the policies studied here, and how light-rail access, to airports currently deprived of them, may impact revenue in the future.

ACKNOWLEDGEMENTS

This research has been funded by the Airport Cooperative Research Program's (ACRP) Graduate Research Award #11-04. The authors thank ACRP for the funding and guidance that helped in shaping this research.

REFERENCES

Agatz, N., Erera, A.L., Savelsbergh, M.W.P., Wang, X., 2011. Dynamic Ride-Sharing: a Simulation Study in Metro Atlanta. Procedia - Soc. Behav. Sci., Papers selected for the 19th International Symposium on Transportation and Traffic Theory 17, 532–550. https://doi.org/10.1016/j.sbspro.2011.04.530

Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., Rus, D., 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. Proc. Natl. Acad. Sci. 114, 462–467. https://doi.org/10.1073/pnas.1611675114

Becker, H., Becker, F., Abe, R., Bekhor, S., Belgiawan, P.F., Compostella, J., Frazzoli, E., Fulton, L.M., Guggisberg Bicudo, D., Murthy Gurumurthy, K., Hensher, D.A., Joubert, J.W., Kockelman, K.M., Kröger, L., Le Vine, S., Malik, J., Marczuk, K., Ashari Nasution, R., Rich, J., Papu Carrone, A., Shen, D., Shiftan, Y., Tirachini, A., Wong, Y.Z., Zhang, M., Bösch, P.M., Axhausen, K.W., 2020. Impact of vehicle automation and electric propulsion on production costs for mobility services worldwide. Transp. Res. Part Policy Pract. 138, 105–126. https://doi.org/10.1016/j.tra.2020.04.021

Bösch, P.M., Becker, F., Becker, H., Axhausen, K.W., 2018. Cost-based analysis of autonomous mobility services. Transp. Policy 64, 76–91. https://doi.org/10.1016/j.tranpol.2017.09.005

Box, P.M. and S., Airport Cooperative Research Program, Transportation Research Board, National Academies of Sciences, Engineering, and Medicine, 2017. Transportation Network Companies: Challenges and Opportunities for Airport Operators. Transportation Research Board, Washington, D.C. https://doi.org/10.17226/24867

Burghout, W., Rigole, P.-J., Andreasson, I., 2015. Impacts of Shared Autonomous Taxis in a Metropolitan Area. Presented at the 94th Annual Meeting of the Transportation Research Board.

Charypar, D., Nagel, K., 2005. Generating complete all-day activity plans with genetic algorithms. Transportation 32, 369–397. https://doi.org/10.1007/s11116-004-8287-y

Davol, A., 2017. A new model for airport ground transportation: Transportation network companies at San Francisco International Airport. J. Airpt. Manag. 11, 147–153.

District Department of Transportation, 2018. Mayor Bowser and DDOT Announce Pick-Up/Drop-Off Zone Pilot Program Expansion | ddot [WWW Document]. URL https://ddot.dc.gov/release/mayor-bowser-and-ddot-announce-pick-updrop-zone-pilot-program-expansion (accessed 7.23.19).

Dockterman, E., 2016. Uber and Lyft Are Leaving Austin After Losing Background Check Vote. Fortune.

Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transp. Res. Part Policy Pract. 77, 167–181. https://doi.org/10.1016/j.tra.2015.04.003

Fagnant, D.J., Kockelman, K.M., 2018. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. Transportation 45, 143–158. https://doi.org/10.1007/s11116-016-9729-z

Federal Aviation Administration, 2017. Economic Impact of Civil Aviation by State, The Economic Impact of Civil Aviation on the U.S. Economy. U.S. Department of Transportation.

Grover, H., 2019. As Uber and Lyft go public, Seattle drivers getting a smaller share of fares, union analysis says. Seattle Times.

Gurumurthy, K.M., Kockelman, K.M., 2019. Modeling Americans' Autonomous Vehicle Preferences: A Focus on Dynamic Ride-Sharing, Privacy & Long-Distance Mode Choices.

