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

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ABSTRACT

With rising use of ride-sourcing apps and, eventually, self-driving vehicles, ground transportation at airports are being impacted. 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 ride-sourcing demand data for the Austin, Texas area to pursue agent-based simulations of a futuristic fleet of shared autonomous vehicles or "SAVs". The work helps anticipate the airport-revenue and -operations impacts of rising ride-sourcing activities, whether in conventional or self-driving vehicles. Results suggest that dynamic ride-sharing of vehicles (especially centrally dispatched SAVs) across strangers (with current airport-related travel patterns, to and from the airport) may lower airport-related ground travel by up to 30%, while reducing airport revenues by 46% assuming ride-sourcing permits are continued 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, or even triple, present-day airport-access revenues. Such policies can come at the cost of adding non-revenue ride-sourcing 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 ride-sharing 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 Aviation Administration (FAA), while car- rental fees, parking charges, and taxi-access fees

1   comprise about 40% of all other U.S. airport revenues (Ibarcena, 2017). More recently, airports
2   have begun charging access fees to ride-sourcing companies as well. Larger airports tend to
3   generate more parking revenues, while popular tourist destinations generate more rental-car
4   revenue.

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

26 SAVs are expected to provide a convenient and cost-competitive alternative to driving oneself or
27 buying a self-driving vehicle in the future (Kockelman et al., 2016). Personal AVs and SAVs are
28 expected to shift American's and others' long-distance travel patterns and mode choices (Perrine
29 et al., 2018; Huang and Kockelman, 2019), impacting highways, airline revenues and airport
30 operations significantly (RSG, Inc. et al., 2019). This is more likely to be true for trips shorter than
31 500 miles. For example, LaMondia et al. (2016) predicted a 20-30% shift in U.S. long-distance
32 mode choices from airlines to AVs for distances under 500 miles (one-way) using Michigan's
33 long-distance travel survey data. Similarly, Perrine et al. (2018) estimated that airline revenues for
34 domestic travel within the U.S. may fall by 53% from the use of personal and shared AVs. Huang
35 and Kockelman (2019) estimate 30% to 50% more vehicle-miles travelled (VMT) on Texas
36 roadways and highways, due to new trip-makers, longer trips, and fewer airline trips, everything
37 else constant. While household-owned AVs will have important impacts, they are expected to be
38 expensive and difficult to own and use initially, with added costs over $25,000 or more, in early
39 release years (IHS Automotive, 2014) and even $100,000 or more with how the technology is
40 developing (Fagnant and Kockelman, 2015). In the future, SAVs operating as a smart and
41 driverless TNC service, like Lyft, Didi and Uber, is expected based on a fleet evolution study
42 (Quarles and Kockelman, 2018), and will change how people will travel in cities and regions.
43 Studies have shown that without adequate policy in place, local, regional and national VMT can
44 increase, further congesting urban and rural networks (Simoni et al., 2019; Huang and Kockelman,
45 2019).

1   SAVs will be less expensive to access, thanks to avoidance of high purchase costs and without
2   driver-related labor costs (Loeb and Kockelman, 2019), which forms the 60-80% of TNC and taxi
3   revenues (Grover, 2019). Low-cost SAVs (at $1 per mile or less, for example [Fagnant and
4   Kockelman, 2018; Loeb and Kockelman, 2019]) are expected to induce new and longer travel
5   demands, while encouraging more single-occupant travel. From an airport operation's perspective,
6   single-use SAVs circulating at airports (for passenger pickups and dropoffs) will exacerbate
7   congestion along many sections of airport networks. Although fees levied on SAVs will generate
8   revenue for the airport, it may not be successful in curbing congestion. Policies to optimally
9   moderate such induced demand merit investigation. Such impacts can be avoided if more travelers
10   are bundled into fewer cars, with SAV systems using dynamic ride-sharing (DRS) as shown by
11   Fagnant and Kockelman (2018) and Gurumurthy and Kockelman (2018). Another option is to
12   price travel entering and exiting the airport using a zone-based toll that is time-varying, similar to
13   the policy applied at the city level in Simoni et al. (2019) and Gurumurthy et al. (2019), but focused
14   within the airport zone. This can help discourage large number of SAVs from waiting near the
15   airport for new trips and can help keep traffic flowing across the airport's roadways and curb
16   spaces.

