How Essential Is Essential Air Service?
The Value of Airport Access for Remote Communities

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Essential Air Service is a federal government program that provides subsidies to airlines that provide commercial service between certain remote communities and larger hubs, which proponents argue are justified because driving to larger airports would be prohibitively expensive for residents of these communities. I estimate the value of Essential Air Service to local communities using a revealed-preferences approach by formulating and estimating a discrete-choice model of domestic air travel purchases that incorporates passengers' geographical proximity to alternative airports. I estimate the model using proprietary data containing millions of domestic airline passengers' residential ZIP codes coupled with their choice of airline product. Simple data tabulations reveal that most travelers living in regions receiving subsidized service have several alternative airports to choose from and generally prefer to drive to larger airports. A counterfactual policy simulation using the estimated model finds that, in aggregate, community members value subsidized commercial air service from their local airport at $16 million per year, compared to an annual cost of over $290 million.

Keywords: airport, airline, subsidy, public finance, substitution, discrete choice

JEL Codes: H54, L93, R53

I. INTRODUCTION

For the last half century, the US domestic aviation industry has operated in a largely unregulated market environment. The Airline Deregulation Act of 1978 removed federal government control over fares, routes, flight frequency, and the entry of new airlines, leading to improvements in service, decreases in fares, and increases in the number of flights, passengers, and miles flown. Today, passenger aviation is a major component of the modern global economy, contributing about 5 percent to US gross domestic product annually (IATA, 2019; FAA, 2020). According to the International Civil Aviation Organization, 4.5 billion passengers globally flew on scheduled air service in 2019, and the Federal Aviation Administration (FAA) provides air traffic control services for more than 2.9 million airline passengers per day (FAA, 2022). According to the Consumer Expenditure Survey, about 13 percent of US households purchased at least one airline ticket in 2019 and spent an average of $3,873 on airfare.

Although the Airline Deregulation Act was largely viewed as a success, there was fear among some at the time of its passage that small communities would be left behind in its wake as airlines shifted their operations to serve large, profitable markets. To assuage this fear, Congress established Essential Air Service (EAS) in 1978, which required carriers to continue providing scheduled air service at pre-deregulation levels—typically two round trips per day—to eligible communities using subsidies if necessary. Although EAS was originally set to expire after 10 years, under the assumption that air traffic would eventually become self-sustaining, Congress reauthorized EAS for another 10 years in 1988 and made it permanent in 1996. As of June 2022, costs for the program have ballooned to over $340 million per year despite fewer communities being eligible today compared to in 1978. Given that EAS still exists nearly a half century after Congress originally intending it to expire, it is reasonable to ask whether EAS still achieves its stated purpose of efficiently and effectively connecting remote communities to commercial air travel opportunities.[1]

Understanding the value of EAS to the communities it serves requires understanding the trade-offs faced by travelers. A key trade-off that community members face is whether to fly from their local airport, which may be more convenient but offer fewer choices, or to drive to a larger airport, which may be far away but offer more choices. To study this trade-off, I analyze proprietary choice data derived from credit card transactions that link travelers' airline product choices with their home ZIP code. The data, which have not been used in any previous economic studies, allow me to easily compute travelers' driving time to alternative airports.[2] Hence, driving time is an observable product characteristic whose marginal value to consumers can be estimated using standard econometric techniques.

The proprietary choice data reveal several important insights about airline markets previously not known to researchers and policymakers. First, since I am able to directly observe which airports are chosen by residents of a particular geographical area, it is relatively straightforward to determine which airports effectively serve the same region.[3] While the presence of multiple airports in a region does not in itself imply that the airports provide substitutable services, the growth of air travel demand since the early 1990s has attracted entry by airlines at different airports within the same region, suggesting a potentially important role for spatial interactions in the airline industry that have been largely overlooked by previous research.[4]

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[1] The Airline Deregulation Act (92 Stat. 1733) requires the Department of Transportation to "consider the desirability of developing an integrated linear system of air transportation whenever such a system most adequately meets the air transportation needs of the communities involved."

