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Are commuter air taxis coming to your city? A ranking of 40 cities in the United States

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A R T I C L E I N F O

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A B S T R A C T

Given the high levels of congestion that many commuters in the United States experience, the urban air mobility community has been exploring the potential of using a new class of electric vertical takeoff and landing (eVTOL) aircraft for commuters. To date, only a few studies have been conducted that compare how potential air taxi demand across cities varies. This study calculates a measure of air taxi demand for commuters for the 40 most populous combined statistical areas (CSAs) in the U.S. by using: (1) cell phone data to identify regular commuters in cities, (2) census data to associate household income characteristics with commuters, and (3) a mode choice model calibrated from a stated preference survey to predict the number of commuters that would use an air taxi. Air taxi commuter demand is concentrated in a handful of CSAs; the CSAs for New York City, Los Angeles, and Washington, D.C., generate 33 percent of the overall air taxi demand. Results are sensitive to location of existing vertiports, existing ground infrastructure and congestion levels on competing modes, and current commute patterns. A resultant set of online maps of potential air taxi routes allows readers to visualize how air taxi commuter routes differ across CSAs. Results will be of value both to aircraft manufacturers seeking to design air taxi vehicles to serve different cities as well as city planners for identifying where investments in port infrastructure may be needed to support a commuter air taxi service.

Abbreviations: ACS, American Community Survey; ARC, Atlanta Regional Commission; AV, autonomous (ground) vehicle; CBD, central business district; CPI, consumer price index; CPM, cost per mile; CSA, combined statistical area; eVTOL, electric vertical takeoff and landing; FAA, Federal Aviation Administration; GDP, gross domestic product; IVTT, in-vehicle travel time; MNL, multinomial logit; MSA, metropolitan statistical area; NFDC, National Flight Data Center; OD, origin–destination; OMB, U.S. Office of Management and Budget; OVTT, out-of-vehicle travel time; SP, stated preference; STEM, science, technology, engineering, and math; UAM, urban air mobility; U.S, United States; VOT, value of time; ZCTA, zip code tabulation area; ZIP, zone improvement plan.

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Nomenclature

A	total number of OD pairs
$\alpha_{0,i}$	mean of the Normal distribution used to capture panel effects that is estimated from the data
α_i	alternative specific constant that is part of the systematic component of utility, also called the intercept term for alternative i
α_{in}	random error term with a Normal distribution with a mean and variance estimated from the data
$\alpha_{S,i}$	standard deviation of the Normal distribution used to capture panel effects that is estimated from the data
β_i	a vector of coefficients associated with x_{nik}
c	an index for CSAs
$Cost_{car,OD_a}$	cost of traveling by car between the two census tract centroids for OD pair a
$Cost_{AV,OD_a}$	cost of traveling by AV between the two census tract centroids for OD pair a
$Cost_{eVTOL,OD_a}$	cost per passenger of traveling by eVTOL aircraft between the two census tract centroids for OD pair a
CPI_c	is the consumer price index associated with the state in which CSA c is located
CPI_{US}	is the average CPI for all states in the U.S.
CPM_{car}	cost per mile of driving a car
CPM_{AV}	cost per mile of an AV
$d_{facilities}$	the haversine distance between the two vertiport locations or the total flight distance
d_{max}	maximum range of the eVTOL aircraft, assumed to be 60 miles
d_{min}	the distance covered in the noncruise segment of the flight path
d_{OD_a}	driving distance between the two census tract centroids for OD pair
ε_{nik}	random error term distributed independently and identically with a Gumbel (or extreme value type I) distribution that is associated with the MNL model
f	is the deadhead ratio, or the fraction of nonrevenue flights required for repositioning (assumed by analyst)
i	index for mode
Inc'_{nc}	individual's annual household income adjusted to account for local consumer price index
Inc_n	is an estimate of an individual n's income obtained from the SP survey
$IVTT^1_{air}$	in-vehicle travel time associated with travel from home to the home-based vertiport (assumed to be via personal car)
$IVTT^2_{air}$	in-vehicle travel time associated with travel from the work-based vertiport to the work location (assumed to be via ride-hailing)
J_{nk}	set of all alternatives that are part of the choice set for individual n and trade-off question k
k	index for trade-off question used in the SP survey
$MktSize_{OD_{z1,z2}}$	market size for zip code pair z_1 and z_2 calculated from cell phone data and SP data
n	index for individual
n_{pax}	the number of passengers on board the eVTOL aircraft
$OpCost$	the hourly aircraft operating cost
$\mathrm{OVTT}_{\mathrm{air}}$	out-of-vehicle travel time associated with waiting for the air taxi, boarding the air taxi, and waiting for the ride-hail vehicle
P_{nik}	probability of individual n choosing alternative i in trade-off question k_n
s_{eVTOL}	is the assumed cruise speed of the vehicle in miles per hour
t_{cruise}	time in minutes associated with the cruise segment of the eVTOL flight
t_{flying}	time in minutes associated with the cruise and noncruise segments of an eVTOL flight, also equivalent to IVTT for the eVTOL mode
t_{min}	time associated with flying distance d_{min}
$t_{noncruise}$	time in minutes associated with the noncruise segment of an eVTOL flight
$\mathrm{TVTT}_{\mathrm{air}}$	total door-to-door travel time for the air taxi mode, given as $IVTT^1_{air} + IVTT^2_{air} + \mathrm{OVTT}_{\mathrm{air}}$
U_{nik}	total utility, given as $U_{nik} = V_{nik} + \varepsilon_{nik}$
V_{nik}	systematic (or observed) component of utility associated with alternative i for individual n in choice set J_{nk}
ω_{in}	random error term with a Normal distribution associated with individual n and alternative i that is used to capture correlation across choice sets shown to the same individual
x_{nik}	a vector comprising alternative attributes and sociodemographic characteristics of individual associated with individual n and alternative i in choice set k
y_{nik}	an indicator variable equal to 1 if individual n chooses mode i from trade-off question k_n and 0 otherwise
z_1 and z_2	indices for zip codes

1. Introduction and motivation

As of 2020, more than $2B had been invested in urban air mobility (UAM) efforts (Sherman, 2020). UAM is a potentially disruptive new technology that would fundamentally change the way in which we travel in cities by allowing individuals to fly over congested roadways and/or by providing more direct connections for heavily traveled origin–destination (OD) pairs. As a new mode of transportation, there are many unanswered questions that aircraft manufacturers, as well as city and regional planners, seek to answer. For example: Which cities should we target for early adoption? Does the existing vertiport infrastructure support the initiation of air taxi service? Where are the potential high-volume air taxi routes within a city? Does the potential demand for an air taxi service vary across cities and, if so, what factors help explain why this demand varies?

This paper provides insight into these questions and contributes to the literature by computing a measure of demand for an air taxi commuter service for the 40 most populous combined statistical areas (CSAs)[1] in the United States (U.S.) We identify regular commuters, their home origins, and their work destinations using cell phone data. We then combine the cell phone data with household income from census data and use a mode choice model calibrated from a stated preference survey of commuters to identify potential air taxi commuter routes in each city. The routes for each city are graphically displayed in a set of online interactive maps (Haan et al., 2020). Our paper is one of the first to rank U.S. cities according to their potential commuter air taxi demand and also one of the first to provide a visualization tool that researchers and practitioners can use to identify the location of these high-volume air taxi commuter routes. To the best of our knowledge, this paper is also the first to use cell phone data to identify regular commuters for the purpose of identifying potential air taxi routes. In this context, our paper complements prior studies that have used anonymous mobile phone data to help understand individual mobility patterns (Gonzalez et al., 2008; Blondel et al., 2015), identify home and work locations (Alexander et al., 2015; Douglass et al., 2015), and generate OD demand matrices for ground transportation modes (Toole et al., 2015; Lenormand et al., 2014).

The balance of this paper contains several sections. Section 2 presents related literature. Section 3 describes the methodology we used to forecast a measure of electric vertical takeoff and landing (eVTOL) aircraft commuting demand and explains how we generated inputs for the forecast. Section 4 presents the results for the base case scenario, and Section 5 presents the results from a sensitivity analysis. We conclude with a discussion of key findings, limitations, and direction for future research in Section 6.

2. Literature review

In 2018, the average commute time in the U.S. was over 27 min (U.S. Census Bureau, 2019a) and the annual total cost of lost productivity due to traffic congestion was more than $87B (INRIX, 2019) and expected to double by 2030 (Center for Economics and Business Research, 2014). For these reasons, much of the initial work on assessing the potential of using air taxis to travel in cities has focused on the commute trip purpose. Other trip purposes have been considered, though, such as an airport shuttle, a corporate campus shuttle, an on-demand air taxi service, medical and emergency operations and service, etc. (NEXA Advisors, 2019; Booz Allen Hamilton, 2018).

A wide range of UAM studies has been conducted in terms of predicting demand for a UAM service. These include global market studies, studies comparing potential travel times savings with UAM against other modes, and survey-based research.

2.1. Global market studies

Global-based market studies use measures of economic activity and transportation service levels to produce estimates of the number of individuals taking a particular mode who travel between OD pairs. Representative economic factors often included in global-based market studies of aviation activity include population; population density; gross domestic product (GDP); GDP per capita; income; employment rate; whether the destination is a capital city; and indices to represent buying power, commercial and business aviation activity (such as the presence of Fortune 1000 companies), and tourism activity. Representative service factors included in global-based market studies of aviation activity include distance, travel time, airfare, flight frequency, aircraft size, load factors, and attributes of competing modes. See Sivrikaya and Tunç (2013), Galli et al. (2016), Olariaga et al. (2018), Zhang and Zhang (2016), and Suprayitno (2020) for representative studies focused on commercial air demand.

Representative global-based market studies specific to UAM include those by Becker et al. (2018), Robinson et al. (2018), Booz Allen Hamilton (2018), KPMG (Mayor and Anderson, 2019), and NEXA Advisors (2019). Becker et al. (2018) used a gravity model to forecast worldwide interurban air passenger demand for trips up to 300 km (186 miles). NEXA Advisors (2019) generated UAM demand forecasts for 74 cities worldwide for different use cases, including an airport shuttle, a corporate campus shuttle, an on-demand air taxi service, medical and emergency operations and service, and regional air transport service. KPMG identified about 70 cities worldwide where UAM could fully emerge by 2050 (Mayor and Anderson, 2019). The KPMG study used multiple factors to predict demand for 2050, including city GDP and GDP growth, city population and population growth, city population density, change in income distribution, wealth concentration, travel times and surface congestion, alternative modes of transportation, current limousine

[1] A CSA is a geographical unit of analysis defined by the U.S. Office of Management and Budget (OMB) for which the employment exchange across adjacent metropolitan and micropolitan statistical areas is at least 15 percent (U.S. Census Bureau, 2016). Given we are focused on examining commuter trips, we base our analysis on the 40 largest CSAs versus the 40 largest metropolitan statistical areas (MSAs) and refer to a CSA as a "city" throughout the paper.

Table 1
U.S. cities identified in the literature as having potential for UAM service with a comparison of rankings between the KPMG report and our analysis.

	Studies*	Rank in KPMG Report	Rank Among U.S. Cities in Our Analysis			
			Baseline	No Access or Egress Times	Lower-Performing Vehicle	Higher-Performing Vehicle
Atlanta	Robinson, KPMG, NEXA	8	14	8	15	13
Baltimore	NEXA	–	2**	2**	2**	2**
Boston	Robinson, KPMG, NEXA	12	6	6	6	6
Charlotte	NEXA	–	8	7	7	12
Chicago	Robinson, Becker, KPMG, NEXA	3	18	10	18	19
Dallas–Ft. Worth	Robinson, BAH, KPMG, NEXA	4	27	30	26	25
Denver	BAH, NEXA	–	10	12	13	8
Detroit	NEXA	–	13	14	12	10
Honolulu	BAH	–	–	–	–	–
Houston	Robinson, BAH, KPMG, NEXA	5	7	13	8	9
Las Vegas	NEXA	–	33	36	34	32
Los Angeles	BAH, Becker, KPMG, NEXA	2	3	3	3	3
Miami	Robinson, BAH, Becker, KPMG, NEXA	6	36	33	36	35
Nashville	NEXA	–	26	18	23	27
New York City	Robinson, BAH, Becker, KPMG, NEXA	1	1	1	1	1
Philadelphia	KPMG, NEXA	9	5	5	4	5
Phoenix	BAH, KPMG, NEXA	11	***	***	***	***
Raleigh	NEXA	–	20	11	16	21
Salt Lake City	NEXA	–	31	28	30	33
San Diego	NEXA	–	–	–	–	–
San Jose	NEXA	–	19**	9**	22**	17**
Seattle	Becker, NEXA	–	4	4	5	4
Silicon Valley / San Francisco	Robinson, BAH, Becker, KPMG, NEXA	7	19**	9**	22**	17**
Syracuse	NEXA	–	–	–	–	–
Tampa	NEXA	–	–	–	–	–
Washington, D.C.	BAH, KPMG, NEXA	10	2**	2**	2**	2**

Source: Adapted from Garrow, German, and Leonard (Forthcoming).
* Reference Key: Robinson = Robinson et al. (2018); BAH = Booz Allen Hamilton (2018); Becker = Becker et al. (2018); KPMG = Mayor and Anderson (2019); NEXA = NEXA Advisors (2019).
** Baltimore is included in the Washington, D.C., CSA for our analysis; San Jose is included in the Silicon Valley / San Francisco Bay Area CSA for our analysis.
*** Phoenix is not part of a CSA in the U.S. (but is the 12th largest MSA).

usage, number of OD pairs within 120 miles, and cost. The studies by Booz Allen Hamilton (2018) and Robinson et al. (2018) identified potential U.S. cities for UAM based on qualitative criteria, including ground transportation congestion, weather, existing infrastructure and ground transportation patterns, the city's level of sprawl, density, presence of water bodies (that could be used to construct barges for potential vertiports), number of airports currently in the city, population wealth, and presence of high-tech industries.

The U.S. cities identified as potential candidates for UAM for the reports discussed above are summarized in Table 1. A large degree of overlap is evident, with NEXA Advisors including more cities in their analysis and, thus, having more smaller cities than the other studies. We will return to Table 1 later in this paper, to compare how the rankings of U.S.-based cities we generated from our analysis relate to the cities from these previous studies.

2.2. Studies comparing door-to-door travel times

The market studies noted are typically used to produce demand estimates for large geographic areas—such as total UAM demand for the city of Atlanta. However, given that eVTOL aircraft will perform missions of relatively short distances within our cities, it is also common for researchers to conduct a more refined analysis that compares door-to-door travel times for UAM and competing modes using smaller levels of aggregation (such as zip codes[2] or census tracts within the U.S.) Numerous door-to-door travel time comparison studies have been conducted, including those by Antcliff et al. (2016), Kreimeier et al. (2016), Roland Berger (2018), Rothfeld et al. (2018), Roy et al. (2018), Vascik et al. (2018), and Akhter et al. (2020).

[2] Zone Improvement Plan (ZIP) Codes, or zip codes, are five-digit numbers designated by the U.S. Postal Service to indicate the destination post office or delivery area, or the geographic area identified by that code.

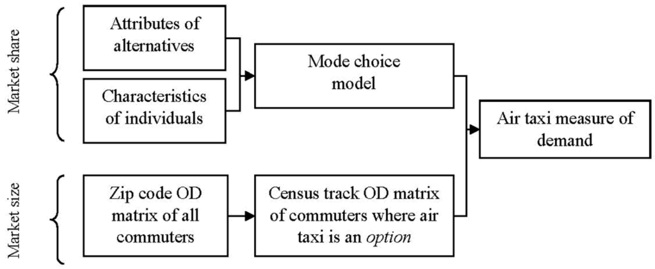

Fig. 1. Methodological overview.