17   In this study, the multi-agent transport simulation tool MATSim is used along with a TNC's paid-
18   trips dataset from Austin, Texas to quantify the impact of SAVs on airport operations. The Austin-
19   Bergstrom International Airport (ABIA) had an annual passenger traffic of about 15.8 M people
20   in 2018[1], and this is rapidly increasing. It is well connected by transit, and provides short-term and
21   long-term parking options. TNC access for drop-offs and pickups are regulated by the airport with
22   a per-trip fee of $2. Data availability for ABIA and the airport's characteristics makes it a suitable
23   case study. Data set descriptions are followed by simulation methods used, results and inference,
24   along with conclusions and recommendations for airport managers.

25   **RIDEAUSTIN DATASET**

26   Ride-sourcing companies currently operate similar to how a future fleet of SAVs may operate,
27   minus the added human factor that may bring down compliance and optimality in SAV operations.
28   Ride-sourcing data are largely unavailable for large, for-profit corporations like Uber and Lyft.
29   However, the Austin-based non-profit TNC RideAustin released its data (https://data.world/ride-
30   austin) in 2017 for trips made through their smartphone application between June 2016 and April
31   2017. A total of nearly 1.5 M trips were logged in that period, with numbers quickly rising to a
32   daily average of about 7,000 paid trips across the City of Austin.

33   RideAustin was created when TNCs lost a vote on drivers being required to undergo fingerprint-
34   based background checks to operate in Austin, and immediately stopped operations (Dockterman,
35   2016). This meant that RideAustin operated without competition for almost a year before the two
36   major TNCs returned. Origins and destinations for airport trips by RideAustin users, who are
37   potential users/more likely adopters of SAVs (Stoiber et al., 2019), adds value to this simulation.
38   All dataset trips are geotagged with coordinates truncated up to 3 decimal places to ensure privacy,
39   with anonymous but consistent/permanent driver and rider IDs provided throughout the 1-year.
40   Trips performed by riders are captured and can be synthetically recreated to use with MATSim
41   (described below). Figure 1 shows the total trips that started or ended at the airport for every day
42   in the dataset. After RideAustin usage stabilized, a daily average of about 700 trips were observed

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

1 either starting at or ending near the airport. A noticeable peak is seen in March, 2017, from higher
2 airport usage during Austin's annual and internationally known South by Southwest (SxSW) event.
3 One 24-hour period from 00:00 to 23:59 hours on 7th April 2017 was chosen to provide a stable
4 share of trips that does not appear affected by any notable random events. Figure 2 shows the
5 access and egress trips by time of day.
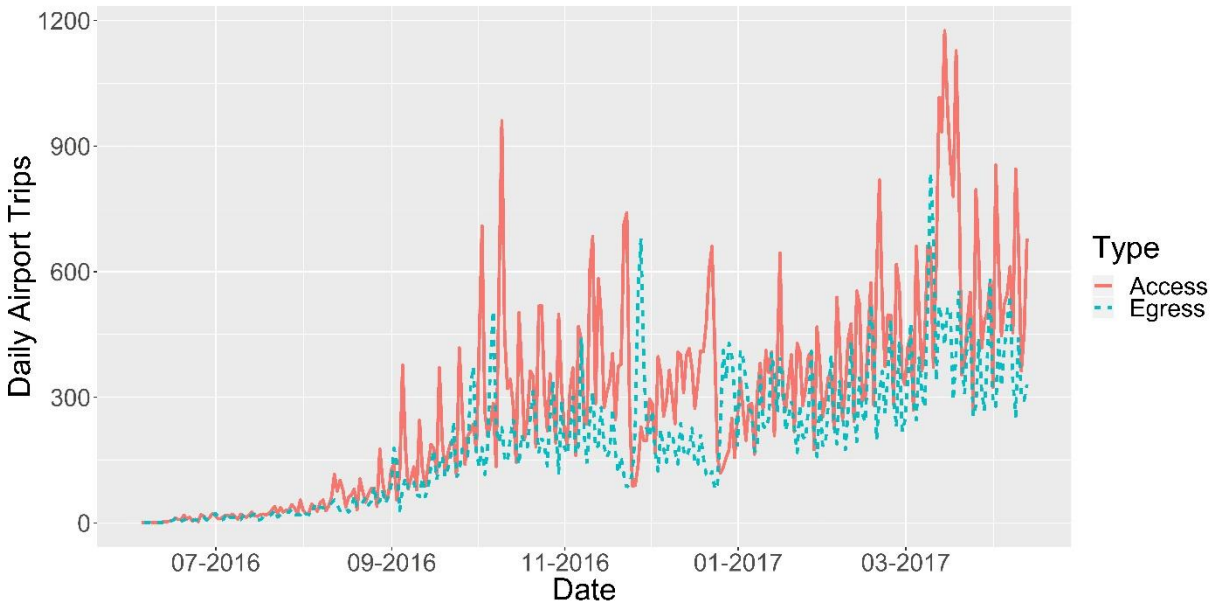
6

