

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

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14 Word Count: 4,652 words + 2 tables x 250 words = 5,152 words (+ 5 figures)

15 Submitted for presentation in the 99th Annual Meeting of the Transportation Research Board,
16 Washington, D.C. in 2020 and publication in *Transportation Research Record: Journal of the*
17 *Transportation Research Board.*

18 **ABSTRACT**

19 With rising use of ride-hailing apps and, eventually, self-driving vehicles, airport operations are
20 being impacted. Demands for airport parking spaces, rental cars, and, one day, airline seats are
21 expected to fall everywhere, relative to background trends. This study uses publicly available ride-
22 hailing demand data for the Austin, Texas area to pursue agent-based simulations of a futuristic
23 fleet of shared autonomous vehicles or “SAVs”. The work helps anticipate the airport-revenue and
24 -operations impacts of rising ride-hailing activities, whether in conventional or self-driving
25 vehicles. Results suggest that dynamic ride-sharing of vehicles (especially centrally dispatched
26 SAVs) across strangers (with current airport-related travel patterns, to and from the airport) can
27 lower airport-related ground travel by up to 30%, while reducing airport revenues by 46% if ride-
28 hailing permits are continued to be charged \$2 per trip. A time-varying cordon-based toll around
29 the airport can help offset lost parking and car-rental (but not seat-mile) revenues and potentially
30 triple present-day airport-access revenues. Such policies can come at the cost of adding non-
31 revenue ride-hailing and SAV miles to the rest of the network, when incentivizing SAVs to leave
32 the airport cordon after a dropoff, in order to avoid curbside congestion. A combination of ride-
33 sharing among strangers and use of access fees on all commercial vehicles dropping off or picking
34 up travelers can achieve a healthy middle ground.

35 **Keywords:** *Airport operations, airport parking, airport revenues, shared autonomous vehicles,*
36 *dynamic ride-sharing, time-varying cordon tolls, ride-hailing*

37 **BACKGROUND**

38 Civil aviation is an important backbone of local, regional and national economies, and U.S.
39 aviation accounts for over \$1 trillion of annual GDP (Federal Aviation Administration, 2017).
40 Airports are key to such contributions, and generally function as non-profits, run by city
41 governments or their subsidiary, typically termed airport authorities , reliant on airline fees and

local concessions, including parking, car-rental, and access fees. U.S. airline-related revenue is regulated by the Federal Aviation Administration (FAA), while car-rental fees, parking charges, and taxi- and TNC-access fees comprise about 40% of all other U.S. airport revenues (Ibarcena, 2017). Larger airports tend to generate more parking revenues, while popular tourist destinations generate more rental-car revenue.

The use of smartphones, and consequent emergence of disruptive technologies, like ride-hailing apps run by Transportation Network Companies (TNCs), tends to lower such revenue streams (Zmud et al., 2017). 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, with Colorado's Denver International Airport charging the highest flat fee of about \$111,250 per year. However, Ibarcena (2017) states that fleet-size dependent fees in Georgia, at \$300,000 per year for permitting more than a 1000 vehicles, may be the largest with growing usage. In medium to large or 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. Without designated pickup and dropoff locations at airports, TNCs can quickly congest arrival and departure curbs (District Department of Transportation, 2018). Hermawan and Regan (2018) also showed that TNCs are making travelers ride solo, and further exacerbate curbside congestion. SAVs and other new 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). AV and SAV options are expected to shift American's 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). 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 should 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). SAVs operating as a smart and driverless TNC service, like Lyft, Didi and Uber, is expected based on a fleet evolution study (Quarles and Kockelman, 2018), 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 forms the 60-80% of TNC and taxi

revenues (Grover, 2019). Low-cost SAVs (at \$1 per mile or less, for example [Fagnant and Kockelman, 2018; Loeb and Kockelman, 2019]) 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. Although fees levied on SAVs will generate revenue for the airport, it may not be successful in curbing congestion. 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 using dynamic ride-sharing, or DRS (Fagnant and Kockelman, 2018; Gurumurthy and Kockelman, 2018). Another option is to price travel entering and exiting the airport using a cordon 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 cordon. This can help discourage large number of SAVs from waiting near the airport for new trips and can help keep traffic flowing across the airport's roadways and curb spaces.