[2] To my knowledge, only two academic papers (Yirgu and Kim, 2021; Yirgu, Kim, and Ryerson, 2021) have used these data, and both papers use only a small geographical subset, in contrast to my data sample which covers the entire United States from 2013 to 2019.

[3] See Fournier, Hartmann, and Zuehlke (2007). Studies that have considered regions with multiple airports vary widely in which airports to include. Berry and Jia (2010, p. 11) consider six regions to have airports that are "geographically close." de Neufville (1995) lists nine regions served by more than one airport. Brueckner, Lee, and Singer (2014) attempt to empirically estimate which airports serve the same metropolitan region based on competition spillovers and specify 13 regions as having multiple competing airports. Drukker and Winston (forthcoming) consider 22 regions to have multiple competing airports.

[4] Studies that consider aspects of spatial competition in non-airline markets include Manuszak and Moul (2009) and Dorsey, Langer, and McRae (2022) (gasoline); Smith (2004) and Katz (2007) (supermarkets); Davis (2006) (movie theaters); Ho and Ishii (2011) and Hatfield and Wallen (2022) (banking); and Murry (2017) and Murry and Zhou (2020) (car dealerships). Studies that consider aspects of spatial competition in airline markets include Fournier,

Relatedly, since I am able to observe the home ZIP code of an airport's users, it is relatively straightforward to determine the geographical boundary of an airport's catchment area (the area from which an airport draws its customers). Administrative and survey data from a variety of sources suggest that most airports draw customers from a large geographical area, but most previous studies of the airline industry have assumed airports have relatively small catchment areas, typically the geographical boundaries of a city.[5] Proper market definition is of first-order concern for almost any industry analysis because it directly influences the scope of available substitutes for consumers and the degree of competition faced by suppliers. Excluding certain viable airports from travelers' choice sets may rule out important substitution patterns, and estimates derived from narrowly defined choice sets will tend to overstate airlines' market power by understating travelers' ability to substitute to alternative products, which in turn could have significant implications for merger evaluations and antitrust enforcement.[6]

The ability to view travelers' choice sets is particularly useful for evaluating the costs and benefits of EAS, since implicit in much of the debate surrounding the program is the assumption that members of communities receiving EAS-subsidized service would have no other viable alternatives for accessing commercial air travel apart from subsidized service from their local airport. My choice data allow me to see which airports residents of an arbitrary geographical area actually use, allowing me to directly check this assumption.[7] Simple tabulations of the proprietary choice data reveal a key insight about the nature of EAS community members' choice sets, namely, that despite their ostensible isolation from the rest of the national air transportation system, members of most EAS communities rarely choose to fly on EAS-subsidized flights from their local airport and instead generally prefer to drive to airports of various sizes offering more products with better characteristics. From an econometric perspective, failing to consider these viable alternatives in travelers' choices sets will make EAS appear more valuable than it actually is because travelers will appear less price sensitive due to having fewer substitutes. From a policy perspective,

Hartmann, and Zuehlke (2007), Hess and Polak (2005, 2006), Ishii, Jun, and Van Dender (2007, 2009), Mahoney and Wilson (2014), Brueckner, Lee, and Singer (2014), McWeeny (2019), and Drukker and Winston (forthcoming).

[5] Airlines For America's 2019 annual survey found that 37 percent of passengers reported flying from an airport that was not the closest to their home or office at some point in the previous year. McWeeny (2019) found that a significant share of travelers surveyed at San Francisco International Airport drove from as far away as Sacramento (a 2-hour drive) and that 57 percent of passengers surveyed at San Francisco International Airport bypassed an airport that was closer to their home. Ishii, Jun, and Van Dender (2007) found that travelers located closest to San Francisco International Airport most often departed from there, but passengers closest to San Jose International Airport or Oakland International Airport often chose to fly from a different airport. Yirgu, Kim, and Ryerson (2021) report significant airport leakage for small and medium-sized airports in the Midwest United States.

[6] The US Department of Justice uses a narrow city-pair market definition in cases involving airline mergers. See, for example, their complaint against the proposed merger between American Airlines and US Airways (78 *Fed. Reg.* 71377) and their complaint against the Northeast Agreement between American Airlines and JetBlue Airways (https://fingfx.thomsonreuters.com/gfx/legaldocs/zjpqkrdlmpx/plaintiffs-brief-american-airlines-2022.pdf).