7 **Figure 1** Number of RideAustin trips starting (egress) and ending (access) at ABIA airport each
8 day
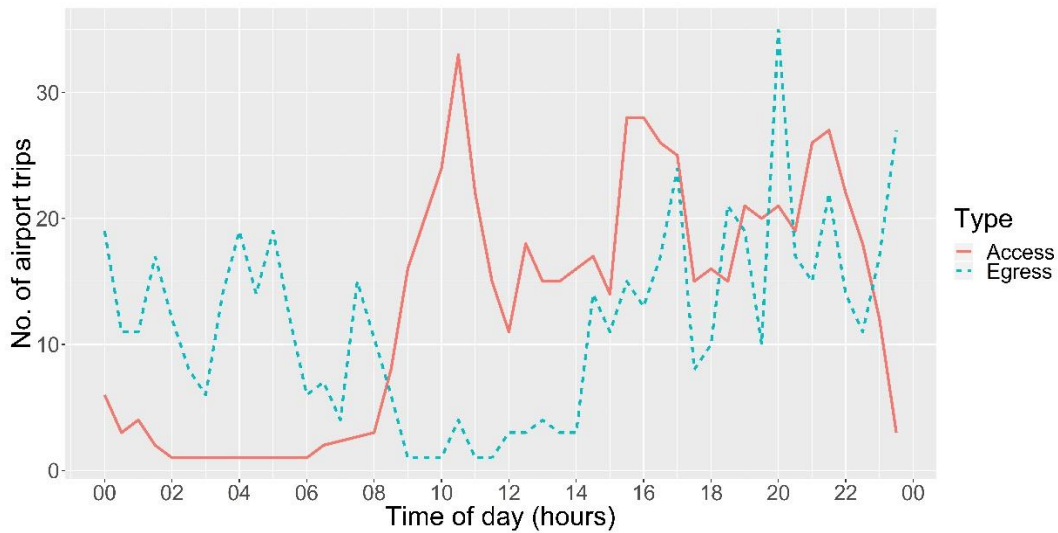
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10 **Figure 2** Access and egress trips made by time of day for chosen date

11 Data for this summary reveals that each of these TNC vehicles served almost 2 trips per day, on
12 averages. Fares were assessed as a fixed (start-up) fare of $1.50, a time-dependent fare of
13 $0.25/min, and distance-dependent fare of $0.99/mi. RideAustin also uses a surge factor applied
14 based on experienced delays and driver availability throughout the day. Fares also rise with larger

4

1   vehicles chosen (to handle larger travel-party sizes or lots of luggage, for example). On average,
2   RideAustin's airport-based (at origin or destination) trips during this 24-hour period costed
3   $1.90/mi. For a clear analysis of TNC trips in the Austin area encompassing the entire dataset,
4   please refer to (Zuniga-Garcia et al., 2018).