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. Data set descriptions are followed by simulation methods used, results and inference, along with conclusions and recommendations for airport managers.

RIDEAUSTIN DATASET

Ride-hailing companies currently operate similar to how a future fleet of SAVs may operate, minus the added human factor that brings down compliance and optimality in SAV operations. Ride-hailing 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 (Stoiber et al., 2019), adds 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 . Trips performed by riders are captured and can be synthetically recreated to use with MATSim (described below). Figure 1 **Error! Reference source not found.** 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 too affected by any notable random events. Figure 2 shows the access and egress trips by time of day.

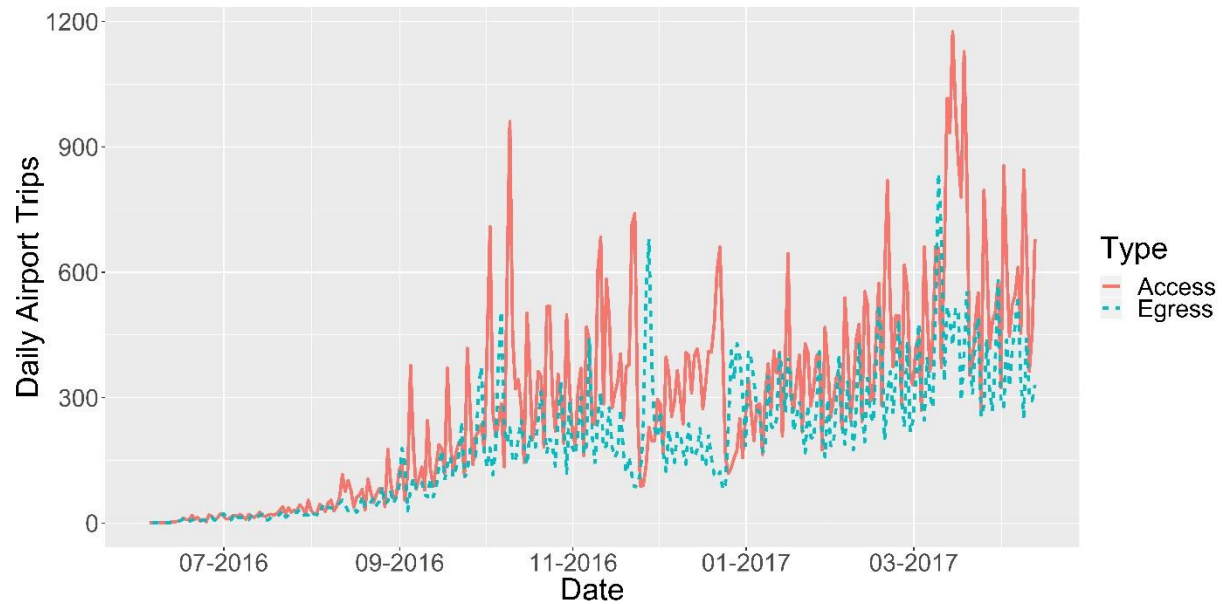


Figure 1 Number of RideAustin trips starting (egress) and ending (access) at ABIA airport each day