The majority of these studies have found that the competitiveness of air taxi is sensitive to access and egress times to and from vertiports. For example, Roland Berger (2018) found that air taxi trips need to be at least 15 to 25 km (about 9 to 16 miles) to provide travel time savings over existing modes. Based on a case study in the Miami area, Wei et al. (2018) found that as range decreases, access and egress times to and from the port become increasingly important. Swadesir and Bil (2019) stressed, based on a case study of Melbourne, Australia, that demand for an air taxi service is sensitive to access and egress times to the vertiport, as well as the times to board and disembark the aircraft. Based on an analysis of UAM service in Sioux Falls, South Dakota, Rothfeld et al. (2018) saw that UAM processing times have a larger influence on UAM adoption than the UAM vehicle cruising speed. Based on a case study of commuters in Silicon Valley, Antcliff et al. (2016) discovered that a key factor in improving door-to-door travel times for air taxis is to minimize preboarding times (e.g., waiting times and security clearance times) as well as the times to board and disembark the aircraft. Finally, based on a case study for intercity travel in Germany, Kreimeier et al. (2016) saw that UAM market shares are highly sensitive to UAM prices, as well as access and egress times.

2.3. Studies using surveys to estimate value of time

Studies that compare door-to-door travel times between UAM and conventional modes typically incorporate assumptions related to individuals' value of time (VOT), or the amount of money that individuals are willing to spend to save an hour of travel time. Given that air taxis are a new mode, several stated preference (SP) surveys have been conducted to estimate individuals' VOT for air taxis and competing modes, including studies by Fu et al. (2019) and Song et al. (2019).

Fu et al. (2019) modeled the choice among private car, public transportation, autonomous ground taxi, and autonomous air values of times for these four modes as 27.55, 27.47, 32.57, and 44.68 €/hour respectively, which correspond to 33.89, 33.79, 40.06, and 54.96 $/hour, respectively.[3] Song et al. (2019) modeled mode choice among traditional auto, transit, UberX, UberPool, and UberAir using an SP survey conducted by Uber of 2607 residents from Dallas–Ft. Worth and Los Angeles. The authors found average VOTs associated with the access time, egress time, flight time, and in-vehicle travel time in $/hour to be 26.03, 34.43, 20.75, and 13.94, respectively.

As seen from the literature review, UAM demand modeling has primarily focused on determining if UAM is a viable concept. UAM demand studies rely on both estimates of market size (or the total number of travelers) and market share (of the percentage of the total demand that will take air taxi). In this paper, we use data from a major U.S. telecommunications company to generate an estimate of the total number of commuters and a mode choice model calibrated from a survey we conducted of 1405 commuters in five U.S. cities (Garrow et al., 2019).

3. Methodology

The methodology we used to calculate a measure of eVTOL aircraft demand in 40 U.S. cities is shown in Fig. 1. To calculate demand, we need to know the overall number of commuters (or market size), as well as how many of these commuters will choose an air taxi (or market share). A mode choice model is used to calculate the probability that an individual selects a particular mode as a function of the attributes associated with the modes and individuals. Data from a major U.S. cell phone service provider are used to produce an OD matrix for each city that contains the total number of commuters traveling between each zip code pair. Given that zip codes in the U.S. cover large geographic areas, we first allocate these commute trips to smaller census tracts. We then identify OD pairs in which air taxi is not available before applying the mode choice model to produce a measure of eVTOL aircraft demand. Total demand is given as the product of market size and market share.

It is important to note that as part of this analysis, we are creating a *measure* of eVTOL aircraft demand that is comparable across cities, and our results should not be interpreted as the *actual* expected number of eVTOL aircraft commuters. This distinction is necessary because we are basing our market share estimates on an SP survey that includes one current mode (conventional auto) and two future modes (a fully autonomous ground vehicle or AV and an air taxi). In practice, when information about actual market shares

[3] An exchange rate of 1 € = 1.23 USD was used based on the average exchange rate in February to April 2018, when the survey data were collected (Pound Sterling Live, 2020).

is known, it is possible to design the SP survey in a way that allows the researcher to forecast *actual demand* for two or more existing modes and one future mode. This procedure, described in Glerum et al. (2016), involves asking a common trade-off question across all respondents that is used to match the survey market shares to the population market shares. We cannot use this procedure, however, as we are forecasting commuter demand under a scenario in which there is only one existing mode (conventional auto) and two future modes (AV and air taxi). Thus, we refer to our forecasts as producing a *measure* of eVTOL aircraft demand but emphasize that the demand estimates reported in this paper should not be interpreted as a forecast of the actual number of people who would take eVTOL flights in a particular city. Our measure of demand is appropriate to use for comparing potential demand across cities and for producing rankings.

This section describes in detail each of the steps shown in Fig. 1, explains how we generated inputs for the mode choice model, and outlines assumptions we used to forecast a measure of eVTOL aircraft commuting demand.

3.1. Mode choice model

The mode choice model we used to forecast a measure of commuter demand for air taxi service across 40 U.S. cities was estimated using survey data that were collected from March 26 to May 10, 2019. The 1,405 respondents were full-time workers with annual household incomes of at least $75 K who have typical one-way commutes of at least 30 min, and reside and work in the Atlanta, Boston, Dallas–Ft. Worth, San Francisco, or Los Angeles CSAs.

As part of the survey, a discrete choice experiment was included in order to estimate a mode choice model of commuter demand. Design of experiment methods were used to generate the trade-off questions. Each respondent was shown eight different choice sets that contained three alternatives. One alternative was based on the respondent's current mode to work (i.e., either a traditional auto or transit). The other two alternatives were a fully autonomous ground vehicle and a piloted air taxi. Given the low number of responses associated with the transit alternative[4], we only included the auto commuters in our mode choice model (resulting in three alternatives: traditional auto, AV, and air taxi).

The attributes associated with these alternatives varied across the choice sets and were customized based on an individuals' average commute distance. The number of attributes in our trade-off questions, combined with the number of levels we tested, would have required that we ask each individual respondent 32 trade-off questions, which clearly is not realistic. In these cases, it is common to create blocks of questions so that each respondent sees a smaller number of questions. Respondents are then randomly assigned to one block. Appendix A provides an example of how a block of eight questions was generated and corresponds to a trade-off question or choice set shown to a respondent. See Garrow, et al. (2019) for additional details on the survey design.

We model the mode choice y_{nik}, for an individual n, who chooses alternative i from one of the k trade-off questions that respondent n was shown on the survey as:

$$y_{nik} = \begin{cases} 1 \quad \text{if} \quad \text{individual} \quad n \quad \text{chooses} \quad \text{mode} \quad i \quad \text{from} \quad \text{tradeoff} \quad \text{question} \quad k_n \\ 0 \quad \text{otherwise} \end{cases}$$

The systematic utility V for individual n in choosing alternative i from choice set J_{nk} is a linear function of $\boldsymbol{x}_{nik}$, written $V_{nik} = \alpha_i + \boldsymbol{\beta}_i^{'}\boldsymbol{x}_{nik}$, where $\boldsymbol{x}_{nik}$ is a vector comprising alternative attributes and sociodemographic characteristics of the individuals, $\boldsymbol{\beta}_i^{'}$ is the transpose of the vector of coefficients associated with all variables, and α_i is the coefficient associated with the alternative specific constant (which can be interpreted as an intercept term). This systematic utility is added to a random utility ε_{nik} to yield the total utility, $U_{nik} = V_{nik} + \varepsilon_{nik}$.

A basic assumption of the multinomial logit (MNL) model is that ε_{nik} is distributed independently and identically with a Gumbel (or extreme value type I) distribution. Using this fact, we can derive the probability of individual n choosing alternative i in trade-off question k_n, which we denote as P_{nik}, as:

$$P_{nik}(\boldsymbol{x}) = Pr(y_{nik} = 1|\boldsymbol{x}) = \frac{e^{V_{nik}}}{\sum_{j\in J_{nk}} e^{V_{njk}}} = \frac{e^{\alpha_i + \boldsymbol{\beta}_i^{'}\boldsymbol{x}_{nik}}}{\sum_{j\in J_{nk}} e^{\alpha_j + \boldsymbol{\beta}_j^{'}\boldsymbol{x}_{njk}}} \tag{1}$$

This probability function shown in Eq. (1) is for models where the vector of parameters $\boldsymbol{\alpha}$ varies over alternatives i, and the vector of parameters $\boldsymbol{\beta}$ potentially varies over alternatives i, but both $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ have known fixed values (i.e., the same constant values) for all individuals n.

The probability function for the logit model relies on an assumption that the random utility ε_{nik} is independent across alternatives and, thus, cannot incorporate correlation across observations. However, our survey data contain k responses from each individual, and we expect the responses from each individual to be correlated with each other. One way to overcome this serial correlation is to use a specification involving an agent effect, i.e., an error component distributed across individuals. In our case, we assume that the agent effects are independently normally distributed with unknown mean and variance that are estimated.

Each random component α_{in} for given i and n is defined in the model as:

[4] According to census, the percentage of workers ages 16 and older who take public transit to work is 2.9%, 8.7%, 1.4%, 4.3%, and 10.7% in the Atlanta, Boston, Dallas-Ft. Worth, Los Angeles, and San Francisco areas, respectively (U.S. Census Bureau, 2017b) which results in an expected number of transit commuters of 82.

Table 2
Mode choice model.

	Random Component Mixed Logit Model
Constants	
Auto mean	1.01 (4.96)
Auto std dev	1.93 (25.1)
AV mean	0.163 (0.522)
AV std dev	−1.77 (−24.1)
Air taxi (reference)	0
In-vehicle travel time (hours)	
Auto	−3.54 (−24.6)
AV	−2.88 (−20.9)
Air taxi	−3.18 (−14.8)
Out-of-vehicle travel time (hours)	
AV	−4.53 (−18.3)
Air taxi	−1.88 (−4.78)
Cost per CPI adjusted income (cost in \$, income in thousands of \$)	
Auto	−22.7 (−9.61)
AV	−29.4 (−11.9)
Air taxi	−12.4 (−16.8)
Own AV (AV)	0.249 (4.08)
Ride guarantee	0.309 (4.94)
Model Statistics	
# parameters in model (K)	14
# parameters in constants only model (K_{MS})	2
# observations (N)	7808
LL constants $LL(C)$	−8555.4
LL at convergence $LL(\beta)$	−6773.4
$\overline{\rho}_c^2$	0.2068
AIC	13,574
BIC	13,672
Value of Time (\$/hr) at CPI = 1 and Income of \$100 K	
IVTT auto	\$15.60
IVTT AV	\$9.80
IVTT air taxi	\$25.70
OVTT AV	\$15.40
OVTT air taxi	\$15.20

Note: Parameter estimate (robust t-stat). $\overline{\rho}_c^2 = 1 - \frac{LL(\beta) - K}{LL(C) - K_{MS}}$. AIC=$2K - 2LL(\beta)$
BIC=$K\ln(N) - 2LL(\beta)$

$$\alpha_{in} = \alpha_{0,i} + \alpha_{S,i} \bullet \omega_{\text{in}}$$

where ω_{in} are drawn from a standard normal distribution for each alternative and individual and the values for $\alpha_{0,i}$ and $\alpha_{S,i}$ are parameters that are estimated from data. We used the Biogeme software[5] (Bierlaire, 2020) to estimate the model.

The model we used to forecast the eVTOL aircraft commuter demand across 40 CSAs appears in Table 2. It includes out-of-vehicle travel time (OVTT), in-vehicle travel time (IVTT), trip cost divided by an income that has been adjusted by a consumer price index (CPI), AV ownership, and a ride guarantee.[6] IVTT describes the time the individual spends traveling in an auto, AV, or air taxi. OVTT includes wait time for a shared AV and access/egress times for an air taxi. By adjusting income by CPI, we account for different cost of living allowances across cities. By dividing cost by the CPI-adjusted income, we account for the fact that travel costs represent a larger percentage of household income for those with lower incomes than higher incomes.

Prior studies of mode choice have found that individuals prefer alternatives with shorter travel time and lower costs. Value of time can be calculated from the coefficients of time and cost and represent the amount of money an individual would be willing to spend to save an hour of travel time. The value of in-vehicle travel time for mode i is computed as the ratio of the IVTT and cost parameters for each mode, multiplied by the local CPI adjustment and the traveler's household income in thousands of dollars, and is reported at the bottom of Table 2 for a CPI of 1 and income of \$100 K. Similar calculations are used to compute the VOTs associated with IVTT and

[5] We used Biogeme version 3.6, referred to as PandasBiogeme.

[6] The SP survey collected additional socioeconomic and sociodemographic data such as age, highest educational attainment level, gender, and race, but many of these variables were not statistically significant in the mode choice model.

OVTT for other modes shown in Table 2. The VOTs for IVTT expressed in $/hr associated with the air taxi, conventional auto, and AV are 25.70, 15.60, and 9.80, respectively. To the extent that higher-income households and/or those who are more time sensitive are more likely to take air taxi, we would expect the VOT for air taxi to be higher than the VOT for other modes. The literature has found that VOTs for new modes are related to potential productivity increases that are possible in the new modes. Correia et al. (2019) and Pudāne and Correia (2020) present a theoretical model for VOT, noting that full automation will enable passengers to perform nondriving-related tasks that will lead to a smaller VOT for AVs than for a conventional auto. Several empirical studies have confirmed this result for commute trips, including those by Correia et al. (2019) and Kolarova et al. (2019).

The VOTs for OVTT expressed in $/hr associated with the air taxi and AV modes are 15.40 and 15.20, respectively, which are similar to the VOT for the auto IVTT that is 15.60. Intuitively, this is because we expect OVTT to be more onerous than IVTT, particularly when individuals need to travel or wait outdoors and are subject to inclement weather. However, in our forecasting application, OVTT for a shared AV would likely occur at the home or work locations, which are not as onerous as waiting outside. Similarly, we assume that individuals use an auto to travel to and from the home vertiport and a rideshare to travel to and from the work vertiport. Thus, we did not impose a constraint that required OVTT to be higher than IVTT for the AV and air taxi modes in our model, but used the VOTs shown in Table 2 for forecasting, as they are reasonable for our particular application.

AV ownership and ride guarantee variables are included in the mode choice model shown in Table 2. AV ownership is an indicator equal to 1 if the individual owns an AV and 0 if the individual shares the AV with another. The ride guarantee applies to the air taxi mode and was described on the survey as follows: “In the event that the eVTOL aircraft option is not available (for example, due to bad weather), a ride guarantee makes sure you receive priority for taking a Lyft or Uber car. To compensate you for the inconvenience, the rideshare option would be discounted and you would pay less than what the cost of an eVTOL flight would have been.” In the mode choice model shown in Table 2, we see that the coefficients associated with owning an AV and the ride guarantee are both positive (0.249 and 0.309, respectively) meaning that individuals are more likely to use an AV if they own it and individuals are more likely to take an air taxi if it includes a ride guarantee.

3.2. Alternative and individual attributes

In order to use the mode choice model in Table 2 to forecast a measure of air taxi demand, we need to generate estimates of IVTT, OVTT, and cost for each mode and each census tract pair. In addition, we need to apply assumptions related to AV ownership and an air taxi ride guarantee. For each census tract, we also need to estimate the number of households within certain income brackets and adjust this income by the CPI for each CSA. This section describes how we generated inputs for all of the alternative and individual attributes.

With respect to commute paths, for the auto and AV modes, we assumed the individual travels from the centroid of the census tract associated with the home location to the centroid of the census tract associated with the work location. We obtained the location of census tract centroids using the U.S. Census Bureau’s Centers of Population by Census Tract file (Census Bureau, 2010a). Travel times and distances for the AV and auto modes were calculated using the Bing Maps Distance Matrix API with traffic information (Microsoft, 2018). Travel times were extracted for a weekday morning at 8 AM local time in the future[7] order to represent a “typical” travel time that individuals would encounter during their typical morning commute. For the AV and auto modes, we assumed cost to be a linear function of distance, as given by Equations 2 and 3:

$$Cost_{car,OD_a} = CPM_{car} \bullet \mathrm{d}_{\mathrm{OD_a}}, \mathrm{a} = 1, 2, \cdots \mathrm{A} \tag{2}$$

$$Cost_{AV,OD_a} = CPM_{AV} \bullet \mathrm{d}_{\mathrm{OD_a}}, \mathrm{a} = 1, 2, \cdots \mathrm{A} \tag{3}$$

where,

$Cost_{car,OD_a}$ is the cost of traveling by car between the two census tract centroids for OD pair a
$Cost_{AV,OD_a}$ is the cost of traveling by AV between the two census tract centroids for OD pair a
CPM_{car} is the cost per mile of driving a car (assumed by the analyst)
CPM_{AV} is the cost per mile of an AV (assumed by the analyst)
d_{OD_a} is the driving distance between the two census tract centroids for OD pair a
A is the total number of OD pairs

We assumed that CPM_{car} is $0.59 per mile based on estimates provided by the American Automobile Association (AAA, 2017); specifically, we applied the cost per mile associated with an average sedan that is driven 15 K miles per year. We assumed that CPM_{AV} is $0.81 per mile[8] based on a study conducted by Bösch et al. (2017). This cost of an AV is 60 percent higher than the cost of a conventional auto. We also assumed that 10 percent of individuals own an AV. We consider the costs of an AV and AV ownership to be reasonable for a forecasting scenario that represents early market entry. These assumptions are also consistent with our overall research objective, which is to rank cities based on their early market eVTOL aircraft potential using existing vertiport infrastructure.