5   **METHODOLOGY**

6   An agent-based simulation of airport access and egress trips was performed using MATSim (Horni
7   et al., 2016) to microscopically (i.e., at the link and person levels) observe the future impact of
8   SAVs at, and around, the airport. The use of a simulation framework adds flexibility in analyzing
9   different policies and a fleet's operational characteristics that are not currently observed from
10 revealed data. Conducting this at the agent level helps modelers keep track of individual trip-
11 makers' behavior throughout the simulation timeframe for all cases tested. Figure 3 shows the
12 MATSim loop that is comprised of a mobility simulation replanning module to innovate agents'
13 daily plans, and scoring to estimate feasibility, in each iteration. A dynamic queue-based traffic
14 assignment algorithm governs the mobility simulation which essentially models a vehicle's
15 movement from link-to-link and within the link. The replanning module uses a co-evolutionary
16 iterative in order to choose modes which conform to a logit structure for choice. The scoring of an
17 agent's progress in the simulation is done based on value of productive time and value of travel
18 time to compare how travelers are reacting to a new mode being available, or to a new policy being
19 incorporated in the simulation. Ultimately, the replanning and scoring module ensures that a
20 convergent set of trip itineraries are produced for the agents being simulated. The results of the
21 mobility simulation provides link-level statistics of travel times and congestion, and can be used
22 to observe effects near the airport. For airport trips, the replanning module in this study is
23 specifically focused on route choice and departure-time choice in lieu of competing modes.
24 Additionally, agents' reactions to future policies implemented within the simulation framework
25 are also captured, and these policies are explained later. Person-level scoring is important to realise
26 how current-day TNCs compare to future operation of SAVs, especially while considering changes
27 in fare structure and operations. This is derived using the scoring schema that is present within
28 MATSim. Parameter assumptions for this schema in order to capture the differences in operation
29 are discussed below.
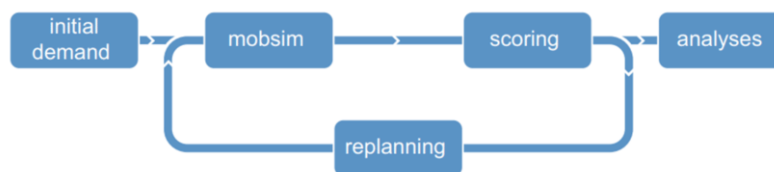
30

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

32 Trip data from the RideAustin dataset (spanning 24-hr for the chosen day) were filtered for airport
33 trips and post-processed to obtain a suitable input for MATSim. Trip itineraries in MATSim
34 consists of tours of activities and legs. That is, an agent starts at an activity location where the
35 agent is assumed to be productive, and the trip between activity locations is called a leg, where the
36 agent is using a preferred mode for travel. Since, the simulation focuses on airport trips, two
37 activity locations are assumed here – home and airport, i.e., the traveler in these simulations are
38 always at home or at the airport. All legs, as stated earlier, as assumed to be TNC/SAV legs to

1 understand airport access and egress using the current services like Uber and Lyft, and future
2 services like that of SAVs. Trip data used here are available with distinct origin and destination
3 coordinates up to the third decimal place owing to privacy concerns. However, even with three
4 decimal places, home locations are spread throughout the region with a fair representation of actual
5 geographic trip distribution.

6 Average trip scores assessed before and after changes in policy will help infer how traveler utility
7 was impacted. In order to standardize inferences on current and future trip-making behavior, travel
8 parameters within the simulation are adapted from Simoni et al. (2019) for the present-day and
9 future scenarios that involve SAVs. The marginal utility of money is set at 0.79 to reflect the value
10 of travel time (VOTT) of $18/hr within MATSim, and SAV travel is assumed to have a 50% lower
11 VOTT, reflected in utility terms by +0.48. This is in concurrence with previous work that have
12 simulated SAVs in MATSim for Austin, Texas (Simoni et al., 2019; Gurumurthy et al., 2019). The
13 positive sign for this marginal utility of money does not indicate that future SAVs have a positive
14 utility of travel time, as they are only relative terms within the simulation to compare changes in
15 traveler utility. Alternative specific constants, required by MATSim for every mode, is set to 0 as
16 there is no mode choice involved in this study. While current day TNC operations are roughly
17 about $2/mi, studies anticipate SAV fares lower than $1/mi (see, for e.g., Bösch et al., 2018;
18 Fagnant and Kockelman, 2018; Loeb and Kockelman, 2019). Changes in traveler utility with fares
19 lower than currently observed will also show propensity for SAV travel. Table 1 summarizes the
20 parameters assumed for this study that helps compare the current-day utility to future utility. As
21 seen from the table, the traveler utility is comprised mainly of the disutility from fares and travel
22 time. Without mode choice, the absolute value of traveler utility is not as useful as the relative
23 change in utility between scenarios. Therefore, the percentage change in utility is reported in the
24 results.