[7] Bao, Wood, and Mundy (2015) and Lowell et al. (2011) compute the cost of subsidizing flights to the cost of subsidizing bus service *to the same location*. They do not consider the costs of subsidizing bus service to alternative airports.

the revelation that EAS community members frequently choose to drive to alternative airports undermines EAS's raison d'être to provide an essential service to communities that would otherwise have no other options to connect to the national air transportation system.[8]

An added benefit of the proprietary choice data is that I can see the home location of any airport's users, which allows me to determine the extent to which an EAS-subsidized airport serves residents of the community. Knowledge of the home location of EAS-subsidized airport users is policy relevant because the purpose of EAS is to connect *residents* of the community to commercial air travel. Without the ability to link purchases to the home location of purchasers, it would not be possible to determine who are the primary users of EAS-subsidized service. Tabulations of the data reveal that the majority of EAS-subsidized airport users are *not* residents of the communities in which the airport is located. This finding has important fiscal policy implications because *all* users of EAS airports benefit from subsidized ticket prices, regardless of residency status, implying a majority of EAS funds go toward subsidizing nonresidents of EAS communities. The problem is further compounded by the fact that nonresidents who use EAS-subsidized airports tend to have higher incomes than residents, which raises serious distributional concerns about the program.

To formally estimate the value that EAS community members derive from the program, I formulate and estimate a discrete-choice model of air travel demand. I formulate my demand model using a nested logit utility specification that closely resembles the canonical models of Berry, Carnall, and Spiller (1996, 2006) and Berry and Jia (2010). A key component of my model is the inclusion of driving time as a product characteristic, which allows me to directly estimate the implicit monetary costs of driving to alternative airports. I estimate my model using the generalized method of moments with a combination of macro and micro data, as described by Berry, Levinsohn, and Pakes (2004) and Petrin (2002). Macro moments are constructed using aggregate data containing information about airline products, their characteristics, and the number of travelers who choose each product, and micro moments are constructed using the proprietary choice data. Intuitively, the micro moments capture spatial variation between driving time and travelers' choices (and non-choices), which is used to identify travelers' preferences for driving.[9]

A useful feature of the discrete-choice modeling framework is that it allows me to analyze counterfactual policy experiments by estimating consumer surplus under two alternative scenarios. In particular, I consider a counterfactual policy experiment in which all EAS subsidies are eliminated, which

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[8] Grubesic and Matisziw (2011) thoroughly studied EAS community members' access to a variety of alternative airports, but their data do not allow them to study the extent of their use.

[9] McWeeny (2019) uses a similar revealed-preferences approach, which, unlike the stated-preferences approach used by Landau et al. (2016), Daly, Tsang, and Rohr (2014), Adler, Falzarano, and Spitz (2005), Hess and Polak (2006), Merkert and Beck (2017), and Hess, Adler, and Polak (2007), does not rely on self-reported or speculative valuations of trip components.

would cause commercial service to cease at most airports currently served by EAS-subsidized airlines. The difference between consumer surplus computed before and after the elimination of commercial service at EAS airports reveals community members' implicit value of the EAS program, and a simple comparison between the costs and benefits of the program can be used to determine whether EAS subsidies are justified.

I conduct my counterfactual policy experiment using data from 2019 for 107 EAS communities in the continental United States. The analysis reveals that the members of these 107 communities collectively value subsidized service from their local airport at $16 million annually, a paltry amount compared to EAS's cost in 2019 of over $290 million. Furthermore, this estimate likely *over*states the effects of eliminating EAS subsidies, since commercial service might not cease at *all* formerly eligible communities. Disaggregating the results by airport reveals that desirable routes tend to be flown by legacy airlines operating in a seemingly competitive environment, which is suggestive of rent-seeking behavior to the extent EAS subsidies act as entry barriers for competitors.