[7] We compared travel times generated by the Bing Maps Distance Matrix API for periods before and after COVID-19 to verify that the historical data being used for prediction were representative of pre-COVID-19 travel times and congestion levels.

[8] In the study by Bösch et al. (2017), the cost of an AV is given in Swiss francs currency as 0.504 CHF/km. Using an exchange rate of 0.9977 CHF = 1 USD for October 15, 2019 (Pound Sterling Live, 2019), and converting km to miles, this gives an estimate of 0.81 USD/mile.

With respect to the air taxi trip, the eVTOL trip was assumed to have three different travel components: (1) traveling from home to the home-based vertiport, (2) traveling in the air taxi from the home-based vertiport to the work-based vertiport, and (3) traveling from the work-based vertiport to work. We assumed that individuals travel from home to the home-based vertiport by personal car, represented as $IVTT^1_{air}$; travel from the work-based vertiport to their work location using rideshare, represented as $IVTT^2_{air}$; and spend an additional 4 min waiting for the air taxi, boarding the air taxi, and waiting for the rideshare, represented as $\mathrm{OVTT}_{\mathrm{air}}$. The value for $\mathrm{OVTT}_{\mathrm{air}}$ is optimistic and set at 4 min to represent a scenario in which there are seamless transitions across modes. Given prior results from the literature that have shown the competitiveness of air taxis with existing modes to be sensitive to access and egress times, we purposefully set these values low in the base case scenario and then conducted a sensitivity analysis to examine the sensitivity of results to $\mathrm{TVTT}_{\mathrm{air}}= IVTT^1_{air} + IVTT^2_{air} + \mathrm{OVTT}_{\mathrm{air}}$. Also, for the forecasting application we limited the first-mile and last-mile modes to personal vehicle and rideshare, as public transit is only used by 5 percent of the population (U.S. Census Bureau, 2019c). Other modes are, of course, possible, but in general would have higher $\mathrm{TVTT}_{\mathrm{air}}$ values and would be reflected in the sensitivity analysis.

We assumed the eVTOL vehicles operate from existing infrastructures that include regional airports and helipads distributed across the CSA. We used the National Flight Data Center's (NFDC's) database provided by the Federal Aviation Administration (FAA) to identify existing vertiport locations (FAA, 2020). The NFDC database contains information on all helipads, heliports, and airports in the U.S. We included all of the facilities in the NFDC database in our analysis, with the exception of those associated with military, police, and hospital facilities, as well as facilities such as Alcatraz[9] that clearly would not be used for commuting. In practice, not all of the facilities included in the NFDC database (and in our analysis) would be practical for eVTOL vehicle operations; for example, some of the facilities are privately owned and some are rural airstrips that support farming, recreational, or other activities. However, we maintain these facilities in the analysis, as the rural locations would be less likely to generate a high volume of commuters and privately owned facilities could potentially be leased to air taxi operators.

Consistent with the methodology used for the AV and air taxi modes, we computed travel times and distances on the ground using the Bing Maps Distance Matrix API for weekday morning at 8 AM local time using the centroids of the census tracts associated with the home and work locations and the actual locations of the home-based and work-based vertiports. For cases in which the home and work vertiports are the same, we note that an eVTOL trip is not available and exclude the corresponding OD pairs from the analysis.

To calculate flying time for those OD pairs in which an eVTOL trip is available, we used a simple mission profile for the eVTOL vehicles that involves taxi-out, takeoff, climb, cruise, descend, landing, and taxi-in as per the eVTOL mission requirement guidelines by Uber (n.d.). The calculation for flying time associated with the eVTOL mode is included as Appendix B.

We calculated the cost of the eVTOL mode, as seen by the traveler, as the total operating cost of the vehicle divided by the total number of passengers on board sharing the air taxi segment of the flight. The cost equation, shown as Eq. (4), was adapted from the previous studies (Roy et al., 2018, 2020):

$$Cost_{eVTOL,OD_a} = t_{flying,OD_a} \bullet \frac{\mathrm{OpCost}}{\mathrm{n_{pax}} \bullet (1 - \mathrm{f})} [\$] \tag{4}$$

where,

OpCost is the hourly aircraft operating cost (assumed by analyst)

n_{pax} is the number of passengers on board (assumed by analyst)

f is the deadhead ratio, or the fraction of nonrevenue flights required for repositioning (assumed by analyst)

The total time spent and the distance covered for the noncruise segments of the flight were estimated using the eVTOL mission guideline presented in Uber (n.d.). See Appendix B for the calculation. We assumed a vehicle cruise speed of 150 mph, which is consistent with the cruise speeds reported by aircraft manufacturers designing vectored[10] thrust aircraft. As reviewed in Garrow, German, and Leonard (forthcoming), "representative examples include the Lilium Jet (2 to 5 seats; 186 mph; 186-mile range), Airbus A3 Vahana (1 seat; 118 mph; 31-mile range), and Bell Nexus 4EX (5 seats; 150 mph; 150-mile range) (Lilium, 2020; Hawkins, 2019; Airbus, 2020; Bell Flight, 2020; Pope, 2019; Goldstein, 2019)."

We assumed an hourly aircraft operating cost of \$662. To put this in context, typical hourly operating costs for helicopters range from \$446 for a Robinson R22 Beta II that has a passenger seat capacity of two to \$5772 for an AgustaWestland AW101 that has a passenger seat capacity of 30 (Aircraft Cost Calculator, 2019a; 2019b). The hourly operating costs for eVTOL vehicles[11] are expected to range from \$625 to \$1100 (Booz Allen Hamilton, 2018). In this study, we used an hourly operating cost of \$662, which is similar to the cost used in other studies (e.g., Roy et al., 2020; Uber Elevate, 2019). We assumed a deadhead ratio (or the fraction of non-revenue flights) of 0.25, which is also consistent with other studies (e.g., Roy et al., 2020; Mane and Crossley, 2009).

In the mode choice model, the cost for each mode was adjusted by a consumer price index and divided by household income. Because CPI estimates were only available for a few of our CSAs from the Bureau of Labor Statistics, we adjusted incomes using a CPI estimate provided for each state from CityRating.com (2020).

We adjusted an individual's income, Inc'_{nc}, to reflect the local cost of living as follows:

[9] Alcatraz is a former prison located on an island near San Francisco that is now a tourist attraction.

[10] We use the word "thruster" to refer to different thrust-producing devices, including propellers, rotors, and ducted fans.

[11] On p. 37, the report by Booz Allen Hamilton (2018) notes eVTOL operating costs that range from \$6.25 to \$11 per passenger mile. If we assume a 15-minute, 25-mile mission, this would be equivalent to \$6.25 pax-miles × 25 miles / 0.25 h = \$625/hour. Similar calculations apply for the \$11 per passenger mile rate.

Table 3
Model assumptions.

	Notation	Values	Unit
Cost of driving a car per mile	CPM_{car}	0.59	\$/mile
Cost of driving an AV per mile	CPM_{AV}	0.81	\$/mile
Operating cost of eVTOL	$OpCost$	662 (463, 861)	\$/hr
Aircraft range	R_{max}	60 (30, 90)	miles
Number of passengers	n_{pax}	3	–
Deadhead ratio	f	0.25	–
Cruising speed	s_{eVTOL}	150 (125, 175)	miles/hour
Distance covered during noncruise segments (range credit)	d_{min}	8.78	miles
Time spent in noncruise segments	t_{min}	8.58	min
AV ownership	AV_{own}	0.10	–
Guaranteed ride	$Guarantee$	0	–
Wait times for air taxi	$OVTT_{air}^{3}$	4	min

$$Inc'_{nc} = Inc_n \frac{CPI_c}{CPI_{US}} \tag{5}$$

where,

Inc_n is an estimate of an individual n's income obtained from the SP survey

CPI_c is the consumer price index associated with the state in which CSA c is located

CPI_{US} is the average CPI for all states in the U.S.

As part of the SP survey, information on household income was collected using interval responses. The intervals were chosen to align with those used by the U.S. census and included the following (expressed in thousands of dollars): [75–100), [100–150), [150–200), [200 or more]. We used values for Inc_n of 87.5, 125, 175, and 300 for the four income brackets, respectively. The distribution of household income at the census tract level was obtained from census table S1901 using 5-year estimates (U.S. Census Bureau, 2017e). We used additional census tables based on 5–year estimates to obtain the number of household earners (i.e., commuters) associated with each household income bracket (U.S. Census Bureau, 2017c; 2017f). Finally, we used several census tables to obtain general population characteristics for interpreting results (U.S. Census Bureau 2017a; 2017b; 2017d; 2017e).

As part of our overall analysis, we varied assumptions related to different eVTOL aircraft designs as reflected in varying hourly operating costs, cruise speed, and maximum aircraft range. The results are reported in Section 4 of this paper. Table 3 summarizes the assumptions discussed in this section.

3.3. Market size estimates

We obtained market size estimates of commuter demand in 40 U.S. cities from a major U.S. telecommunications company that has a cell phone market penetration of about 33 percent. One of the benefits of using cell phone data compared to census data is that cell phone users align with the way many are envisioning an on-demand air-taxi service would work, i.e., that individuals would use a cell phone to travel with in-app reservations. The telecommunications company has proprietary algorithms they applied to their cell phone records to identify home and work locations for residents in these 40 U.S. cities. Conceptually, these algorithms consider where individuals are located during the evening hours and at night (to identify a home location), whether they regularly travel outside the home during peak period commuting periods (e.g., from 6 AM to 9 AM and 4 PM to 7 PM), and where they are located during the day in a regular workweek (to identify work location). The subset of commuters identified by these assumptions is representative of the potential customers that an air taxi operator would initially market their service to, but it is important to note that these assumptions identify regular commuters and are only a subset of the working population in a given area. For example, consultants who regularly travel by air and work outside of their home city would not be captured in the analysis. Nor would individuals who regularly commute but, due to high levels of congestion, travel before and/or after the peak travel periods be identified. Part-time and seasonal employees, as well as those who regularly worked from home before the COVID-19 pandemic, are also not represented in the cell phone database.

The telecommunications company provided a file that contained the average number of daily commuters traveling between a pair of zip codes. The average was calculated across a month and represents commuters traveling on weekdays (Monday through Friday). To comply with the U.S. telecommunications company's data dissemination and privacy guidelines, only zip code pairs with 50 or more observations were provided. The file we received from the U.S. telecommunications company contained estimates for the number of daily weekday commuters for 16 K zip code pairs. Given this U.S. cell phone company's market penetration of about 33 percent, we multiplied their commuter numbers by three to represent the overall number of commuters. We also accounted for the fraction of the

Table 4
A measure of eVTOL demand for base case assumptions.

1 CSA	2 Total Population (Census)	3 Total HH* (Census)	4 Total HH* with Income > 75 K (Census)	5 Total Workers (Census)	6** # Ports	7** # Ports per 10 K Capita	8** Avg. Travel Time to Port (min)	9 Total Commuter Trips (Cell phone)	10 Total eVTOL-eligible Trips	11 eVTOL Trips for Income greater than 75 K
New York	23,739,538	8,482,875	4,088,746	11,301,139	603	2.5	15.3	460,716	337,402	9,713
Washington, D.C.	9,611,943	3,488,700	1,967,627	4,946,037	321	3.3	18.5	291,264	205,821	5,437
Los Angeles	18,585,594	5,925,586	2,577,630	8,426,775	328	1.8	14.8	352,260	218,207	4,464
Seattle	4,603,633	1,789,544	882,245	2,281,837	241	5.2	14.1	155,295	129,354	3,605
Philadelphia	7,176,716	2,661,845	1,168,550	3,376,650	383	5.3	12.8	191,103	159,151	3,499
Boston	8,148,625	3,117,547	1,546,303	4,172,180	335	4.1	14.5	152,550	112,400	2,675
Houston	6,834,348	2,340,029	989,832	3,183,157	304	4.4	12.8	110,211	95,065	1,982
Charlotte	2,584,937	967,996	362,031	1,229,002	171	6.6	15.5	189,243	153,817	1,826
Portland, OR	3,105,069	1,179,281	494,119	1,478,052	194	6.2	12.9	105,615	85,094	1,826
Denver	3,401,195	1,300,650	621,711	1,774,677	108	3.2	16.4	115,998	85,729	1,767
Columbus, OH	2,426,577	932,288	348,676	1,167,834	178	7.3	14.5	146,463	123,773	1,734
Cincinnati	2,215,759	861,116	336,696	1,059,640	126	5.7	15.1	126,081	109,914	1,722
Detroit	5,325,207	2,085,214	775,700	2,385,445	212	4.0	14.5	148,989	109,103	1,656
Atlanta	6,354,028	2,258,972	901,330	2,987,874	268	4.2	17.9	160,950	124,219	1,488
Cleveland	3,493,279	1,431,331	482,359	1,634,637	227	6.5	14.9	180,288	141,979	1,391
Pittsburgh	2,643,262	1,121,557	404,882	1,257,464	171	6.5	15.1	100,134	80,115	1,223
Virginia Beach	1,820,598	679,137	272,334	896,040	70	3.8	16.2	114,069	78,308	1,068
Chicago	9,921,410	3,625,246	1,591,483	4,747,119	225	2.3	16.0	129,579	89,895	1,064
San Francisco	8,686,062	3,037,770	1,716,340	4,180,640	119	1.4	21.1	182,511	80,814	1,049
Raleigh	2,115,747	792,997	333,059	1,030,771	119	5.6	15.3	162,996	122,980	1,007
Minneapolis	3,868,014	1,487,169	716,815	2,059,511	197	5.1	16.0	111,843	79,505	934
Indianapolis	2,371,030	908,070	326,905	1,136,192	160	6.7	12.8	76,326	62,946	827
Grand Rapids	1,433,362	529,783	184,364	677,813	100	7.0	12.7	85,302	67,069	749
Greenville, SC	1,425,211	547,045	160,284	626,993	88	6.2	15.2	115,374	83,346	671
Hartford	1,483,895	577,541	278,952	738,790	94	6.3	13.9	39,552	33,135	670
Nashville	1,951,608	736,433	278,372	960,486	120	6.1	21.8	132,210	104,068	657
Dallas	7,540,444	2,657,612	1,116,197	3,646,757	234	3.1	12.4	33,777	27,694	605
Greensboro	1,639,944	646,648	187,528	735,555	94	5.7	17.0	127,497	90,181	479
Orlando	3,131,288	1,138,700	359,829	1,392,930	173	5.5	16.2	45,387	36,888	467
Sacramento	2,537,070	909,997	386,749	1,097,392	90	3.5	17.7	57,819	35,919	442
Salt Lake City	2,468,558	768,383	345,004	1,174,516	50	2.0	15.6	74,199	41,395	388
New Orleans	1,491,008	566,667	185,300	667,949	75	5.0	15.1	25,200	18,113	354
Las Vegas	2,360,423	851,837	281,958	1,051,154	36	1.5	16.6	28,311	17,754	324
Louisville	1,505,880	586,286	204,614	713,588	71	4.7	14.1	28,221	22,517	293
Jacksonville	1,572,571	589,083	210,303	721,239	64	4.1	17.4	45,834	36,111	290
Miami	6,662,481	2,322,492	794,292	3,060,163	120	1.8	16.6	31,008	22,503	250
Milwaukee	2,045,538	810,435	309,586	1,006,477	88	4.3	15.1	27,747	17,203	134
St. Louis	2,909,551	1,153,633	445,302	1,397,915	83	2.9	19.4	21,327	14,573	107
Kansas City	2,429,779	943,138	370,653	1,203,553	77	3.2	14.4	17,253	11,136	92
Oklahoma City	1,425,118	531,804	185,068	670,773	46	3.2	14.2	6,882	4,235	31

* Household ** Ports is used as an abbreviation for vertiports in the table.

population that would “never” consider using an air taxi based on our findings from stated preference surveys, which we estimated to be 16 percent in our survey. Multiple studies from the technology adoption literature related to new modes of transportation have identified a significant percentage of the population who state they would never consider using the new mode. In the context of UAM, these studies include Al Haddad et al. (2020) at 3 percent and Ljungholm and Olah (2020) at 14 percent. After applying these two adjustments (one for market penetration of cell phone data and the second for non-adopters in our survey), we obtained the market size for zip code pair z_1 and z_2 or $MktSize_{OD_{z1,z2}}$.