25 **Table 1** Scoring Parameters for Current and Future Services

Scoring Parameters	Current (TNC)	Future (SAV)
Fare	$2/mi	$0.50/mi
Marginal Utility of Travel Time (per hour)	0.00 ($18/hr)	+0.48 ($9/hr)

26

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

31 **Policy 1: Dynamic Ride-Sharing and Fleet-Sizing**

32 Using up empty seats in traditional 4-seat passenger vehicles can be an effective policy to reduce
33 congestion and has been studied for several years (e.g., Agatz et al., 2011; Martinez and Viegas,
34 2017; Fagnant and Kockelman, 2018; Gurumurthy and Kockelman, 2018; Gurumurthy et al.,
35 2019). Just like Uber Pool and Lyft Line allow better seat usage presrntly, SAVs are likely to be
36 assigned multiple travelers that have similar origins and destinations so as to increase revenue
37 earned per mile and to reduce congestion. This en route vehicle-to-request matching is termed as
38 dynamic ride-sharing (DRS). Willingness to share rides is only slowly improving now

6

1   (Gurumurthy and Kockelman, 2019) but is widely expected in the future, and can potentially
2   impact airport trips the most since they are strong attractors and generators of trips. In this study,
3   and similar to Gurumurthy et al. (2019), DRS is implemented using Hörl's (2017) contribution to
4   MATSim. To maintain a realistic and acceptable matching, a maximum waiting threshold of 30-
5   min is used. This includes vehicle-to-request assignment, as well as response time taken by the
6   vehicle to reach the request. When DRS is enabled, vehicle assignment refers to an SAV being
7   assigned to as many trip requests as possible after trip requests are aggregated for a short amount
8   of time.

9   As previously seen in this type of methodological setup, the extent of DRS was found to be
10   dependent on fleet size, assuming that all travelers are willing to participate in DRS. To understand
11   how DRS works for these airport trips, the total number of TNC drivers that served the requests in
12   the dataset are used as a reference for maximum fleet size. The operation of that fleet is compared
13   to reduced fleet sizes where one SAV serves every 5 and 10 requests. The average vehicle
14   occupancy (AVO) for different fleet sizes provides information about how effective the reduced
15   fleet is, relative the larger fleet. This information, along with the average response times observed,
16   helps quantify how the fleet is operating. Other metrics of interest from this policy is the change
17   in overall VMT that is achieved with DRS, which is an indicator of congestion at the airport.

18   **Policy 2: Time-Varying Zone-Based Tolling**

19   Airports today charge TNCs either annually or on a trip-by-trip basis. This generates a steady
20   source of revenue, but may not be effective with low-cost SAVs in terms of reducing the number
21   of SAVs crowding in airport curbsides and creating congestion. A time-varying charge is tested in
22   this study and levied on SAVs once they enter the airport area demarcated by a zone or geofence.
23   Although other modes are not simulated, this charge is expected to be applied only on SAVs, and
24   not on personal vehicles, using sensors on-board that can uniquely identify these vehicles. These
25   SAVs would simply need to log and report how many times they crossed a geofence - and when,
26   and report this to the airport. Figure 4 shows the geofence that is a two-mile perimeter around the
27   airport. It is bounded by the U.S. route 183 and state route 71 in the north, and the airport perimeter
28   in the south. Advanced positioning and navigation that is expected in SAVs will make it
29   considerably easy to track and enforce time-varying tolls. SAVs in the geofenced area are charged
30   10¢, 25¢ and 50¢ for every minute spent inside the area to obtain the resulting sensitivity. These
31   tolls are similar to a time-varying toll applied throughout the city in Gurumurthy et al. (2019).
32   Ideally, this toll is adjusted based on prevalent access and egress times across all modes at an
33   airport. However, the link-level rates used in Gurumurthy et al. (2019) are updated to match the
34   airport area under consideration with some variations to test sensitivities. Revenue generated from
35   such a toll is compared to revenue for the same number of vehicles at the current per-trip average
36   rate of $2/trip (Box et al., 2017). Although SAVs are expected to leave the airport area immediately
37   to avoid tolls, this may increase the fleet's VMT from leaving the airport after dropoff and can
38   increase response times for consecutive pickups that start at the airport. This added VMT and
39   response times are reported in the results for all time-varying zone-based tolling scenarios to
40   understand the policy's viability.