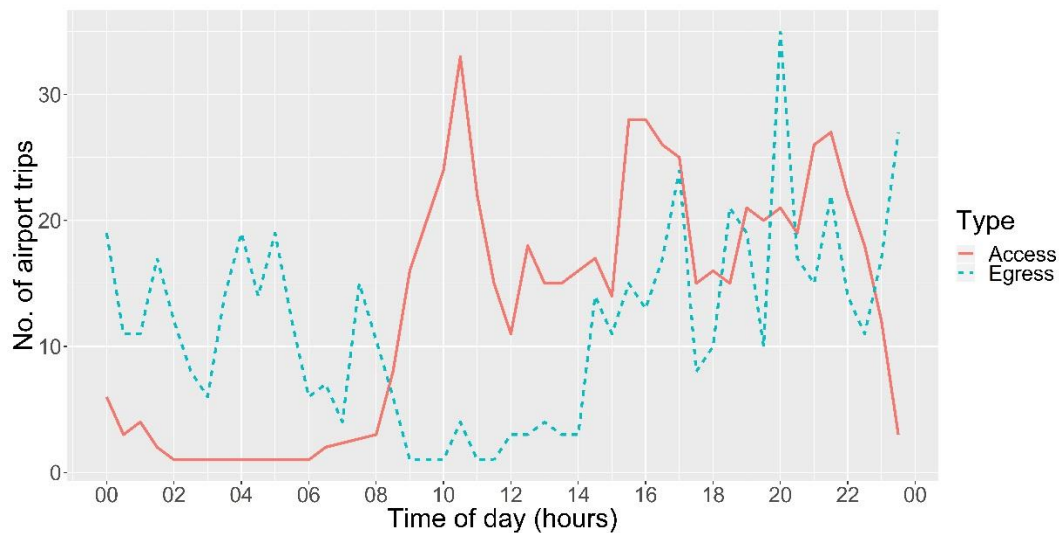


Figure 2 Access and egress trips made by time of day for chosen date

Data for this summary reveals that each of these TNC vehicles served almost 2 trips per day, on averages. Fares were assessed as a fixed (starting) 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., 2018).

METHODOLOGY

1 An agent-based simulation of airport access and egress trips is performed here using MATSim
 2 (Horni et al., 2016) to microscopically observe the future impact of SAVs at, and around, the
 3 airport. Figure 3 shows the MATSim loop that is comprised of a mobility simulation, replanning
 4 module to innovate agents' daily plans, and scoring to estimate feasibility, in each iteration. A
 5 dynamic queue-based algorithm governs the mobility simulation, whereas a co-evolutionary
 6 approach is taken for replanning and scoring to obtain the convergent set of trip itineraries. The
 7 results of the mobility simulation provides link level statistics of travel times and congestion, and
 8 can be used to observe effects near the airport. For airport trips, the replanning module in this study
 9 is specifically focused on route choice and departure-time choice, in addition to reacting to the two
 10 policies tested. Scoring is important to compare current-day TNCs to future operation of SAVs.
 11 Parameter assumptions to capture the differences in operation are discussed below.

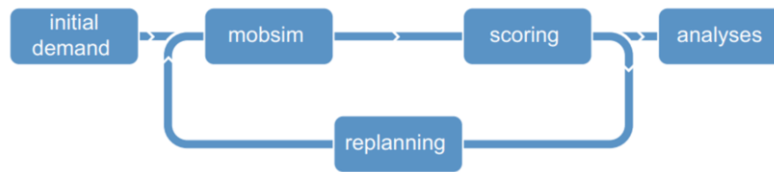


Figure 3 MATSim's multi-agent transport simulation loop (Horni et al., 2016)

14 Trip data from the RideAustin dataset were filtered for airport trips and post-processed to obtain a
 15 suitable input for MATSim. Trip itineraries in MATSim consists of tours of activities and legs.
 16 That is, an agent starts at an activity location, and the trip between activity locations is called a leg.
 17 Since, the simulation focuses on airport trips, two activity locations are assumed here – home and
 18 airport. All legs, as stated earlier, as assumed to be SAV legs. Figure 4 shows one-way airport trips
 19 for three randomly-selected people generated from the RideAustin dataset. A closer look reveals
 20 that origin and destination coordinates are truncated in the dataset at the third decimal place owing
 21 to privacy concerns. However, even with three decimal places, home locations are spread
 22 throughout the region with a fair representation of actual trip distribution.