The remainder of this paper is organized as follows. In Section II, I provide a brief history and overview of Essential Air Service. In Section III, I describe my data and present several novel insights based on descriptive statistics. In Section IV, I formulate an empirical model of demand, and in Section V, I describe the estimation strategy and sources of identification. In Section VI, I present the estimation results and perform post-estimation checks. In Section VII, I present the results of my counterfactual policy analysis to compute the consumer surplus that communities derive from EAS and consider distributional implications. Section VIII concludes with a summary of the findings, policy recommendations, and suggestions for future research.

II. ESSENTIAL AIR SERVICE

The EAS program provides subsidies to airlines to provide regular service to eligible communities.[10,11] To be eligible for EAS, a community must be located more than 70 miles from the nearest medium or large hub airport, require a per-passenger subsidy rate of $200 or less ($1,000 or less if the community is farther than 210 miles from a hub), and have 10 or more enplanements per day.[12] EAS typically subsidizes one airline to provide two to four round trips per day, six days per week, from an EAS community to a larger hub. Although EAS eligibility is based on a community's distance to the nearest medium or large hub,

[10] A handful of communities participate in the Alternate EAS program, which allows communities to forgo traditional EAS for a prescribed amount of time in exchange for a flexible grant. In 2019, all communities participating in the Alternate EAS used their funds to subsidize charter air service.

[11] EAS contracts do not give an airline the exclusive right to serve a community, and airlines may decide to serve a community under an EAS contract without the use of subsidies.

[12] See Appendix C for a summary of the legal statutes and DOT practice regarding eligibility determination. Tang (2018) provides an excellent primer on EAS, its history, and eligibility requirements.

airlines that receive EAS contracts are not required to fly passengers to the nearest hub nor to a medium or large hub.[13]

Airlines compete for EAS contracts through a bidding process, and the DOT typically receives 1–3 proposals per airport every 1–3 years, when EAS contracts typically expire. By law, the DOT must take into account the views of the community when deciding which proposal to accept, as well as the carrier's service reliability and any arrangements it has with larger carriers at the hub. Notably, subsidy cost is not among the factors the DOT is required by law to consider when evaluating bids, and if more than one carrier proposes to offer service then local officials are under no obligation to favor the proposal that entails the lowest cost to the federal government.

EAS has long been a target of critics who have derided the program as wasteful spending and an inefficient means of connecting rural communities to commercial air travel, arguing that the statutes governing EAS do not encourage cost efficiency and that the market, not government subsidies, should decide which airports survive. But community stakeholders argue that EAS provides an essential service to communities that would otherwise lose access to commercial air travel, arguing that EAS community members value their local airport and without government subsidies the airport would cease to be commercially viable. Several papers have argued that ending EAS subsidies would not necessarily reduce service at eligible communities.[14] But the question of whether and the extent to which EAS community members value their local airport has not been studied and is one that I take up in the present paper.