41   **Policy Interactions**

42   The future is uncertain and it is difficult to know what people will prefer while traveling in an SAV
43   in the future to a high degree of accuracy. A combination of policies mentioned above are also
44   tested in this research. The use of DRS by SAVs to serve these trips is enabled and these vehicles

1   are charged the time-varying zone-based toll to ensure that they do not crowd the curbside.
2   Additionally, some airports have begun the use of a staging area so that TNCs can avoid the pickup
3   road segments during ground egress. Since Austin's ABIA is also one such arirport, a vehicle lot
4   less than a mile away has been included in the study. This is compared to incentivizing SAVs to
5   add miles by leaving the airport area. To ensure that SAVs are close by, the size of the geofence
6   is shrunk to a radius of one mile.
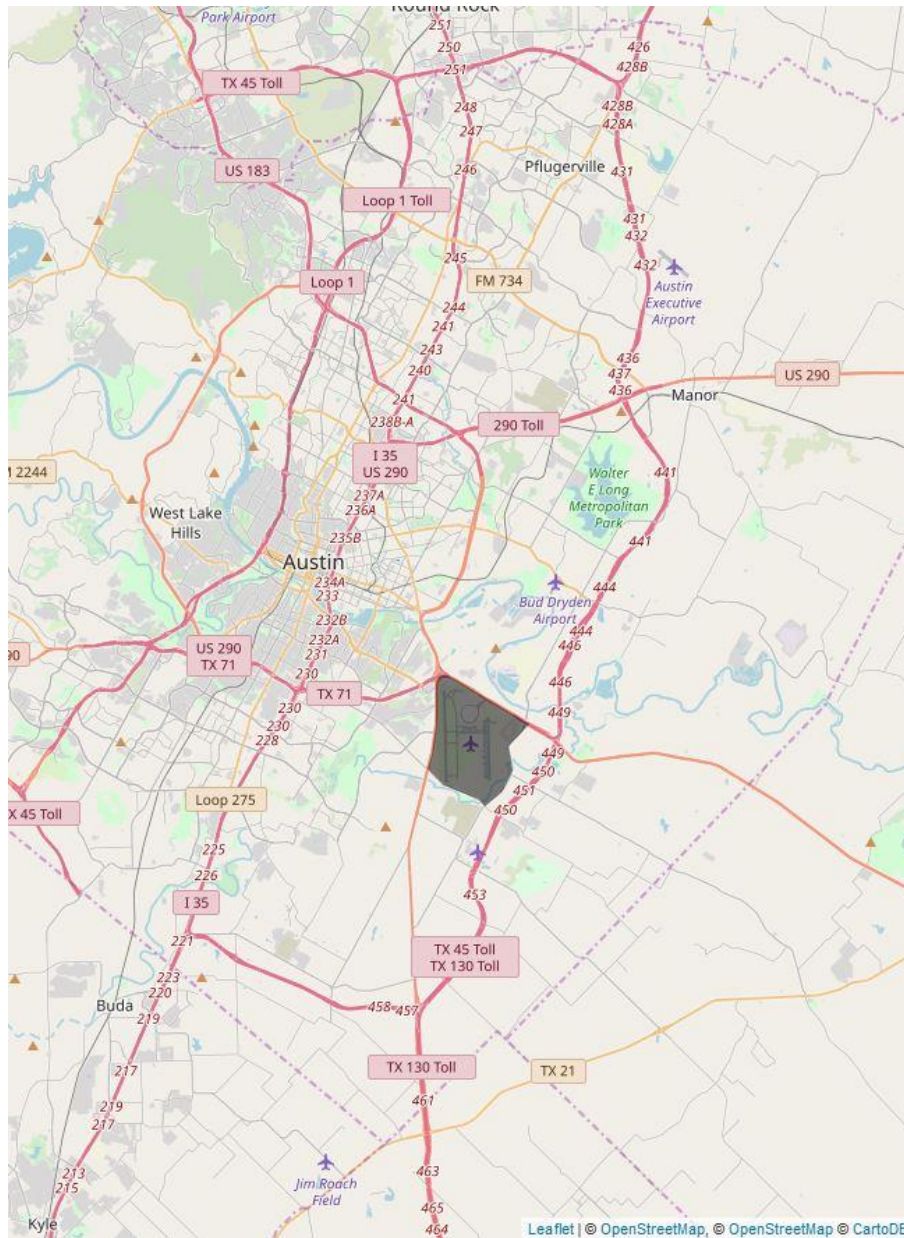
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8   **Figure 4** Austin's ABIA airport area geofenced for time-varying tolling is shown as the shaded
9   area

10   **RESULTS**

8

1   A 100-iteration simulation of each policy described above was conducted using MATSim on a
2   supercomputer. This was compared with different fleet sizes to determine whether smaller fleet
3   sizes managed to service trips with the same response time. The base case refers to the simulation
4   of the RideAustin dataset for the 24-hour period. Results from this case were validated with the
5   dataset available to ensure that trip costs, travel times, response times and average trips executed
6   per vehicle were well within range of each other. Table 2 shows the changes in permit revenue
7   received by the airport and changes in fleet characteristics that indicate curbside congestion that is
8   expected at the airport.