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      <act end_time="00:00:18" type="home" x="-97.668" y="30.202"/>
      <leg dep_time="00:00:18" mode="av"/>
      <act end_time="00:38:05" type="airport" x="-97.867" y="30.353"/>
    </plan>
  </person>
  <person id="253934">
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      <act end_time="00:00:23" type="home" x="-97.667" y="30.202"/>
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  </person>
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    </plan>
  </person>

```

Figure 4 Example MATSim trips generated from RideAustin data

Average trip scores assessed before and after changes in policy will help infer how traveler utility was impacted. In order to standardize inference, parameters are adapted from Simoni et al. (2019). The marginal utility of money is set at 0.79 to reflect the VOTT of \$18/hr within MATSim, and SAV travel is assumed to have a 50% lower VOTT, reflected in utility terms by +0.48. The positive sign does not indicate that future SAVs have a positive utility of travel time, as they are only relative terms. 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). Table 1 summarizes the parameters assumed for this study that helps compare the current-day utility to future utility. 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.

Table 1 Scoring Parameters for Current and Future Services

Scoring Parameters	Current (TNC)	Future (SAV)
Fare	\$2/mi	\$0.50/mi
Alternative Specific Constant	0	0
Marginal Utility of Travel Time (per hour)	0 (\$18/hr)	+0.48 (\$9/hr)

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). Willingness to share rides is only slowly improving now (Gurumurthy and Kockelman,

2019) but is expected in the future. In this study, and similar to Gurumurthy et al. (2019), DRS is implemented using Hörl's (2017) contribution to MATSim. To maintain a realistic and acceptable matching, a maximum waiting threshold of 30-min is used. This 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.

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 are used as a reference for maximum fleet size. The operation of that fleet is compared to reduced fleet sizes of 1 SAV serving every 5 and 10 requests. The average vehicle occupancy (AVO) for different fleet sizes provides information about how effective the reduced fleet is, relative the larger fleet. This information, along with the average response times observed, helps quantify how the fleet is operating. Other metrics 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.

Time-Varying Cordon 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 in 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 cordon. Figure 5 shows the cordon that is a one mile perimeter around the airport. Advanced positioning and navigation that is expected in SAVs will make it considerably easy to track and enforce time-varying tolls. SAVs in the cordoned area are charged 50¢ for every minute spent inside the cordoned area. 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 to avoid tolls, this may increase the fleet's VMT from leaving the airport after dropoff. This can increase response times for consecutive pickups that start at the airport. This added VMT and response times are reported for all time-varying cordon tolling scenarios to understand the policy's viability.

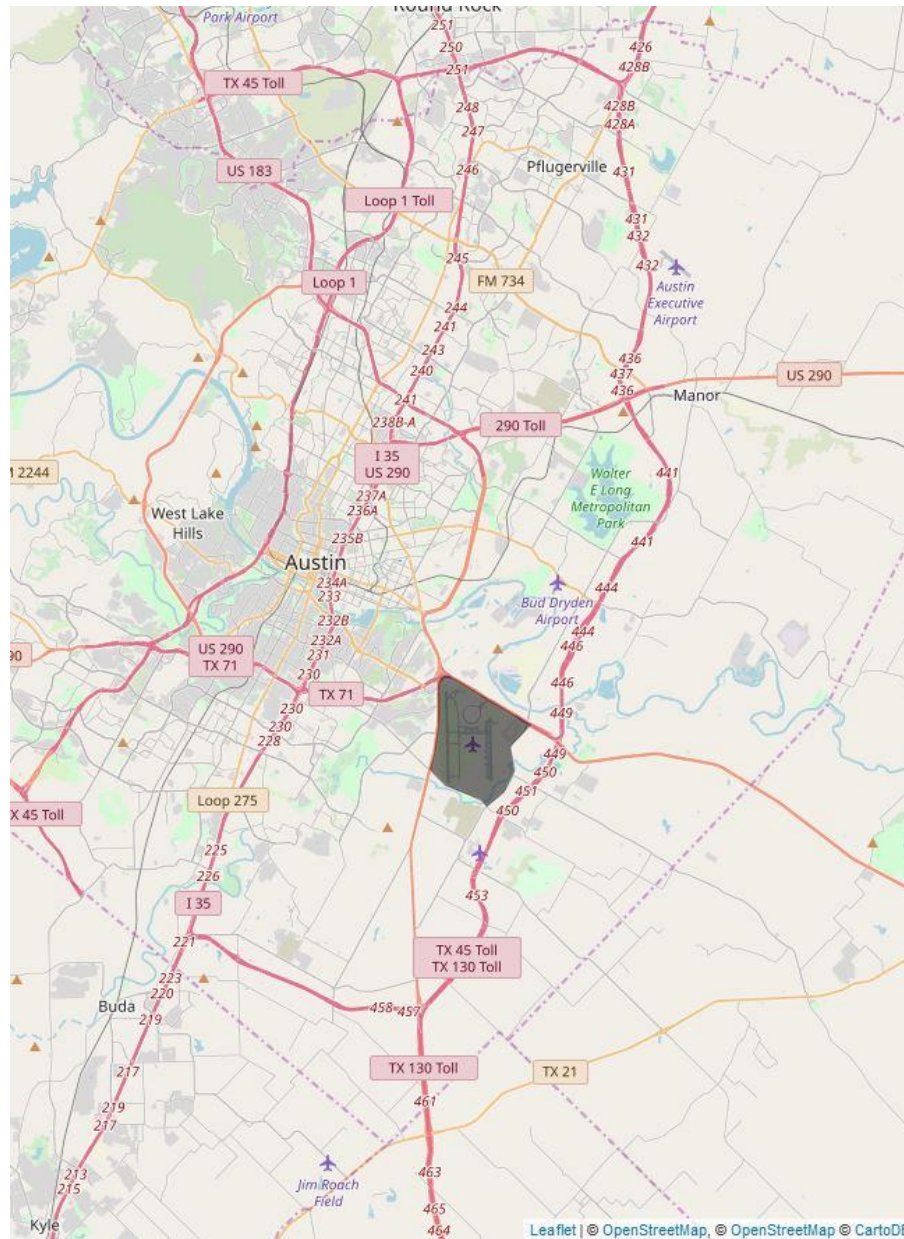


Figure 5 Austin’s ABIA airport area cordoned off for time-varying tolling

RESULTS