Because zip codes represent a large geographic area, we distributed trips to census tracts located within the zip code. Relating zip codes to census tracts is challenging because census tracts can belong to more than one zip code. The U.S. Census Bureau provides

Table 5
Statistics associated with eVTOL demand measure for base case scenario.

CSA	% HH with Income > 75 K	% Commuters in Cell Phone Data	% Trips eVTOL-eligible	% eVTOL for Income greater than 75 K	CSA Ranking	eVTOL Ranking
New York	48	4.1	73	*2.9*	1	1
Washington, D.C.	*56*	5.9	71	*2.6*	4	2
Los Angeles	44	4.2	**62**	2.0	2	3
Seattle	*49*	6.8	*83*	*2.8*	13	4
Philadelphia	44	5.7	83	*2.2*	8	5
Boston	*50*	3.7	74	*2.4*	6	6
Houston	42	3.5	*86*	2.1	9	7
Charlotte	37	*15.4*	81	1.2	21	8
Portland, OR	42	7.1	81	2.1	18	8
Denver	48	6.5	74	2.1	16	10
Columbus, OH	37	12.5	*85*	1.4	25	11
Cincinnati	39	11.9	*87*	1.6	28	12
Detroit	37	6.2	73	1.5	12	13
Atlanta	40	5.4	77	1.2	11	14
Cleveland	34	11.0	79	1.0	15	15
Pittsburgh	36	8.0	80	1.5	20	16
Virginia Beach	40	12.7	69	1.4	32	17
Chicago	44	2.7	69	1.2	3	18
San Francisco	*56*	4.4	**44**	1.3	5	19
Raleigh	42	*15.8*	75	0.8	29	20
Minneapolis	48	5.4	71	1.2	14	21
Indianapolis	36	6.7	82	1.3	26	22
Grand Rapids	35	12.6	79	1.1	38	23
Greenville, SC	**29**	*18.4*	72	0.8	39	24
Hartford	*48*	5.4	*84*	2.0	37	25
Nashville	38	*13.8*	79	**0.6**	31	26
Dallas	42	**0.9**	82	2.2	7	27
Greensboro	**29**	*17.3*	71	**0.5**	33	28
Orlando	**32**	3.3	81	1.3	17	29
Sacramento	43	5.3	62	1.2	22	30
Salt Lake City	45	6.3	**56**	0.9	23	31
New Orleans	**33**	3.8	72	2.0	36	32
Las Vegas	**33**	2.7	63	1.8	27	33
Louisville	35	4.0	80	1.3	35	34
Jacksonville	36	6.4	79	0.8	34	35
Miami	34	**1.0**	73	1.1	10	36
Milwaukee	38	2.8	**62**	**0.8**	30	37
St. Louis	39	**1.5**	68	**0.7**	19	38
Kansas City	39	**1.4**	65	0.8	24	39
Oklahoma City	35	**1.0**	**62**	**0.7**	40	40

Key: Bold percentages = least likely to support an air taxi service.
Italicized percentages = most likely to support an air taxi service.

relationship files that show the relationships between two types of geography for the same period. We used the 2010 Zip Code Tabulation Area (ZCTA) to Census Tract Relationship file (U.S. Census Bureau, 2010b) to create a one-to-one mapping between census tracts and zip codes. For those census tracts that were located within multiple zip codes, we assigned the census tract to the zip code that had the highest percentage of the census tract's land area.

Zip codes and census tracts are two distinct geographic levels. Census tracts are a smaller geographic unit of analysis than zip codes. Aa market share of 20% for air taxi means that 20% of the individuals who travel for work between two zip codes travel by air taxi. Because zip codes represent larger geographic areas than census tracts, researchers will often work with smaller geographic areas such as census tracts. The smaller geographic unit of analysis provides more accurate estimates of travel times and costs. Instead of assuming that the total number of air trips between a zip code pair is uniformly distributed across the census tract pairs, we distributed air taxi trips based on the percentage of the population within the zip code that resides in a particular census tract. That is, given $MktSize_{OD_{z1,z2}}$ and a list of census tracts within zip codes z_1 and z_2, we distributed commute trips based on population weights associated with each census tract.

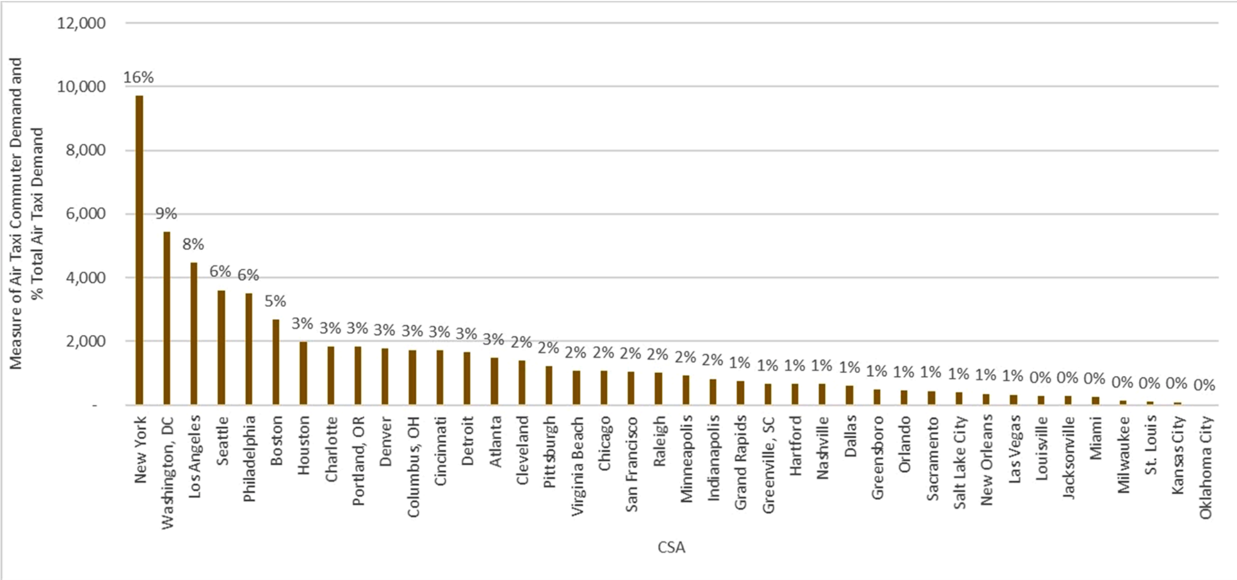

Fig. 2. A comparison of commuter air taxi demand across CSAs based on cell phone data.

4. Results

This section provides an overall summary of results using the base case scenario. We then compare our city ranking with other rankings reported in the literature, and present a deeper analysis for five of the CSAs. We conclude with a summary of the key insights obtained from the base case scenario.

4.1. Summary information

Table 4 provides summary information associated with our base case scenario and ranks the CSAs according to their potential eVTOL demand; the CSAs with the largest potential demand appear at the top of the table. Table 5 maintains the same ordering of CSAs and provides additional metrics that are computed from the data presented in Table 4. For each of the metrics reported in Table 5, dark shaded and bolded percentages correspond to a metric that is least likely to support an air taxi service and light shaded and italicized percentages correspond to a metric that is most likely to support an air taxi service.

Table 4 provides information on the total population, total number of households, total number of households with incomes greater than 75 K, and total number of workers for each CSA (U.S. Census Bureau, 2017a; 2017b; 2017d; 2017e). As seen in Table 5, across the 40 CSAs, a large variation exists in the percentage of households that have an annual income greater than 75 K. On average, 40 percent of the households in a CSA have an annual income greater than 75 K. CSAs with the lowest percentages of households with annual incomes above 75 K include Greensboro (29 percent), Greenville (29 percent), Orlando (32 percent), Las Vegas (33 percent), and New Orleans (33 percent). These five represent smaller CSAs. Approximately half of the households have annual incomes above 75 K in the CSAs associated with San Francisco (56 percent); Washington, D.C. (56 percent); Boston (50 percent); and Seattle (49 percent). Across these four CSAs, at least 10 percent of workers are employed in science, technology, engineering, and math (STEM) fields (Suneson and Stockdale, 2019).

Table 4 reports the number of vertiports (column 6) and the average time to travel from home and/or work to the nearest vertiport (column 8). The number of vertiports varies across the CSAs, with a low of 36 in Las Vegas (one of the smaller CSAs included in our analysis) and a high of 603 for New York City (the largest CSA). After adjusting for the population, the average vertiports per 100 K population is 4.5 (column 7). Those cities with the smallest number of vertiports per 100 K capita include two large West Coast cities, San Francisco (1.4) and Los Angeles (1.8), in addition to three less populous CSAs: Las Vegas (1.5), Miami (1.8), and Salt Lake City (2.0). Those cities with the largest number of vertiports per capita notably include several Midwestern cities with flat terrains, including Cleveland, Columbus, Grand Rapids, and Indianapolis.

Table 4 also reports the total number of commuter trips, as derived from the cell phone data (column 10). Percentages of commuter

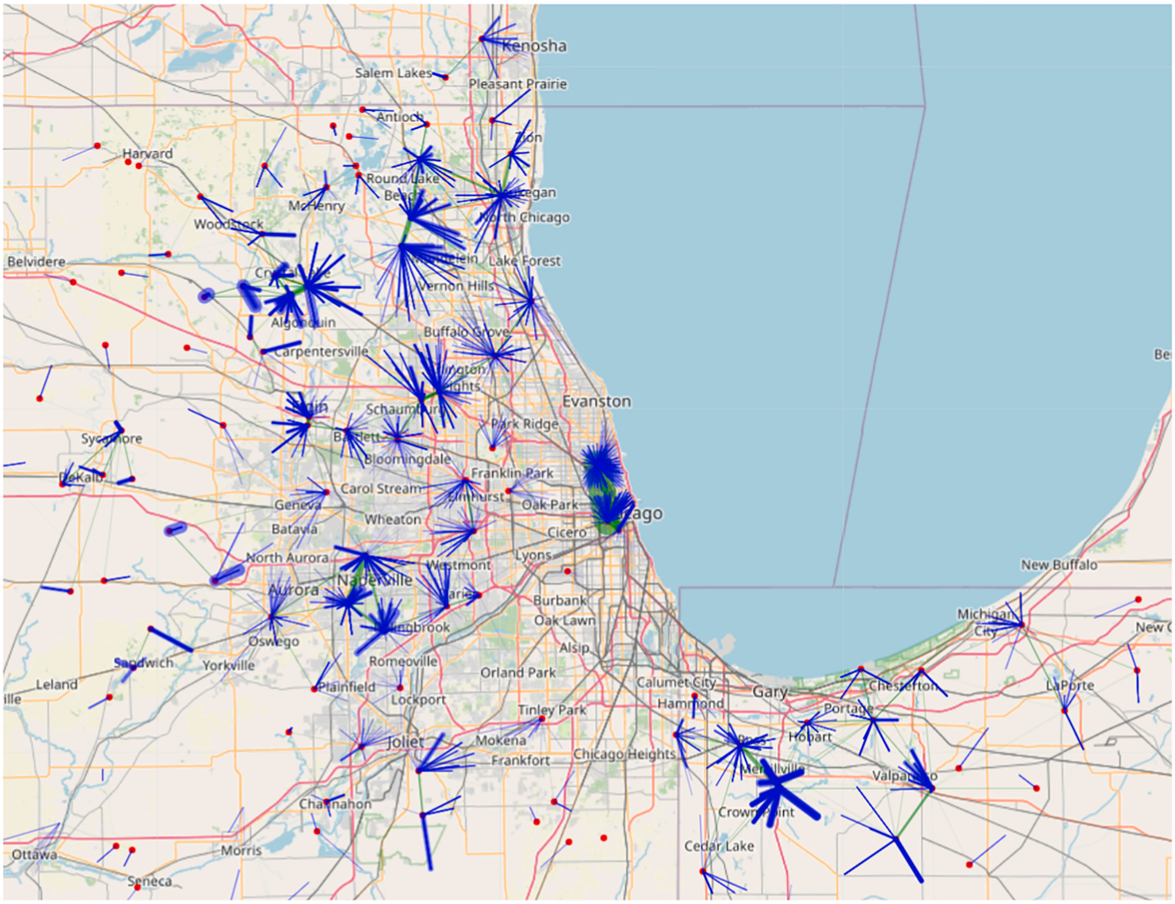

Fig. 3. Potential air taxi commuter routes in Chicago are dispersed and do not serve the CBD.
Note: Leaflet | Data by © OpenStreetMap, under ODbL.

trips identified from the cell phone data are, in general, small and vary across the CSAs. The "% Commuters in Cell Phone Data" column in Table 5 is calculated as the ratio of total commuter trips and the total number of workers in the CSA. For example, in New York City, this percentage is just 4.1 percent. *A priori*, we may have expected this percentage to be closer to 49 percent, which represents the (pre-COVID-19) percent of the population in the New York CSA who commuted and arrived at work between 7 AM and 8:59 AM (U.S. Census Bureau, 2019b). However, as noted earlier, the lower percentages observed from the cell phone database are due to several factors, i.e., the cell phone database only includes zip code pairs with at least 50 daily commuters for which the home and work locations are in different zip codes, and the cell phone database represents a subset of the population of workers reported by the census. There are several other reasons why a direct comparison with census data may not be reliable. The latest decennial census from 2020 is known to have had major issues because of the pandemic, the previous decennial census from 2010 is now more than 10 years old, and the American Community Survey (ACS) census product that is released more frequently is known to have issues with commute patterns because the employer location in the database is not always the physical location where the individual works. With cell phone data, estimates of eVTOL demand can be updated regularly if commute patterns and population density change, and may be a more accurate representation of the actual commutes compared to census products. Thus, it is important to note that we do expect the number of commuters identified from the cell phone data to differ from the total number of workers represented in census data based on the assumptions that were used to identify regular commuters from the cell phone records, as well as the fundamental difference of how cell phone data and census products identify commuters.