Presented at the 98th Annual Meeting of the Transportation Research Board, Washington, D.C.
Gurumurthy, K.M., Kockelman, K.M., 2018. Analyzing the dynamic ride-sharing potential for shared autonomous vehicle fleets using cellphone data from Orlando, Florida. Comput. Environ. Urban Syst. 71, 177–185. https://doi.org/10.1016/j.compenvurbsys.2018.05.008
Gurumurthy, K.M., Kockelman, K.M., Loeb, B.J., 2019. Sharing Vehicles & Sharing Rides in Real Time: Opportunities for Self-Driving Fleets, in: Advances in Transport Policy and Planning: The Sharing Economy and the Relevance for Transport.
Gurumurthy, Krishna Murthy, Kockelman, K.M., Simoni, M.D., 2019. Benefits and Costs of Ride-Sharing in Shared Automated Vehicles across Austin, Texas: Opportunities for Congestion Pricing. Transp. Res. Rec. 2673, 548–556. https://doi.org/10.1177/0361198119850785
Henao, A., Sperling, J., Garikapati, V., Hou, Y., Young, S., 2018. Airport Analyses Informing New Mobility Shifts: Opportunities to Adapt Energy-Efficient Mobility Services and Infrastructure: Preprint. Presented at the Intelligent Transportation Society of America 2018 Annual Meeting, Detroit, Michigan, p. 8.
Hermawan, K., Regan, A.C., 2018. Impacts on Vehicle Occupancy and Airport Curb Congestion of Transportation Network Companies at Airports. Transp. Res. Rec. 2672, 52–58. https://doi.org/10.1177/0361198118783845
Hörl, S., 2017. Agent-based simulation of autonomous taxi services with dynamic demand responses. Procedia Comput. Sci. 109, 899–904. https://doi.org/10.1016/j.procs.2017.05.418
Horni, A., Nagel, K., Axhausen, K.W. (Eds.), 2016. The Multi-Agent Transport Simulation MATSim. Ubiquity Press. https://doi.org/10.5334/baw
Huang, Y., Kockelman, K.M., 2019. What will autonomous trucking do to U.S. trade flows? Application of the random-utility-based multi-regional input–output model. Transportation. https://doi.org/10.1007/s11116-019-10027-5
Ibarcena, C., 2017. Going Under The Hood: The Winners And Losers Of Florida’s Transportation Network Companies Law. Nova Law Rev. 42.
IHS Automotive, 2014. Autonomous Cars: Not if but When.
Kockelman, K., Boyles, S., Avery, P., Claudel, C., Loftus-Otway, L., Fagnant, D., Bansal, P., Levin, M.W., Zhao, Y., Liu, J., Clements, L., Wagner, W., Stewart, D., Sharon, G., Albert, M., Stone, P., Hanna, J., Patel, R., Fritz, H., Choudhary, T., Li, T., Nichols, A., Sharma, K., Simoni, M., 2016. Bringing Smart Transport to Texans: Ensuring the Benefits of a Connected and Autonomous Transport System in Texas (No. FHWA/TX-16/0-6838-2). TxDOT.
Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. Transp. Res. Part C Emerg. Technol. 69, 343–355. https://doi.org/10.1016/j.trc.2016.06.015
LaMondia, J.J., Fagnant, D.J., Qu, H., Barrett, J., Kockelman, K., 2016. Shifts in Long-Distance Travel Mode Due to Automated Vehicles: Statewide Mode-Shift Simulation Experiment and Travel Survey Analysis. Transp. Res. Rec. 2566, 1–11. https://doi.org/10.3141/2566-01
Lavieri, P.S., Garikapati, V.M., Bhat, C.R., Pendyala, R.M., Astroza, S., Dias, F.F., 2017. Modeling Individual Preferences for Ownership and Sharing of Autonomous Vehicle Technologies. Transp. Res. Rec. 2665, 1–10. https://doi.org/10.3141/2665-01

Loeb, B., Kockelman, K.M., 2019. Fleet performance and cost evaluation of a shared autonomous electric vehicle (SAEV) fleet: A case study for Austin, Texas. Transp. Res. Part Policy Pract. 121, 374–385. https://doi.org/10.1016/j.tra.2019.01.025