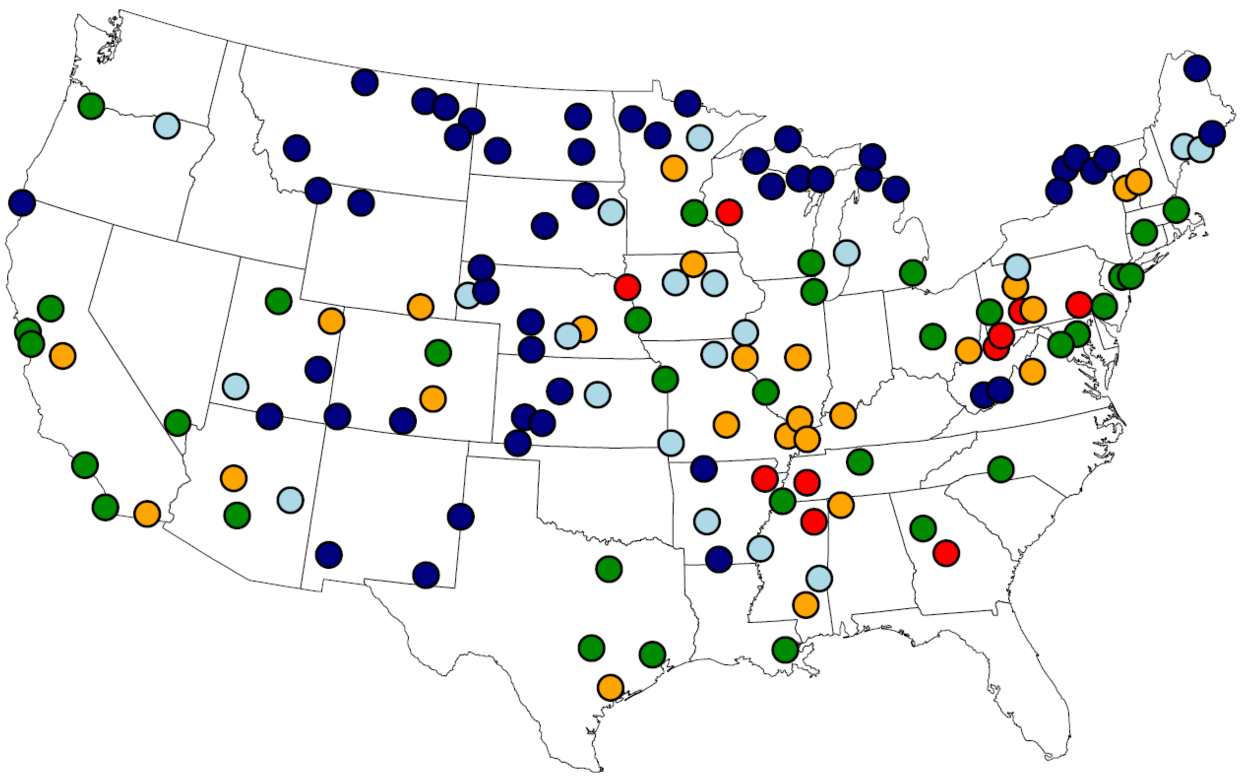
Figure 1 shows the locations of 107 airports receiving EAS-subsidized service as of September 2021.[15] Following the Eno Center for Transportation's (2018) convention, red dots represent communities that are between 70 and 100 miles from a medium or large hub, orange dots represent communities that are between 100 and 150 miles from a medium or large hub, light blue dots represent communities that are between 150 and 210 miles from a medium or large hub, and dark blue dots represent communities that are more than 210 miles from a medium or large hub (DOT, 2021c). The green dots correspond to medium or large hubs that are nearest to EAS communities or which are used by airlines serving EAS communities even if not geographically closest (DOT, 2019a, 2022b).

[13] For example, Cape Air currently serves several EAS communities in Montana through their small hub at Billings Logan International Airport. See Appendix C for the FAA's definition of hub size.

[14] Cunningham and Eckard (1987) suggest that EAS subsidies may have actually reduced flight frequency because EAS contracts serve as entry barriers that discourage competition. Morrison and Winston (1986) note that service to small communities actually increased following deregulation—suggesting EAS subsidies mask profit opportunities. Bao, Wood, and Mundy (2015) note 10 of the 34 EAS communities that have had their EAS subsidies terminated since 1993 have experienced a substantial increase in their outbound passenger levels. Furthermore, subsidized airlines currently provide commercial service alongside unsubsidized airlines at several EAS airports, most notably Allegiant Air, which serves five currently eligible communities and one formerly eligible community.

[15] Appendix Table H3 lists the status of the 51 communities that have lost their EAS eligibility since 1989.