The number of these commuter trips for which air taxi is an available option is shown in Table 4 as column 9. As seen in Table 5, on average, 74 percent of the commuter trips represented in the cell phone database would have eVTOL vehicles (i.e., air taxi) as an available option. A positive correlation (0.71) is found between the number of vertiports per capita and the percent of commute trips

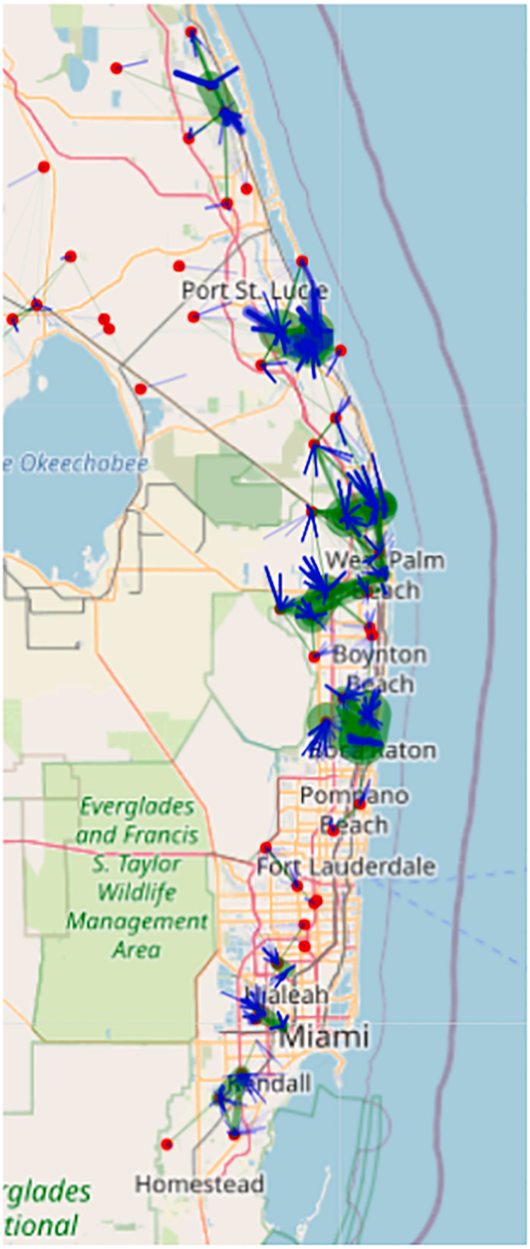

Fig. 4. Potential air taxi commuter routes in Miami are dispersed and do not serve the CBD.
Note: Leaflet | Data by © OpenStreetMap, under ODbL.

for which air taxi is available. San Francisco and Los Angeles—two of the cities that had the smallest number of vertiports per capita—also have the smallest number of eligible trips (44 and 62 percent, respectively), whereas Columbus—one of the cities that had the highest number of vertiports per capita—has one of the largest percentages of eligible trips (85 percent).

Table 4 shows the number of eVTOL trips in column 11, which is derived from the mode choice model and Table 5 shows the percentage of commuters (from the population of cell phone commuters for which air taxi is an available option) who chose the air taxi. The last two columns in Table 5 compare the ranking of the CSAs by eVTOL trips to the ranking of the CSAs by population. Fig. 2 shows

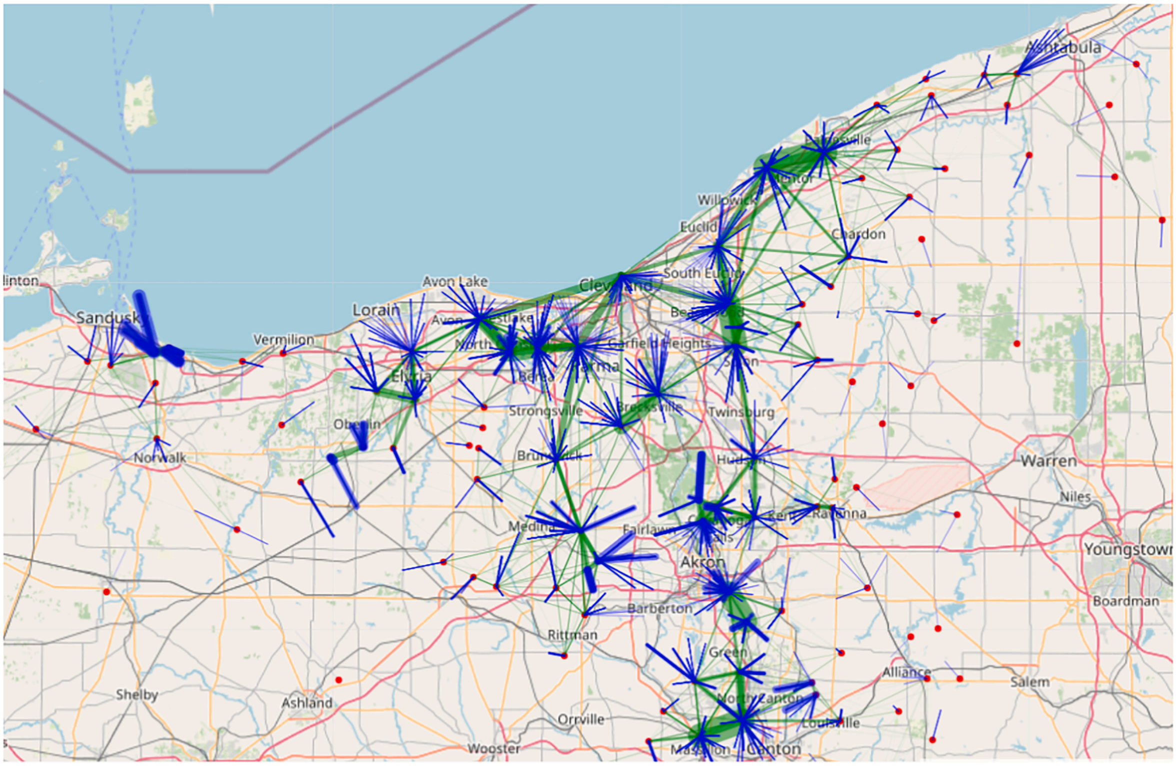

Fig. 5. Potential air taxi commuter routes in Cleveland provide connectivity to the CBD.
Note: Leaflet | Data by © OpenStreetMap, under ODbL.

how the eVTOL demand measure varies across the CSAs. Overall, larger cities generate more eVTOL trips. New York City, Los Angeles, and Washington, D.C., not only rank highest in terms of overall air taxi commuter demand, but also represent a disproportionate number of potential air taxi commute trips—more than 33 percent of all of the air taxi demand trips predicted by our model occur in these three CSAs, and 50 percent of all air taxi demand occurs in the top six CSAs. This is an interesting finding, as it suggests that a commuter air taxi service may be viable only in a handful of cities and/or that additional port infrastructure investments will be required in order to support a commuter air taxi service in smaller cities. That is, the potential market may be concentrated in a few cities and initiating service in smaller cities may not make financial sense.

4.2. Overall rankings of CSAs and a deeper analysis of Chicago, Miami, Cleveland, Portland, and Atlanta

Table 1 compares our ranking of CSAs to the rankings identified in other studies. When comparing rankings, it is important to note that they each use different units of analyses. Our study used CSAs that define geographic boundaries based on economic relationships, whereas other studies have conducted rankings based on smaller MSAs or other geographic boundaries. For example, both Washington, D.C., and Baltimore are included in our “Washington, D.C.” CSA but are considered as separate geographic areas in other studies. Likewise, San Jose, San Francisco, and Oakland are included in our “San Francisco” CSA but have been considered as one or more distinct geographic areas in other studies. Finally, other researchers have produced rankings that included Phoenix, Arizona, but this city was omitted from our analysis as it is not classified as a CSA but rather an MSA by the U.S. OMB.

We observe that our ranking of U.S. cities is similar to that produced by the KPMG report by Mayor and Anderson (2019), but with a few key differences. Both our study and the KPMG report rank Houston, Los Angeles, New York City, Philadelphia, and Washington, D.C., in the top 10. The KPMG report also ranks Atlanta, Chicago, Dallas–Ft. Worth, Miami, and San Francisco among the “top 10” cities with potential air taxi demand; however, our analysis ranks those cities lower, particularly for Dallas–Ft. Worth, Miami, Chicago, and San Francisco. The difference in ranking for Dallas–Ft. Worth and Miami can be explained in part due to the very low percentage of commute trips represented in the cell phone database (0.9 percent, the lowest percentage among all 40 CSAs examined, for Dallas–Ft. Worth and 1.0 percent for Miami).

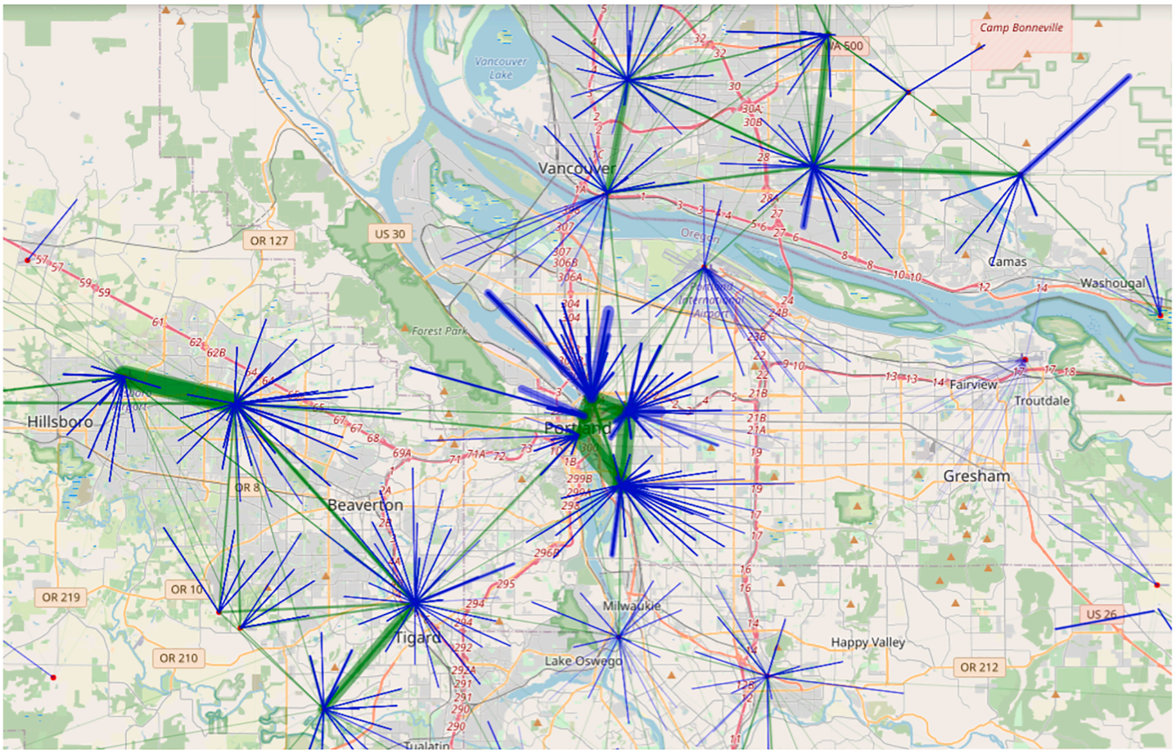

Fig. 6. Potential air taxi commuter routes in Portland, Oregon, provide connectivity to the CBD.
Note: Leaflet | Data by © OpenStreetMap, under ODbL.

The difference in rankings for Chicago, San Francisco, and Miami are influenced by multiple factors including the location of existing vertiports. Fig. 3 shows the air taxi commuter routes we identified for Chicago. An accompanying online map allows readers to zoom in on this area to examine the routes in more detail. In the online maps, the red dots represent existing vertiports, the blue lines connect the home and/or work destination to the nearest vertiport, and the green lines represent the air taxi portion of the trip. The thicker the line, the greater the volume of potential commuters.

In Chicago, many of the routes are dispersed throughout the metro area and are not directed to the central business district (CBD) or "the loop."[12] In part, this is because there is no port that is located close to the loop; the nearest port is in the west loop area near the Illinois Medical District close to the intersection of West Roosevelt and South Ashland. The highest volume of potential air taxi commuters in Chicago is between this west loop location and the neighborhood near Wrigley Field (on Addison Street). Readers familiar with Chicago will recognize that although these locations are about 7 miles apart, there are no arterials that directly connect these areas and the main heavy-rail public transit lines have many local stops. Thus, we would expect the potential travel time savings on air taxi compared to ground transportation to be higher, but the overall number of commuters traveling between this OD pair is small. This helps explain why Chicago did not rank as high in our analysis. San Francisco also exhibits a similar issue in that there is no vertiport located near the CBD. Thus, to make eVTOL travel competitive in such cities by serving the business districts, new vertiport development may be required, which would warrant additional cost–benefit analyses.

Fig. 4 provides additional insights into why Miami ranks lower in our analysis. Note that the development pattern of Miami is limited on the east by the Atlantic Ocean and on the west by wildlife refuges and parks. Consequently, the development patterns have occurred in a narrow band following the coast. Similar to Chicago and San Francisco, there is no port that is located directly within the CBD of Miami, which is a major employment center. The potential air taxi routes tend to be short and concentrated in northern areas, including Boca Raton and West Palm Beach (See Fig. 4).

While Chicago, San Francisco, and Miami ranked lower in our analysis compared to other studies, several cities, including Portland, Oregon, and the Ohio cities of Columbus, Cincinnati, and Cleveland, ranked much higher and were not included in any of the prior studies reported in Table 1. The three Ohio cities all have high representation of workers in the cell phone database (from 11 to 12.5 percent), which can partially explain why these cities are ranking higher, but additional factors are also influencing these rankings. Fig. 5 shows the potential commuter air taxi routes for Cleveland. Similar to Miami, Cleveland's development pattern has been influenced by the presence of a major body of water (Lake Erie in this case). However, unlike Miami, Cleveland has a port located along the lakefront near its CBD and has additional vertiports located near residential areas both along the lakefront as well as in more

[12] The CBD is referred to as "the loop" in Chicago because the elevated train lines make a circle or loop around the CBD.

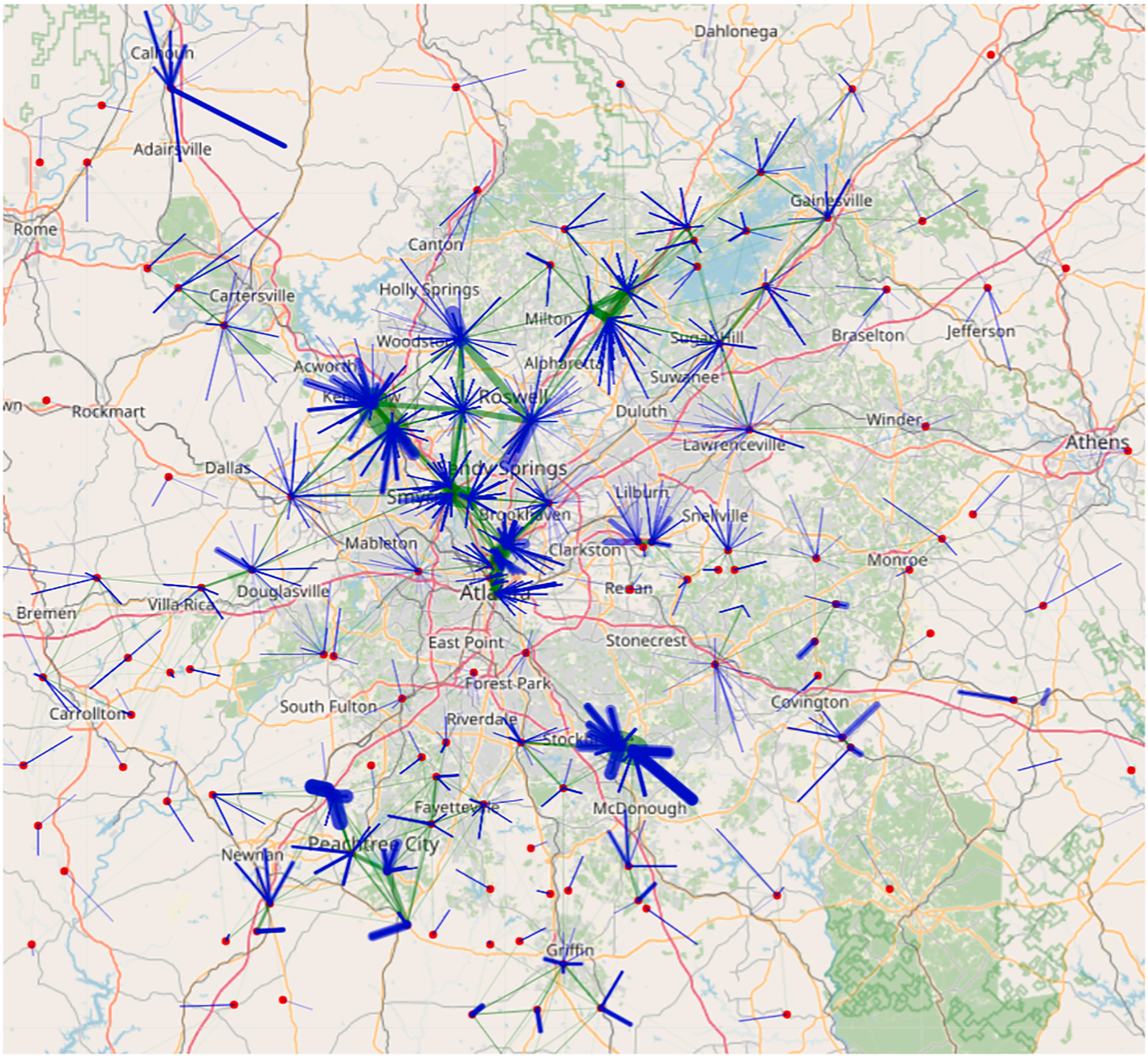

Fig. 7. Potential air taxi commuter routes in Atlanta increase connectivity in northern suburbs.
Note: Leaflet | Data by © OpenStreetMap, under ODbL.

interior areas. The existing ground infrastructure connecting these lakefront communities (and to a certain degree the interior communities) is also mainly on surface streets versus high-speed arterials and highways. These factors help explain why Cleveland, despite its smaller population, is able to generate a higher overall volume of air taxi commuter trips, as the air taxi routes are providing better connections between the residential areas along the lakefront and interior to the major downtown employment center. Similar patterns are seen for Portland, shown in Fig. 6, which has several vertiports located near the CBD, to the Old Town neighborhood just to the north and in the Lloyd District on the east side of the river that Portland borders. Additional vertiports located near communities to the west and north also facilitate the movement of commuters from Vancouver, Washington, and the suburbs of Tigard, Beaverton, and Hillsboro in Oregon to the CBD, as well as between suburb areas.