Martinez, L.M., Viegas, J.M., 2017. Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of Lisbon, Portugal. Int. J. Transp. Sci. Technol., Connected and Automated Vehicles: Effects on Traffic, Mobility and Urban Design 6, 13–27. https://doi.org/10.1016/j.ijtst.2017.05.005

Narayanan, S., Chaniotakis, E., Antoniou, C., 2020. Shared autonomous vehicle services: A comprehensive review. Transp. Res. Part C Emerg. Technol. 111, 255–293. https://doi.org/10.1016/j.trc.2019.12.008

Perrine, K.A., Huang, Y., Kockelman, K., 2018. Anticipating Long-Distance Travel Shifts Due to Self-Driving Vehicles. Presented at the Transportation Research Board 97th Annual MeetingTransportation Research Board.

Quarles, N.T., Kockelman, K.M., Lee, J., 2020. Americans’ Plans for Acquiring and Using Electric, Shared and Self-Driving Vehicles. Presented at the 99th Annual Meeting of the Transportation Research Board, Washington, DC.

RSG, Inc., Coogan, M., Hansen, M., Marchi, R., McGuckin, N., Ryerson, M., Welch, M., 2019. Air Demand in a Dynamic Competitive Context with the Automobile. Transportation Research Board, Washington, D.C. https://doi.org/10.17226/25448

Schwanz, M., n.d. Sea-Tac Establishes Environmental Guidelines for Ridesharing Companies | Airport Improvement Magazine [WWW Document]. URL https://airportimprovement.com/article/sea-tac-establishes-environmental-guidelines-ridesharing-companies (accessed 7.23.19).

Shaheen, S., Cohen, A., 2019. Shared ride services in North America: definitions, impacts, and the future of pooling. Transp. Rev. 39, 427–442. https://doi.org/10.1080/01441647.2018.1497728

Simoni, M.D., Kockelman, K.M., Gurumurthy, K.M., Bischoff, J., 2019. Congestion pricing in a world of self-driving vehicles: An analysis of different strategies in alternative future scenarios. Transp. Res. Part C Emerg. Technol. 98, 167–185. https://doi.org/10.1016/j.trc.2018.11.002

Spieser, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D., Pavone, M., 2014. Toward a Systematic Approach to the Design and Evaluation of Automated Mobility-on-Demand Systems: A Case Study in Singapore, in: Meyer, G., Beiker, S. (Eds.), Road Vehicle Automation, Lecture Notes in Mobility. Springer International Publishing, Cham, pp. 229–245. https://doi.org/10.1007/978-3-319-05990-7_20

Stoiber, T., Schubert, I., Hoerler, R., Burger, P., 2019. Will consumers prefer shared and pooled-use autonomous vehicles? A stated choice experiment with Swiss households. Transp. Res. Part Transp. Environ. https://doi.org/10.1016/j.trd.2018.12.019

Tscharaktschiew, S., Evangelinos, C., 2019. Pigouvian road congestion pricing under autonomous driving mode choice. Transp. Res. Part C Emerg. Technol. 101, 79–95. https://doi.org/10.1016/j.trc.2019.02.004

Walker, J., Johnson, C., 2016. Peak Car Ownership: The Market Opportunity of Electric Automated Mobility Services.

Zmud, J., Goodin, G., Moran, M., Kalra, N., Thorn, E., National Cooperative Highway Research Program, Transportation Research Board, National Academies of Sciences, Engineering, and Medicine, 2017. Advancing Automated and Connected Vehicles: Policy and Planning

Strategies for State and Local Transportation Agencies. Transportation Research Board, Washington, D.C. https://doi.org/10.17226/24872

Zuniga-Garcia, N., Tec, M., Scott, J.G., Ruiz-Juri, N., Machemehl, R.B., 2020. Evaluation of ride-sourcing search frictions and driver productivity: A spatial denoising approach. Transp. Res. Part C Emerg. Technol. 110, 346–367. https://doi.org/10.1016/j.trc.2019.11.021