9   With DRS enabled, smaller fleets are able to serve the same number of trips, but with marginally
10   higher response times. With fares expected to be lower, the added delay from sharing rides is
11   perceived as acceptable indicated by the nearly 100% increase in traveler utility. These large
12   changes in utility is also a byproduct of simulating a small sample (i.e., only airport trips). As
13   expected, the VMT of these fleets are up to 30% lower than before from better empty seat usage.
14   Smaller fleets find it harder to match trips within acceptable margins of delays, therefore, a smaller
15   change in VMT is observed. However, larger fleets also go unused for most parts of the day, so
16   they may add congestion if found idling in the airport area for new trips, however, idling on the
17   network when not in use was not explicitly modeled here. An AVO of approximately 1.20 shows
18   that fewer SAVs are accessing the airport during the day, which translates to a reduction in revenue
19   of up to 46% compared to how much a fleet serving single trips might contribute to the airport.

20   Time-varying zone-based tolling is seen to alleviate some of the losses arising from SAVs with
21   DRS enabled. However, the choice of charge levied for the time-varying toll is crucial. Fleets of
22   size similar to present-day TNCs shows a 21% decrease in revenue for a 10¢/min toll, but a 100-
23   300% increase in revenue for higher charges. Since the tolling is time-varying, SAVs tend to leave
24   the airport after a dropoff, as expected, and, therefore, a higher response time is observed likely
25   owing to subsequent pickup. This added VMT by the fleet, which is more than 2 times compared
26   to VMT from the observed data, may add congestion outside of the airport network due to travel
27   without a passenger. However, this will free up the infrastructure for airport ground access and
28   egress. It is interesting to see that the magnitude of toll does not have an impact on the fleet's
29   performance. Since the policy incentivizes SAVs to leave the airport, the magnitude can be
30   adjusted to obtain appropriate revenue. Tolls being passed on to travelers will be the only concern.
31   The change in traveler utility is lower than when served with DRS, but higher than the base case.
32   This could be arising from long response times when smaller fleets are offered without DRS.

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

1 **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 (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	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 Zone-based Toll	10 ¢/min	1 : 2	76.6%	1.00	-21.5%	101.3%	4.0	1.7
		1 : 5	65.3%	1.00	-0.2%	153.7%	14.7	5.6
		1 : 10	53.1%	1.00	4.0%	178.2%	19.1	11.3
	25 ¢/min	1 : 2	76.6%	1.00	96.2%	101.3%	4.0	1.7
		1 : 5	62.4%	1.00	149.4%	153.2%	14.5	5.6
		1 : 10	53.1%	1.00	159.9%	178.2%	19.2	11.3
	50 ¢/min	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 Zone-based Toll	10 ¢/min	1 : 2	68.3%	1.22	-18.9%	81.5%	18.1	1.4
		1 : 5	55.6%	1.19	-38.2%	67.2%	23.4	4.7
		1 : 10	74.5%	1.20	-39.1%	72.7%	26.5	9.4
	25 ¢/min	1 : 2	62.1%	1.21	101.6%	84.2%	17.8	1.4
		1 : 5	55.0%	1.19	56.6%	67.3%	22.9	4.7
		1 : 10	37.3%	1.20	51.9%	68.2%	26.1	9.5

2

3 Table 3 shows the impact of policies described and tested, but with the addition of a staging area
4 for a smaller tolled-zone. The use of a vehicle cuts the average response time in half as observed

10

1   when SAVs are incentivized to leave the area and marginally improves trip matching for DRS.
2   Smaller geofence to accommodate the lot translated to a lesser tolls collected, and, therefore, the
3   airport revenue was low. Under particular scenarios, like the use of the 50¢/min charge and the
4   existing fleet size translated to an increase in revenue by about 60%. The size of fleet serving a
5   fixed demand is expected to be lower thanks to DRS so the chances of this rise in revenue may be
6   less likely. Overall, the improvement in service parameters for the fleet improved the traveler
7   utility considerably and similar to the scenario with only DRS and no tolls. This means that
8   providing a staging area is key to make low-cost access and egress to airports more favorable, but
9   it may come at the cost of a decrease in revenue.