Figure 1. The Locations of EAS Airports and Their Nearest Hubs

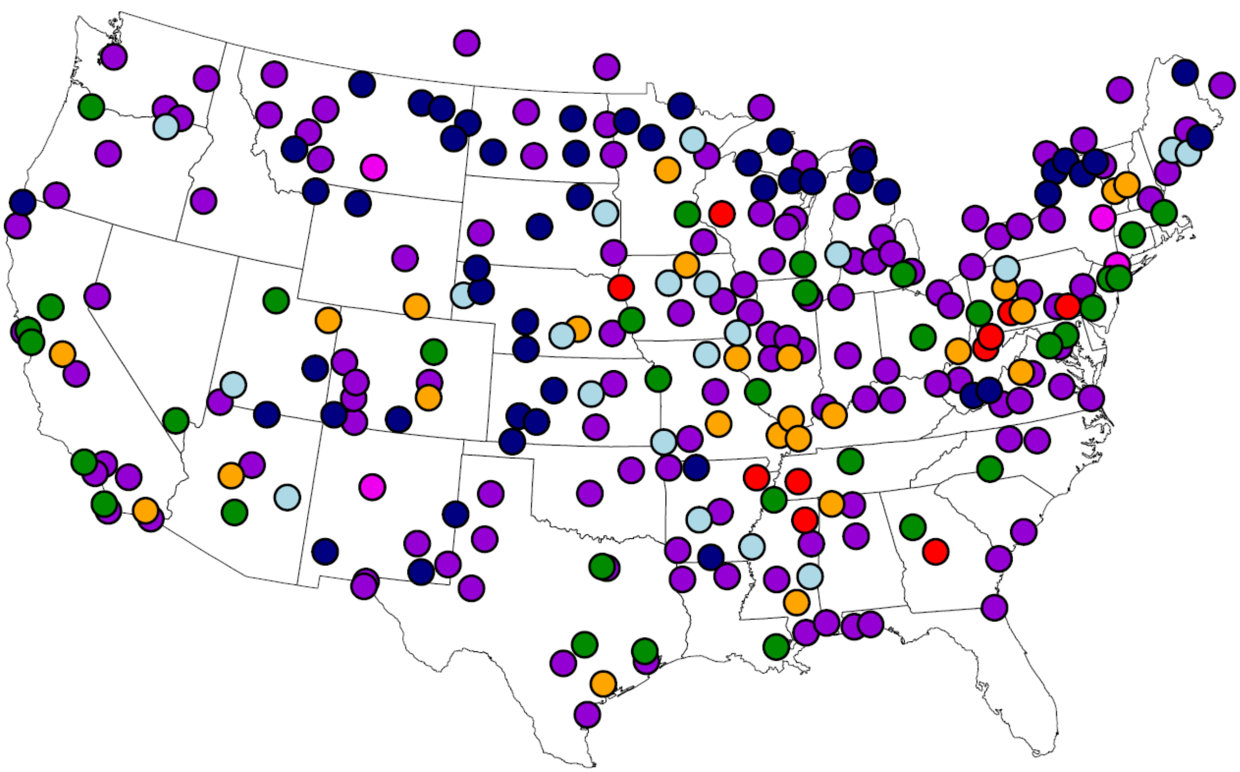


Source: Federal Aviation Administration.

Notes: Green dots are medium or large hubs that are geographically closest to EAS communities or are used by EAS-subsidized carriers. Red, orange, light blue, and dark blue dots are EAS airports located less than 70 miles, 70–100 miles, 100–210 miles, and more than 210 miles, respectively, from the nearest medium or large hub.

Although it would appear from Figure 1 that many EAS communities face considerable barriers to access commercial air travel without the assistance of EAS, the color-coding belies the full picture by restricting the notion of viability to medium hubs or larger. Figure 2 presents a fuller picture, augmenting Figure 1 by including a host of viable airports that are classified as smaller than medium hubs. For example, Figure 1 suggests Butte in southwest Montana is relatively isolated, located 6 hours to Salt Lake City to the south and 10 hours to Portland or 9 hours to Seattle to the west. But Figure 2 reveals that there are four additional airports within a 3-hour drive from Butte: Great Falls International Airport, Missoula Montana Airport, Helena Regional Airport, and Bozeman Yellowstone International Airport, a small hub served by 8 major airlines flying to more than 20 destinations. The pink dots correspond to small hubs that are or have been used by airlines to serve certain EAS communities, but which are too small to factor into the distance calculation for maximum allowable per-passenger subsidies.[16]

Figure 2. The Locations of EAS Airports and Viable Nearby Airports



Sources: Federal Aviation Administration; Airlines Reporting Corporation.
Notes: See the notes to Figure 1. Pink dots are small hubs that are or have been used by EAS-subsidized carriers. Purple dots are airports used by a nontrivial share of EAS community members.