A 100-iteration simulation of each policy described above was conducted using MATSim on a supercomputer. The base case here refers to the simulation of the RideAustin dataset for the 24-hour period. Results from this case was 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 2 shows the changes in permit revenue received by the airport and changes in fleet characteristics that indicate curbside congestion that is 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 sharing rides is

perceived as acceptable indicated by the nearly 100% increase in traveler utility. These large changes in utility is 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 from 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, however, idling on the network when 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 46% compared to how much a fleet serving single trips might contribute to the airport.

Time-varying cordon tolling is seen to alleviate some of the losses arising from SAVs with DRS enabled. Fleets of size similar to present-day TNCs still show a 300% increase in revenue. 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 compared to 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. 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 2 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	Avg. #Trips per SAV per day
Base Case with TNCs	1 : 2	-	1.00	-	-	1.3 min	1.8
DRS	1 : 2	97.9%	1.23	-46.3%	-30.0%	6.3	1.5
	1 : 5	99.1%	1.22	-43.0%	-26.4%	7.9	4.8
	1 : 10	90.3%	1.20	-33.9%	-14.2%	12.4	9.6
Time-varying Cordon Toll	1 : 2	76.6%	1.00	292.4%	101.3%	4.0	1.7
	1 : 5	62.3%	1.00	400.1%	153.8%	14.6	5.6
	1 : 10	58.9%	1.00	417.2%	176.3%	18.9	11.3

DRS + Time-varying Cordon Toll	1 : 5	66.4%	1.19	213.0%	68.8%	23.2	4.7
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CONCLUSIONS

Airport and airline use continue to rise over time, along with population and incomes, but ridehailing apps and self-driving vehicles will impact such demands. This research explores how airport operations can be affected by use of low-cost SAVs for airport access and egress. Airports are set to lose parking revenues from a shift toward shared vehicle fleets (conventional and self-driving) and dynamically shared rides (DRS among strangers). Results of this work's agent-based simulation suggest that airports will lose 30-40% revenues from airport-access fees levied on TNCs and taxis in a future world of SAVs, where DRS reduced the number of SAVs serving airport with the same level of service.

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 cordon toll levied at 50¢/min was also tested here, to lower curbside congestion during peak times of day, and delivering large revenue gains, while still leaving SAVs operable with revenues earned at 50¢/mi. However, this would mean that egress from the airport may be affected with large response times since SAVs no longer are within the airport area. 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.

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. For example, many cities 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. 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 simply helps airport managers adjust parking and access and fee plans, to ensure more-optimal operations long term.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm the contribution to the paper as follows: study conception and design: Gurumurthy. K.M., and Kockelman, K.; Data cleaning: Gurumurthy. K.M.; Analysis and interpretation of results: Gurumurthy. K.M., and Kockelman, K.; Manuscript preparation: Gurumurthy, K.M., and Kockelman, K. All authors reviewed the results and approved the final version of this manuscript.

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.

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