The influence of the existing ground infrastructure on potential commuter air taxi routes is also clear in Atlanta. Fig. 7 shows the potential commuter air taxi routes for the Atlanta CSA. The majority of the routes are located in the northern suburbs and provide connections both from the suburbs to the employment centers inside the perimeter,[13] including the downtown and Buckhead areas, as well as from one northern suburb to another northern suburb. Atlanta is a city that has experienced tremendous population growth over the past 10 years, with much of this growth occurring in the northern suburbs (Atlanta Regional Commission [ARC], 2020). Traveling from east to west across these suburbs is difficult due to the lack of higher-speed arterials and highways and public transit

[13] In Atlanta, locations are often referred to as whether they are “inside the perimeter” or “outside the perimeter,” where the perimeter boundary is delimited by the I285 highway that forms a loop around the city.

Table 6
Sensitivity of eVTOL demand measure to air taxi access/egress/wait times and eVTOL operating cost and range for households with annual incomes > $75 K.

CSA	eVTOL Trip Measure				Ranking of eVTOL Trips				
	Baseline Case	No Access/ Egress	Low-Performing Vehicle	High-Performing Vehicle	Baseline Case	No Access/ Egress	Low-Performing Vehicle	High-Performing Vehicle	Scaled Cell Phone Data
New York	9,713	32,309	15,135	6,349	1	1	1	1	1
Washington, D.C.	5,437	22,437	8,757	3,478	2	2	2	2	3
Los Angeles	4,464	17,626	7,316	2,804	3	3	3	3	2
Seattle	3,605	10,739	6,181	2,201	4	4	5	4	8
Philadelphia	3,499	10,729	6,513	1,987	5	5	4	5	6
Boston	2,675	10,226	4,544	1,601	6	6	6	6	4
Houston	1,982	6,320	4,121	1,017	7	13	8	9	7
Charlotte	1,826	7,803	4,173	896	8	7	7	12	25
Portland, OR	1,826	5,757	3,160	1,123	8	19	14	7	13
Denver	1,767	6,321	3,186	1,084	10	12	13	8	11
Columbus, OH	1,734	6,096	3,956	826	11	16	9	14	20
Cincinnati	1,722	5,963	3,523	923	12	17	10	11	18
Detroit	1,656	6,242	3,218	1,000	13	14	12	10	12
Atlanta	1,488	7,026	3,029	844	14	8	15	13	10
Cleveland	1,391	6,176	3,289	647	15	15	11	15	21
Pittsburgh	1,223	4,773	2,626	620	16	22	17	16	17
Virginia Beach	1,068	5,087	2,146	581	17	21	19	18	27
Chicago	1,064	6,716	2,173	547	18	10	18	19	9
San Francisco	1,049	6,982	1,950	583	19	9	22	17	15
Raleigh	1,007	6,414	2,660	417	20	11	16	21	32
Minneapolis	934	5,088	1,990	465	21	20	20	20	16
Indianapolis	827	2,905	1,966	390	22	23	21	23	23
Grand Rapids	749	2,861	1,698	370	23	24	24	24	34
Greenville, SC	671	2,849	1,539	313	24	25	25	26	38
Hartford	670	2,403	1,153	391	25	29	27	22	22
Nashville	657	5,899	1,854	269	26	18	23	27	36
Dallas	605	2,018	1,189	329	27	30	26	25	5
Greensboro	479	2,833	1,065	257	28	26	28	29	40
Orlando	467	1,965	914	252	29	32	29	30	19
Sacramento	442	2,649	883	226	30	27	31	31	28
Salt Lake City	388	2,458	908	182	31	28	30	33	33
New Orleans	354	1,043	528	259	32	35	35	28	26
Las Vegas	324	993	572	192	33	36	34	32	24
Louisville	293	1,173	604	148	34	34	33	34	29
Jacksonville	290	1,999	684	133	35	31	32	36	37
Miami	250	1,330	468	140	36	33	36	35	14
Milwaukee	134	918	309	62	37	37	37	37	35
St. Louis	107	822	244	51	38	38	38	38	30
Kansas City	92	593	239	43	39	39	39	39	31
Oklahoma City	31	255	82	12	40	40	40	40	39

connecting these areas. The potential commuter air taxi routes identified for Atlanta are able to provide travel time savings for these areas that have expanding residential and employment opportunities. Naively, one might expect eVTOL travel options to relieve existing large congested arterials, but our results suggest a more complex picture, such that in some cases, *lack of* large arterials in increasingly congested residential areas might, rather, be alleviated by eVTOL transit development.

4.3. Summary of key findings from base case scenario

Based on the results of the base case scenario, we gain several key insights. The potential for air taxi commuting demand varies across cities and is influenced by several key factors. From Table 4, we see that those cities that generate commuter air taxi demand

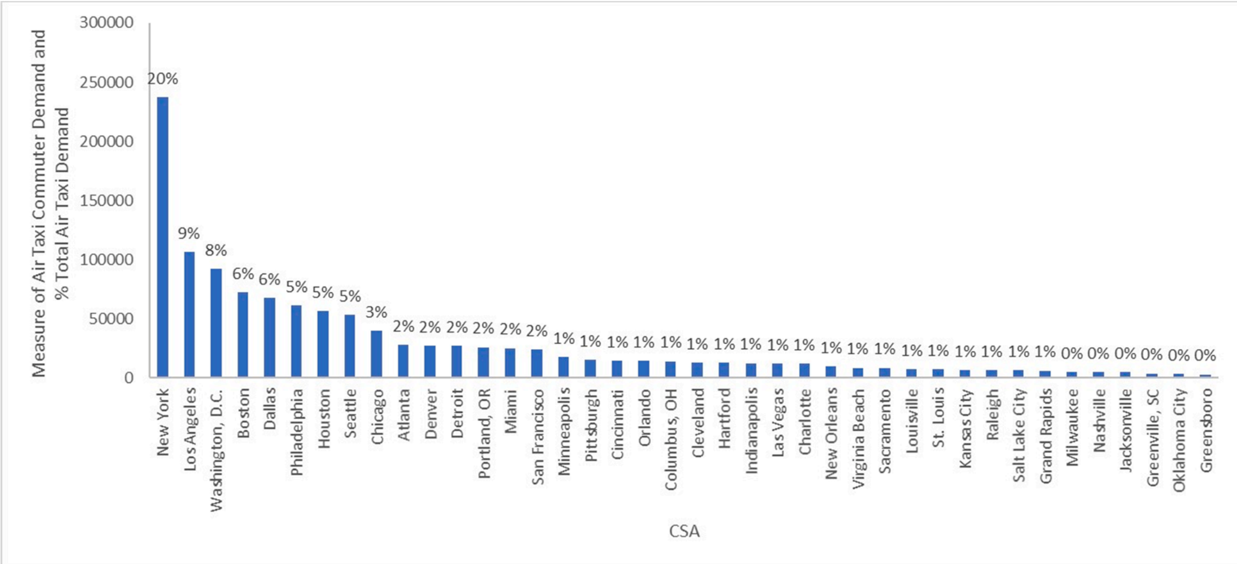

Fig. 8. A comparison of commuter air taxi demand across CSAs with cell phone data scaled to total commuter trips in census data.

tend to have higher percentages of higher-income households and higher percentages of individuals who regularly commute to a single destination for work. The availability of vertiports per capita is correlated with air taxi demand, but as seen in the detailed analysis for Chicago and Miami, the placement of these existing vertiports near key employment centers is crucial in order to generate air taxi demand. Interestingly, several of the high-volume air taxi routes are providing better connections to areas that have recently experienced population growth (such as Atlanta) and/or for areas in which the existing ground infrastructure connections are dominated by lower-speed surface streets. All of these factors underscore the need for researchers, aircraft manufacturers, and city and regional planners to consider multiple factors when identifying initial launch cities for air taxis. In addition, multiple aircraft that have different ranges, operating costs, and cruise speeds may be needed to better serve demand across cities. We explore this point in the next section.

5. Sensitivity analysis

In an effort to identify the sensitivity of demand estimates to different inputs, we varied assumptions related to air taxi access and egress times and different eVTOL aircraft designs as reflected in varying hourly operating costs, cruise speed, and maximum aircraft range. In addition, we ran sensitivity analyses on the number of passengers on board, the provision of a ride guarantee for the air taxi mode, and the AV ownership percentage. Given the rankings were not as sensitive to these latter factors, we do not include a discussion here but refer the reader to Haan (2019) for more details. Finally, we conducted a sensitivity analysis to examine the sensitivity of results to potential differences between cell phone and census data.

5.1. Access and egress times

Prior studies that have compared door-to-door travel times of UAM and ground modes have found that air taxi travel time savings are highly sensitive to access and egress times (e.g., see Antcliff et al., 2016; Kreimeier et al., 2016; Rothfeld et al., 2018; Wei et al., 2018). Access and egress times can also vary across modes, so conducting a sensitivity analysis around access and egress times provides additional insights into potential challenges with integrating UAM with other modes. In our study, we examined the sensitivity of results to access, egress, and wait times by designing a scenario in which all of these travel components were zero, i.e., we assumed that the air taxi could take off from and land at the home and work locations. While having air taxis depart and land at the home and work locations is clearly not realistic, this scenario represents an upper bound on the potential air taxi demand based on existing commute patterns in a city. The results, summarized in Table 6, confirm that these travel time components do have a large impact on the potential air taxi demand—in eliminating these travel components, the overall air taxi demand increases by a factor of four.

Table 6 also shows how the ranking of the 40 CSAs changes when no vertiports are required. Chicago and San Francisco are two areas that rise in the ranking by 8 or more points (and are now in the "top 10" CSAs). This is another indication that the current port infrastructure is not well aligned with current commute patterns in these two areas and that strategic investments in vertiports in these cities may generate higher levels of air taxi demand compared to investments in other similar-sized cities. The investment level required will depend on multiple factors, including the location (and cost of real estate) for the vertiports, infrastructure upgrades required to connect to the electric grid, and the number and size of the vertiports required.

5.2. Cost and design range limitations

When designing an aircraft, manufacturers face a difficult decision: should they design a high-performance aircraft that has a longer range and faster cruise speed or a low-performance aircraft that has a shorter range and slower cruise speed? The performance of the aircraft is directly related to operating costs, with higher performance aircraft having higher operating costs than the lower performing aircraft. The decision on which aircraft to design is directly related to demand; for example, if the distribution of commute length has a high percentage of longer distances, a high-performance aircraft may make more sense, as it would be able to capture this demand that a low-performance aircraft would not be able to serve.

To examine the sensitivity of results to aircraft design configurations, we designed two additional scenarios: one representing a low-performance aircraft (with range of 30 miles, cruise speed of 125 mph, and hourly operating costs of $463) and the other representing a high-performance aircraft (with range of 90 miles, cruise speed of 175 mph, and hourly operating costs of $861). All other design parameters were the same as the base case (as reported in Table 3). Results of this sensitivity analysis are reported in Table 6. Overall, the rankings are stable and we see that the low-performing vehicle is able to capture more air taxi commute trips than the high-performing vehicle. The low-performing vehicle captures about twice as much additional demand compared to the base case. The higher cost of the high-performing vehicle results in an air taxi demand level that is 0.6 times lower than the base case, whereas the low-performing vehicle is able to generate about 1.9 times more demand than the base case, but not as much as the scenario in which there are no access and egress times, which generated about 4.0 times more demand.

5.3. Commuters represented in cell phone versus census data

As noted in Section 4.1, there are several other reasons why a direct comparison between the cell phone and census data may not be reliable. Nonetheless, it may be helpful to compare the ranking of cities if we scale the cell phone data so that they represents the number of commuters in the census data. Fig. 8 presents the results.

Across the 40 CSAs, potential eVTOL commuter demand remains concentrated in a handful of cities. With the scaled cell phone data, New York, Washington, DC, and Los Angeles remain in the top three positions and represent 37 percent (versus 33 percent in the base case) of potential eVTOL demand. As expected, Dallas–Ft. Worth and Miami, two CSAs for which the cell phone data may underrepresent commuter trips, move up in the rankings. When the cell phone data are scaled to represent commuters in census, Dallas–Ft. Worth moves from a rank of 27 to 5 and Miami moves from a rank of 36 to 14. Table 6 summarizes the revised rankings of the CSAs for the scaled cell phone data. Overall, the rankings are relatively stable with seven of the 40 CSAs moving more than 10 positions in the ranking. Among those CSAs that decrease the most in the rankings, the majority are in North Carolina and include Charlotte, Raleigh, and Greensboro.

The results of this sensitivity analysis should be viewed with caution, as it assumes that the commute patterns in the cell phone data are similar to those in census data.

5.4. Summary of insights from sensitivity analysis

The sensitivity analysis confirms several observations noted in prior research studies, namely that overall demand for an air taxi service within cities is highly sensitive to the placement of vertiports (which, in turn, influences access and egress times) and aircraft operating costs. For commute trip purposes, aircraft with shorter ranges and lower operating costs will likely be able to generate more air taxi demand than aircraft with longer ranges and higher operating costs.

6. Discussion, limitations, and directions for future research

In this study, we used cell phone data, census data, and a mode choice model calibrated from a stated preference survey to identify potential air taxi commuter routes in 40 U.S. cities. We designed several scenarios to test the sensitivity of air taxi demand estimates to different inputs and reported the results for the two inputs that had the largest influence on air taxi demand: access/egress times and aircraft operating costs. Results show that air taxi commute demand is sensitive to multiple factors, including the placement of vertiports, access/egress times, current commute patterns, city morphology, and existing ground infrastructure. Our paper is one of the first to rank U.S. cities according to their potential commuter air taxi demand and also one of the first to provide a visualization tool that researchers and practitioners can use to identify the location of these high-volume air taxi commuter routes. To the best of our knowledge, this paper is also the first to use cell phone data to identify regular commuters for the purpose of identifying potential air taxi routes.