10   **Table 3 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	73.6%	1.21	-21.2%	26.0%	13.6	1.5
		1 : 5	78.0%	1.20	-56.8%	2.0%	14.4	4.7
		1 : 10	77.0%	1.19	-59.3%	2.6%	16.7	9.4
	50 ¢/min	1 : 2	93.0%	1.22	63.3%	26.4%	13.7	1.4
		1 : 5	90.1%	1.21	-16.1%	-0.1%	14.7	4.7
		1 : 10	82.6%	1.21	-18.7%	1.5%	16.3	9.5

11

12   **CONCLUSIONS**

13   Airport and airline use continue to rise over time, along with population and incomes, but TNC
14   applications and SAVs will impact such demands. This research explores how airport operations
15   may be affected by use of low-cost SAVs for airport access and egress. Availability of AVs in the
16   future is expected to cause a shift in long-distance travel demand from airlines to road-based
17   transport in either personal AVs or SAVs. Airports are set to lose parking revenues from this
18   reduction in demand. Dynamically shared rides (DRS) to access airports will further limit revenue
19   earned through access fees as fewer vehicles can serve the same number of trip requests with
20   comparable response times. Results of this work's agent-based simulation suggest that airports
21   may lose 30-60% revenues from airport-access fees levied on TNCs in a future world of SAVs,
22   where DRS reduced the number of SAVs serving airport with the same level of service.

23   DRS use is simulated to lower TNC-sourced revenues by up to 30% for a medium-hub airport like
24   Austin's ABIA, even without taking into account losses in parking and car-rental revenues
25   expected from a change in demand. Such shifts can impact some airports' financial viability, but
26   planning ahead (to reduce investments in parking garages and applying different access fees) can
27   help ensure airport solvency. A time-varying zone-based toll levied at 10¢, 25¢ and 50¢ per min

1   were also tested here, to lower curbside congestion during peak times of day, and delivering large
2   revenue gains, while still leaving SAVs operable with revenues earned at 50¢/mi. However, this
3   would mean that egress from the airport may be affected with longer response times since SAVs
4   no longer are within the airport area. The choice of the magnitude of toll is important to maintain
5   falling revenues. However, this study does control for other modes being utilized and may only
6   prove useful in keeping commercial SAVs away from the curbside. A combination of the two
7   policies may increase revenue, but may do so at the cost of excessively-long SAV response times,
8   making air travel even less attractive in a world of AVs for long-distance travel. The use of a
9   staging area was tested along with the combinations of the other two policies, and average response
10 times were cut in half. Some airports already use such staging areas for quicker access to TNCs,
11 but the decline in revenues observed from this behavior needs to be kept in mind, and an
12 appropriate toll for such a case needs to carefully assessed. The results of this study are arrived at
13 with the assumption that all current-day TNC demand is expected to switch over to SAV use in
14 the future. However, the reality is that SAVs will also be competing with other modes for daily
15 trips made for other purposes. This means that there is expected to be a larger demand for SAV
16 use which is expected to translate into more airport trips made by SAVs, thereby reinforcing the
17 results.

18 Two broad limitations exist in this study: data- and simulation-related. TNC trip data from 2016-
19 17 is used in this study for the specific case of Austin's medium-hub airport. The airport authority
20 at ABIA has revised TNC egress recently, in 2019, in order to manage curbside congestion by
21 moving pickup areas to a nearby garage parking lot. Although this supports the case for rising
22 curbside congestion, the results from this study are based on TNCs and SAVs providing curb-to-
23 curb convenient access and egress to airports without much of a walk. It is too soon to say how the
24 added walking distance to egress impacts TNC use, but can be assumed to not make much of a
25 difference in terms of future demand with lower fares studied here. Several enhancements can still
26 be made for more realistic airport access and egress simulations. For example, endogenous
27 calculation of SAV access and egress times for SAV-demand feedback would be valuable. Data
28 sets for other airports and future air travel conditions will be valuable. The analysis here is
29 rigorously made for a medium-hub airport such as the ABIA, however, many large cities (like
30 Chicago or New York City) may have more trips originating from or destined to common
31 locations, such as a high-density downtown, providing for higher DRS use, but also lower airport
32 revenues. Smaller airports charging annual fees may see smaller changes in revenue, if revenue
33 from daily demand by SAVs does not exceed the annual fee.

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

44 **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.

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