As one of the first studies to compute a measure of air taxi demand across multiple U.S. cities, our study confirms prior findings—e.g., New York City and Los Angeles are markets in which air taxi service could potentially operate at profitable levels early after launch. Our study furthermore uncovers some cities that show the potential for supporting an air taxi service that have not been previously identified in prior studies. These include several cities in Ohio—namely Cleveland, Cincinnati, and Columbus. While this result is influenced by the higher representation of commuters in the cell phone database, it is of particular interest given the state of Ohio has a long history of supporting aviation, e.g., Ohio is the nation's leading supplier state to Airbus and Boeing (JobsOhio, 2020). Similarly, our study also finds that cities that have been used as case studies in the past—most notably San Francisco, Chicago, Dallas–Ft. Worth, and Miami—do not rank as highly—at least not in the context of commuter demand. In the case of San Francisco and Chicago, the rankings are sensitive to existing placement of vertiports. In the case of Dallas–Ft. Worth and Miami, this is due in part to the lower number of commuters identified from the cell phone database. Nonetheless, the lower ranking of Dallas–Ft. Worth is interesting given that both Dallas–Ft. Worth and Los Angeles were selected as launch cities in the U.S. for Uber Elevate (n.d.). It remains to be seen whether the smaller number of commuters we identified is an anomaly of the cell phone data, or if the commuting patterns in the Dallas–Ft. Worth area are more dispersed than in other cities.

Many large cities in the U.S. tend to aim at connecting the heart of the city to the suburbs. Yet, recent population growth and the changing landscape of large employer locations suggest that connections between suburbs are lacking, and that eVTOL aircraft could provide a more flexible alternative to build connectivity. eVTOL services could use existing infrastructure and avoid costly long-term investments in re-zoning areas and building new roads. In the future, eVTOL routes can also evolve if population density changes drastically. eVTOL service may also be a viable alternative for new or existing business campuses, such as Apple's campus in Cupertino, California, or Amazon's new campuses being developed. These campuses tend to result in an influx of commuters, which can result in increased traffic ground congestion for their employees and nearby communities. eVTOL travel may help relieve traffic ground congestion for these types of new developments by providing an alternate mode for commuting to work. Finally, whereas this study focused on work-oriented mobility, a large proportion of congestion does happen on weekends for leisure, and eVTOL transit can provide flexible options for those times, too.

Our research raises many new questions that would be interesting to explore as future research. How does air taxi demand change if additional vertiports are added? Would the ranking of cities change if additional trip purposes, such as an air taxi shuttle service to airports or recreational trips, were included in the analysis? If air taxis provide better connections between communities that are currently served by local streets, will this lead to longer-term residential and/or employment changes—for example, if we initiate an air taxi service in the northern Atlanta suburbs, will this increase housing prices in these areas and lead to further sprawl? Given that potential demand for a commuter air taxi service appears to be concentrated in a handful of cities in the U.S., will air taxi service be profitable only in megacities? How do we ensure that the introduction of an air taxi service is equitable and benefits both higher-income and lower-income households? What level of eVTOL adoption would result in congestion alleviation for the rest of the population? In places that have repeatedly voted against public transportation expansion, such as the northern Atlanta suburbs, would eVTOL service be more favorably accepted?

As with any analysis, there are limitations to be noted. Our database of commuters is derived from cell phone records and represents a subset of all commuters in a metropolitan area. Our analysis is based on existing facilities from the NFDC database, and results may change if additional locations for vertiports were included, particularly those that serve business districts. Our study also does not consider how demand would be impacted if operational or weather constraints were incorporated. For example, battery duration and charging requirements may limit eVTOL routing and the availability of some vertiports. As the density of UAM operations increase, constraints on the air space and congestion at vertiports may constrain the demand that could be served. Longer-term impacts, such as changes in residential location that could occur as a result of the introduction of an air taxi service, are also not considered. Finally, it is important to note that our analysis was conducted pre-COVID-19 and it is unclear how commute patterns will change after the pandemic. On one hand, there may be more interest in using an air taxi to commute to work on a less-than-daily basis as individuals move out of cities and into suburbs and work from home multiple days per week. On the other hand, if more individuals work from home after the pandemic, congestion levels and travel times on surface transportation modes will decrease and any travel time savings associated with air taxis will decrease.

Despite these limitations and additional questions that will ultimately arise as we adjust to a post-COVID-19 environment, what is clear is that cities differ greatly in their potential to support an air taxi service. As we move forward in identifying potential early-adopter cities—both in the U.S. and internationally—it will be critical to consider the distinct features of a particular city and to use care when attempting to transfer the results obtained in one city to other locations.

CRediT authorship contribution statement

Julien Haan: Data curation, Formal analysis, Methodology, Writing – original draft. **Laurie A. Garrow:** Conceptualization, Methodology, Writing – original draft. **Aude Marzuoli:** Conceptualization, Data curation, Methodology, Visualization, Writing – review & editing. **Satadru Roy:** Conceptualization, Data curation, Methodology, Writing – review & editing. **Michel Bierlaire:** Conceptualization, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Generation of choice sets for stated preference survey

To generate the trade-off questions (or the choice sets) for a stated preference survey, the analyst determines the alternatives and attributes to be included in the mode choice model. Next, the analyst assigns levels to each of the attributes. The levels create variation in the attributes shown to respondents, which is required in order to estimate parameters of the mode choice model. Design of experiment methods are used to generate an efficient or optimal design (different criteria can be used to define efficiency or optimality). The design provides information on: (1) the combination of levels associated with the attributes that should be shown to respondents in a single trade-off question; and, (2) how many trade-off questions need to asked.

Often times, when conducting stated preference surveys for mode choice modeling, the design contains a large number of trade-off questions and it not possible to ask a single respondent all of these trade-off questions. In these situations, the design is divided into blocks, e.g., given a design that includes 32 trade-off questions, four blocks that contain eight trade-off questions can be created and a respondent is shown only one of the four blocks.

As part of our stated preference survey, each respondent was shown eight different trade-off questions or choice sets that contained three alternatives. One alternative was based on the respondent's current mode to work (i.e., either a traditional auto or transit). The other two alternatives were a fully autonomous ground vehicle and a piloted air taxi. Fig. A1 shows an example of a trade-off question and the attributes associated with each alternative for the case when the respondent's current mode to work was a traditional auto. Table A1 shows an example of how we set the levels for one of the attributes, travel time, for each of the alternatives. Note that to make the range of travel times shown to a respondent more representative of the travel times they currently experience, the levels of the travel time were based on the individual's current commute length. Finally, Table A2 shows an example of a trade-off block generated using the design of experiments methodology presented above. The first line of Table A2 corresponds to the trade-off question shown in Fig. A1. See Garrow, et al. (2019) for additional details on the stated preference survey.

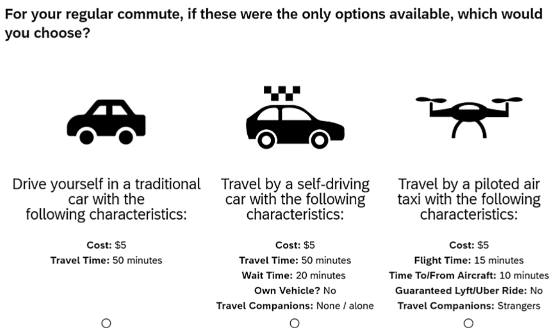

Fig. A1. Example of a trade-off question.

Table A1
Travel times used in survey.

Distance(miles)	Level 1				Level 2				Level 3				Level 4			
	AIR	CAR	TR	AV	AIR	CAR	TR	AV	AIR	CAR	TR	AV	AIR	CAR	TR	AV
0 – 24	0:15	0:30	0:30	0:30	0:25	0:40	0:40	0:40	0:30	0:50	0:50	0:50	0:40	1:00	1:00	1:00
25 – 39	0:15	0:30	0:30	0:30	0:25	0:45	0:45	0:45	0:30	1:00	1:00	1:00	0:40	1:15	1:15	1:15
40 – 54	0:20	1:00	1:00	1:00	0:30	1:15	1:15	1:15	0:40	1:30	1:30	1:30	0:45	1:45	1:45	1:45
55+	0:25	1:00	1:00	1:00	0:45	1:30	1:30	1:30	0:45	1:45	1:45	1:45	1:00	2:00	2:00	2:00

Note: AIR = eVTOL, CAR = traditional (non-autonomous) car; AV = self-driving car, TR = transit.

Table A2
Example of levels for a block of eight trade-off questions.

Block	Ques	Cost car	TT car	Cost AV	TT AV	Other TT AV	Own AV	Companion AV	Cost Air	TT Air	Other TT Air	Ride G Air	CompanionsAir
1	1	5	50	5	50	20	No	Alone	5	15	10	No	Stranger s
	2	5	1:00	5	1:00	10	Yes	Stranger s	5	40	10	Yes	Stranger s
	3	5	40	5	1:00	N/A	Yes	N/A	5	25	20	No	Known
	4	2.5	1:00	2.5	50	N/A	Yes	N/A	10	40	10	Yes	Known
	5	2.5	30	2.5	30	N/A	Yes	N/A	5	25	10	No	Stranger s
	6	2.5	50	2.5	30	20	No	Known	5	40	20	Yes	Known
	7	5	30	5	40	20	No	Alone	10	25	10	No	Known
	8	2.5	40	2.5	40	N/A	Yes	N/A	5	30	10	Yes	Stranger s

Note: AIR = eVTOL, CAR = traditional (non-autonomous) car; AV = self-driving car, TT = travel time.

Appendix B. Calculation of flight times (or IVTT) for eVTOL mode

To calculate flying time for those OD pairs in which an eVTOL trip is available, we used a simple mission profile for the eVTOL vehicles that involves taxi-out, takeoff, climb, cruise, descend, landing, and taxi-in as per the eVTOL mission requirement guidelines by Uber (n.d.). In their mission requirement report, Uber provided each segment of the mission along with the initial and the final velocities in the vertical and the horizontal directions. We used this information to estimate the time and the distance covered in each of the mission segments, assuming a stall speed (Vstall) of 80 mph and a nominal 25-mile mission at cruise speed of 150 mph would take about 15 min of total flight time. The inputs and our associated calculations for this application are summarized in Table B.1.

The combined time required for the noncruise segment of the flight is estimated using Equation (B.1):

$$t_{noncruise} = t_{min}\bullet\frac{\min(\mathrm{d}_{\mathrm{facilities}}, \mathrm{d}_{\mathrm{min}})}{\mathrm{d}_{\mathrm{min}}}[\mathrm{min}] \tag{B.1}$$

where,

d_{min} is the range credit or the distance covered in the noncruise segment of the flight path obtained by adding the H_{dist} column for all segments except the cruise segment shown in Table B.1
$d_{facilities}$ is the haversine distance[14] between the two vertiport locations or the total flight distance

Table B1
Detailed calculation assumptions for eVTOL flight times.

	Mission Segments	Vertical Speed [ft/min]	Initial	Final	Horizontal Speed [mph]	Initial	final	AGL Ending Altitude [ft]	Acceleration (vertical) [ft/sq.min]	Time [hr]	[min]	H_{dist} [mi]
A	Ground Taxi	0			3			0		0.02	1.00	0.00
B	Hover Climb	0 to 500	0	500	0	0	0	40	−3125.0	0.00	0.16	0.00
C	Transition + Climb	500	500	500	0 to 1.2 Vstall	0	96	300	0.0	0.01	0.52	0.42
D	Departure Terminal Procedures	0	0	0	1.2Vstall	60	60	300	0.0	0.02	1.05	1.05
E	Accel + Climb	500	500	500	1.2Vstall to 150	96	150	1000	0.0	0.02	1.40	2.87
F	Cruise	0	0	0	150	150	150	1000	0.0	0.11	6.49	16.22
G	Decel + Descend	500	500	500	150 to 1.2Vstall	150	96	300	0.0	0.02	1.40	2.87
H	Arrival Terminal Procedures	500	500	500	1.2Vstall	60	60	300	0.0	0.02	1.05	1.05
I	Transition + Descend	500 to 300	500	300	1.2Vstall to 0	96	0	40	307.7	0.01	0.65	0.52
J	Hover Descend	300 to 0	300	0	0	0	0	0	1125.0	0.00	0.27	0.00
K	Ground Taxi	0			3			0		0.02	1.00	0.00
									Mission	**0.25**	**14.99**	**25**

Source: Adapted from Uber (n.d.).

[14] Here we assumed the haversine or "straight-line" distance between two vertiports. This assumption would not be valid in locations with mountainous terrains, as more circuitous routes would be required to avoid obstacles.

t_{min} is the time it takes to fly distance d_{min}, i.e., adding the column *Time* [min] for all segments except the cruise segments shown in Table B.1

By defining d_{min} as the distance required for both the climbing and descending phases, we can ensure that d_{min} does not exceed the total distance between the two vertiport locations and adjust the flying altitude to be lower for these short trips (as well as decrease the time to climb and descend). The analyst assumes values of d_{min} and t_{min} to reflect realistic operational performance for a particular air taxi vehicle design.

Applying a similar logic, the cruising time, t_{cruise}, was calculated from Equation (B.2):

$$t_{cruise} = \frac{max(0, d_{facilities} - d_{min}) \bullet 60}{s_{eVTOL}} \text{ [min]} \tag{B.2}$$

where,

s_{eVTOL} is the assumed cruise speed of the vehicle in miles per hour

The total flying time, t_{flying}, is given in Equation (B.3) as the sum of the quantities in Equations (B.1) and (B.2):

$$t_{flying} = t_{noncruise} + t_{cruise} \tag{B.3}$$

Finally, we assumed the maximum range of the eVTOL aircraft, d_{max}, is 60 miles.

References

NEXA Advisors, 2019. UAM study prospectus. https://www.nexaadvisors.com/uam-global-markets-study. Accessed September 3, 2020.
Airbus, 2020. Vahana Aircraft. https://www.airbus.com/innovation/zero-emission/urban-air-mobility/vahana.html. Accessed September 2, 2020.
Aircraft Cost Calculator, 2019a. AGUSTA Westland 101 price and operating cost. https://www.aircraftcostcalculator.com/AircraftOperatingCosts/545/Agusta+Westland+101. Accessed October 18, 2020.
Aircraft Cost Calculator, 2019b. ROBINSON R22 II Beta price and operating cost. https://www.aircraftcostcalculator.com/AircraftOperatingCosts/528/Robinson+R22+II+Beta. Accessed October 18, 2020.
Akhter, M.Z., Raza, M., Iftikhar, S.H., Raza, M., 2020. Temporal and economic benefits of vertical take-off and landing vehicles in urban transport. In: 2020 Advances in Science and Engineering Technology International Conferences (ASET). https://doi.org/10.1109/ASET48392.2020.9118256.
Al Haddad, C., Chaniotakis, E., Straubinger, A., Plötner, K., Antoniou, C., 2020. Factors affecting the adoption and use of urban air mobility. Transport. Res. Part A: Pol. Pract. 132, 696–712. https://doi.org/10.1016/j.tra.2019.12.020.
Alexander, L., Jiang, S., Murga, M., Gonzalez, M.C., 2015. Origin–destination trips by purpose and time of day inferred from mobile phone data. Transport. Res. Part C: Emerg. Technol. 58, 240–250. https://doi.org/10.1016/j.trc.2015.02.018.
Antcliff, K.R., Moore, M.D., Goodrich, K.H., 2016. Silicon Valley as an early adopter for on-demand civil VTOL operations. In: 16th AIAA Aviation Technology, Integration, and Operations Conference. https://doi.org/10.2514/6.2016-3466.
American Automobile Association (AAA), 2017. AAA reveals true cost of vehicle ownership. AAA NewsRoom, News Releases, August 23. http://newsne-aaa.iprsoftware.com/news/releases-20170823. Accessed September 5, 2020.
Atlanta Regional Commission (ARC), 2020. Atlanta region population estimates. https://atlantaregional.org/atlanta-region/population-forecasts-estimates/atlanta-region-population-estimates/#:~:text=Atlanta%20Region%202020%20Population%20Estimates,Atlanta%20Regional%20Commission%20(ARC). Accessed November 18, 2020.
Becker, K., Terekhov, I., Niklaß, M., Gollnick, V., 2018. A global gravity model for air passenger demand between city pairs and future interurban air mobility markets identification. In: 2018 Aviation Technology, Integration, and Operations Conference. https://doi.org/10.2514/6.2018-2885.
Bell Flight, 2020. Bell Nexus Aircraft. https://www.bellflight.com/products/bell-nexus. Accessed September 2, 2020.
Roland Berger, 2018. Urban Air Mobility: The Rise of a New Mode of Transportation. https://www.rolandberger.com/en/Publications/Passenger-drones-ready-for-take-off.html#:~:text=As%20the%20Roland%20Berger%2Dstudy,ease%20the%20existing%20traffic%20situation. Accessed September 2, 2020.
Bierlaire, M., 2020. A short introduction to PandasBiogeme. Technical report TRANSP-OR 200605. Transport and Mobility Laboratory, ENAC, EPFL. https://transp-or.epfl.ch/documents/technicalReports/Bier20.pdf.
Blondel, V.D., Decuyper, A., Krings, G., 2015. A survey of results on mobile phone datasets analysis. EPJ Data Sci. 4 (1), 10. https://doi.org/10.1140/epjds/s13688-015-0046-0.
Booz Allen Hamilton, 2018. Urban Air Mobility (UAM) Market Study. Technical Out Brief to the U.S. National Aeronautics and Space Administration (NASA).
Bösch, P.M., Becker, F., Becker, H., Axhausen, K.W., 2017. Cost-based analysis of autonomous mobility services. Updated version. Working paper, ETH Zurich. https://www.research-collection.ethz.ch/bitstream/handle/20.500.11850/128144/ab1225.pdf?sequence=5&isAllowed=y. Accessed October 18, 2020.
U.S. Census Bureau, 2010a. Centers of population by census tract. https://www.census.gov/geographies/reference-files/time-series/geo/centers-population.html; direct link available at https://www2.census.gov/geo/docs/reference/cenpop2010/CenPop2010_Mean_ST.txt. Accessed October 18, 2020.
Center for Economics and Business Research, 2014. 50% rise in gridlock costs by 2030. https://cebr.com/reports/the-future-economic-and-environmental-costs-of-gridlock/. Accessed November 14, 2020.
CityRating.com, 2020. Cost of living. https://www.cityrating.com/costofliving.asp. Accessed November 30, 2020.
Correia, G.H. de A., Looff, E., van Cranenburgh, S., Snelder, M., van Arem, B., 2019. On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. Transportation Research Part A: Policy and Practice 119, 359–382. DOI: 10.1016/j.tra.2018.11.016.
Douglass, R.W., Meyer, D.A., Ram, M., Rideout, D., Song, D., 2015. High resolution population estimates from telecommunications data. EPJ Data Sci. 4 (1), 4. https://doi.org/10.1140/epjds/s13688-015-0040-6.
Uber Elevate, 2019. Day 2: Uber Elevate Summit 2019. YouTube video, Cost estimates provided at 6:02:42. https://youtu.be/E0Ub9Z8ifiQ?t=22176. Accessed September 26, 2020.
Uber Elevate, n.d. Uber Air's international launch market. https://www.uber.com/us/en/elevate/cities/. Accessed November 18, 2020.
Federal Aviation Administration (FAA), 2020. Airport data contact information. https://www.faa.gov/airports/airport_safety/airportdata_5010/#importers. Accessed January 15, 2020.

Fu, M., Rothfeld, R., Antoniou, C., 2019. Exploring preferences for transportation modes in an urban air mobility environment: Munich case study. Transport. Res. Rec.: J. Transport. Res. Board 2673 (10), 427–444. https://doi.org/10.1177/0361198119843858.
Galli, P., Fraga, C., de Sequeira Santos, M.P., 2016. Gravitational force exerted by Brazilian tourist destinations on foreign air travelers. J. Air Transp. Manage. 55, 76–83. https://doi.org/10.1016/j.jairtraman.2016.04.011.
Garrow, L.A., German, B.J., Leonard, C.E., Forthcoming. Urban air mobility: A comprehensive review and comparative analysis with autonomous and electric ground transportation. Transportation Research Part C.
Garrow, L.A., Mokhtarian, P., German, B.J., Glodek, J., Boddupalli, S.-S., 2019. A survey to model demand for eVTOL urban air trips and competition with autonomous ground vehicles. In: In Proceedings from the American Institute of Aeronautics and Astronautics, p. 45.
Glerum, A., Stankovikj, L., Thémans, M., Bierlaire, M., 2016. Forecasting the demand for electric vehicles: accounting for attitudes and perceptions. Transport. Sci. 48 (4), 483–499. https://doi.org/10.1287/trsc.2013.0487.
Goldstein, M., 2019. Bell Nexus VTOL air taxi makes a splash at 2019 consumer electronics show. Forbes, January 14. https://www.forbes.com/sites/michaelgoldstein/2019/01/14/bell-nexus-vtol-air-taxi-makes-a-splash-at-2019-consumer-electronics-show/#338f564a2e31. Accessed September 2, 2020.
Gonzalez, M.C., Hidalgo, C.A., Barabasi, A.-L., 2008. Understanding individual human mobility patterns. Nature 453, 779–782. https://doi.org/10.1038/nature06958.
Haan, J., 2019. Demand estimation for an eVTOL commuting service: An application to the 40 largest American cities. M.S. Thesis. École Polytechnique Fédérale de Lausanne, Switzerland.
Haan, J., Garrow, L.A., Marzuoli, A., Roy, S., Bierlaire, M., 2020. Commuter air taxi demand in 40 U.S. cities. Online maps accompanying this paper. http://garrowlab.ce.gatech.edu/research/116.
Hawkins, A.J., 2019. Electric air taxi startup Lilium completes first test of its new five-seater aircraft. The Verge. https://www.theverge.com/2019/5/16/18625088/lilium-jet-test-flight-electric-aircraft-flying-car. Accessed September 2, 2020.
INRIX, 2019. Congestion costs each American 97 hours, $1,348 a year. https://inrix.com/press-releases/scorecard-2018-us/. Accessed October 19, 2020.
JobsOhio, 2020. Aerospace and aviation. https://www.jobsohio.com/industries/aerospace-aviation/. Accessed November 18, 2020.
Kolarova, V., Steck, F., Bahamonde-Birke, F.J., 2019. Assessing the effect of autonomous driving on value of travel time savings: a comparison between current and future preferences. Transport. Res. A: Pol. Pract. 129, 155–169. https://doi.org/10.1016/j.tra.2019.08.011.
Kreimeier, M., Stumpf, E., Gottschalk, D., 2016. Economical assessment of air mobility on demand concepts with focus on Germany. In: 16th AIAA Aviation Technology, Integration, and Operations Conference. https://doi.org/10.2514/6.2016-3304.
Lenormand, M., Picornell, M., Cantu-Ros, O.G., Tugores, A., Louail, T., Herranz, R., Barthelemy, M., Frias-Martinez, E., Ramasco, J.J., 2014. Cross-checking different sources of mobility information. PLoS ONE 9 (8), e105184. https://doi.org/10.1371/journal.pone.0105184.
Lilium, 2020. Lilium Jet aircraft. https://lilium.com/the-jet. Accessed September 2, 2020.
Ljungholm, D.P., Olah, M.L., 2020. Will autonomous flying car regulation really free up roads? Smart sustainable air mobility, societal acceptance, and public safety concerns. Linguistic Philos. Investigat. 19, 100–106. https://doi.org/10.22381/LPI1920206.
Mane, M., Crossley, W.A., 2009. Importance of aircraft type and operational factors for air taxi cost feasibility. J. Aircraft 46 (4), 1222–1230. https://doi.org/10.2514/1.40146.
Mayor, T., Anderson, J., 2019. Getting mobility off the ground. KPMG insight. https://institutes.kpmg.us/content/dam/advisory/en/pdfs/2019/urban-air-mobility.pdf. Accessed September 2, 2020.
Microsoft, 2018. Calculate a distance matrix. https://docs.microsoft.com/en-us/bingmaps/rest-services/routes/calculate-a-distance-matrix. Accessed October 18, 2020.
Olariaga, O.D., Bolívar, N., Gutiérrez, R.M., Galeana, O.R., 2018. Gravitational analysis of the air transport network. Application to the case of Colombia. Transp. Res. Procedia 33, 51–58. https://doi.org/10.1016/j.trpro.2018.10.075.
Pope, S., 2019. Bell unveils Nexus eVTOL air taxi. Flying, January 8. https://www.flyingmag.com/bell-unveils-nexus-evtol-air-taxi/#:~:text=Five%2Dseat%20hybrid%2Dpropulsion%20air,top%20speed%20of%20150%20mph. Accessed September 2, 2020.
Pound Sterling Live, 2019. Historical rates for the USD/CHF currency conversion on 15 October 2019. https://www.poundsterlinglive.com/best-exchange-rates/us-dollar-to-swiss-franc-exchange-rate-on-2019-10-15. Accessed October 18, 2020.
Pound Sterling Live, 2020. The euro to U.S. dollar historical exchange rates conversion page for 2018 and 2019. https://www.poundsterlinglive.com/best-exchange-rates/best-euro-to-us-dollar-history-2019. Accessed September 12, 2020.
Pudāne, B., Correia, G., 2020. On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: theoretical insights and results from a stated preference survey – a comment. Transport. Res. A: Pol. Pract. 132, 324–328. https://doi.org/10.1016/j.tra.2019.11.019.
Robinson, J.N., Sokollek, M.-D., Justin, C.Y., Mavris, D.N., 2018. Development of a methodology for parametric analysis of STOL airpark geo-density. In: *2018* Aviation Technology, Integration, and Operations Conference. https://doi.org/10.2514/6.2018-3054.
Rothfeld, R.L., Balac, M., Ploetner, K.O., Antoniou, C., 2018. Initial analysis of urban air mobility's transport performance in Sioux Falls. In: 2018 Aviation Technology, Integration, and Operations Conference. https://doi.org/10.2514/6.2018-2886.
Roy, S., Kotwicz Herniczek, M.T., German, B.J., Garrow, L.A., 2020. User base estimation methodology for a business airport shuttle air taxi service. Journal of Air Transportation, (2). DOI: 10.2514/1.D0216.
Roy, S., Maheshwari, A., Crossley, W.A., Delaurentis, D.A., 2018. A study on the impact of aircraft technology on the future of regional transportation using small aircraft. In: 2018 Aviation Technology, Integration, and Operations Conference. https://doi.org/10.2514/6.2018-3056.
Sherman, J., 2020. eVTOLS – What are they? Presentation for: An introduction to urban air mobility for state and local decision makers: A virtual workshop, sponsored by the Community Air Mobility Initiative (CAMI). https://www.communityairmobility.org/uam101.
Sivrikaya, O., Tunç, E., 2013. Demand forecasting for domestic air transportation in Turkey. Open Transport. J. 7 (1), 20–26. https://doi.org/10.2174/1874447820130508001.
Song, F., Hess, S., Dekker, T., 2019. Fancy sharing an air taxi? Uncovering the impact of variety seeking on the demand for new shared mobility services. Working paper, Institute for Transport Studies, University of Leeds. https://pdfs.semanticscholar.org/73a1/fd6f648e9ea3b1223d757b15ae2713d18adb.pdf?_ga=2.227001565.1548836095.1592830089-1396384243.1592830089.
Suneson, G., Stockdale, C., 2019. STEM jobs on the rise: Here are 15 cities hiring the most high-tech workers. USA Today, March 25. https://www.usatoday.com/story/money/business/2019/03/25/stem-jobs-15-cities-hiring-most-high-tech-workers-us/39125247/. Accessed November 17, 2020.
Suprayitno, H., 2020. Developing a direct gravity trip distribution model for air passenger demand. 2020 IOP Conference Series: Earth and Environmental Science 419 (1) 012092. https://doi.org/10.1088/1755-1315/419/1/012092.
Swadesir, L., Bil, C., 2019. Urban Air Transportation for Melbourne Metropolitan Area. AIAA Aviation 2019 Forum, Dallas, TX, June 17. DOI: 10.2514/6.2019-3572.
Toole, J.L., Colak, S., Sturt, B., Alexander, L.P., Evsukoff, A., Gonzalez, M.C., 2015. The path most traveled: travel demand estimation using big data resources. Transport. Res. C: Emerg. Technol. 58 (B), 162–177. https://doi.org/10.1016/j.trc.2015.04.022.
U.S. Census Bureau, 2019a. Average travel time to work in the United States by metro area. https://www.census.gov/library/visualizations/interactive/work-travel-time.html. Accessed October 19, 2020.
U.S. Census Bureau, 2010b. Zip code tabulation area (ZCTA) to census tract relationship file. https://www.census.gov/geographies/reference-files/time-series/geo/relationship-files.html#par_textimage_674173622; direct link available at https://www2.census.gov/geo/docs/maps-data/data/rel/zcta_tract_rel_10.txt. Accessed October 18, 2020.
U.S. Census Bureau, 2016. Glossary. https://www.census.gov/programs-surveys/metro-micro/about/glossary.html. Accessed November 15, 2020.
U.S. Census Bureau, 2017a. B01003: Total population. Based on American Community Survey 5–year estimates subject tables and pulled for CSAs. https://data.census.gov/cedsci/table?q=B01003&g=0100000US.330000&tid=ACSDT5Y2017.B01003&moe=false&hidePreview=false. Accessed November 15, 2020.

U.S. Census Bureau, 2017b. B08128: Means of transportation to work by class of worker. Based on American Community Survey 5-year estimates subject tables and pulled for CSAs. https://data.census.gov/cedsci/table?q=ACSDT1Y2019.B08202&text=workers&g=0100000US.330000&tid=ACSDT5Y2017.B08128&moe=false&hidePreview=true. Accessed November 15, 2020.

U.S. Census Bureau, 2017c. B19122: Number of earners in family. Based on American Community Survey 5-year estimates subject tables and pulled for tracts and CSAs. https://data.census.gov/cedsci/table?q=B19122&g=0400000US13.140000&tid=ACSDT5Y2017.B19122&hidePreview=true.

U.S. Census Bureau, 2017d. S1101: Households and families. Based on American Community Survey 5-year estimates subject tables and pulled for CSAs. https://data.census.gov/cedsci/table?q=ACSST1Y2019.S2002&g=0100000US.330000&tid=ACSST5Y2017.S1101&moe=false&hidePreview=false. Accessed November 15, 2020.

U.S. Census Bureau, 2017e. S1901: Income in the past 12 months (in 2017 inflation-adjusted dollars). Based on American Community Survey 5-year estimates subject tables and pulled for CSAs. https://data.census.gov/cedsci/table?q=ACSST1Y2017.S1901&g=0100000US.330000&tid=ACSST5Y2017.S1901&hidePreview=true. Accessed November 15, 2020.

U.S. Census Bureau, 2017f. S2001: Earnings in the past 12 months. Based on American Community Survey 5-year estimates subject tables and pulled for tracts and CSAs. https://data.census.gov/cedsci/table?q=ACSST1Y2017.S2001&g=0400000US13.140000&tid=ACSST5Y2017.S2001&hidePreview=true. Accessed November 15, 2020.

U.S. Census Bureau, 2019b. S0804: Means of transportation to work by selected characteristics for workplace geography. https://data.census.gov/cedsci/table?q=commute%20by%20auto&g=330M500US408&y=2019&tid=ACSST1Y2019.S0804&hidePreview=true. Accessed November 30, 2020.

U.S. Census Bureau, 2019c. Mode of transportation to work: Public transportation. https://www2.census.gov/programs-surveys/commuting/guidance/acs-1yr/DY2019-Percent-public-transportation.pdf. Accessed June 4, 2021.

Uber, n.d. UberAir vehicle requirements and missions. https://s3.amazonaws.com/uber-static/elevate/Summary+Mission+and+Requirements.pdf. Accessed October 18, 2020.

Vascik, P.D., Hansman, R.J., Dunn, N.S., 2018. Analysis of urban air mobility operational constraints. J. Air Transport. 26 (4), 133–146. https://doi.org/10.2514/1.D0120.

Wei, L., Justin, C.Y., Briceno, S.I., Mavris, D.N., 2018. Door-to-door travel time comparative assessment for conventional transportation methods and short takeoff and landing on demand mobility concepts. In: 2018 Aviation Technology, Integration, and Operations Conference. https://doi.org/10.2514/6.2018-3055.

Zhang, Y., Zhang, A., 2016. Determinants of air passenger flows in China and gravity model: Deregulation, LCCs, and high-speed rail. J. Transp. Econ. Pol. 50 (3), 287–303.