[16] For example, Yellowstone Regional Airport in Cody, Wyoming, is only about 100 miles from Billings Logan International Airport, but since Billings is considered a small hub it does not factor into the distance calculation; Salt Lake City International Airport is the nearest large hub (about 450 miles away), so a carrier serving Yellowstone Regional Airport would be exempt from the $200 per-passenger subsidy limit (DOT, 2019a).

III. DATA AND DESCRIPTIVE STATISTICS

Before describing the model and estimation strategy, I describe the data used to estimate the model and present several figures showing the key features of the data. The data come from six primary sources. Table 1 (presented at the end of this section) provides summary statistics for several key variables.

A. Market Locator

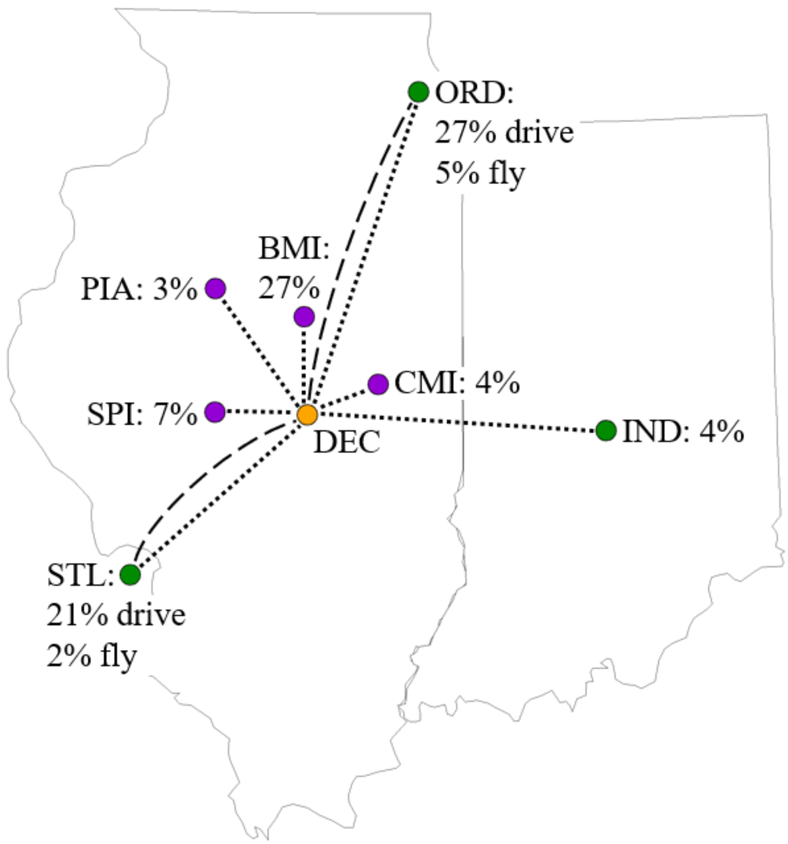
The primary data set used for the analysis comes from the Airlines Reporting Corporation's (ARC's) Market Locator tool. Owned by the airline industry, ARC acts as a clearing system for all travel agencies, including online travel agencies such as Booking Holdings, Expedia Group, and their subsidiaries, which process about 35 percent of all domestic tickets sold in the United States. According to ARC, the clientele is representative of the universe of domestic leisure and unmanaged business travelers.[17] About 20 percent of all tickets that come through the ARC clearing system are sent to a credit card processing company that matches customers' chosen product to their credit card billing ZIP code.[18] The data are associated with the point of sale of the airline ticket purchaser, which is likely to be the passenger in most cases.[19] Thus, the data are a roughly 7 percent representative sample of US domestic leisure passengers.

The Market Locator data contain monthly passenger counts by ZIP code for 2013–19. Tabulations of the Market Locator data reveal which airports travelers drive to without a priori selecting which airports to include in a traveler's choice set. For example, Figure 3 shows the 8 airports most commonly chosen by residents of Decatur, Illinois and their respective market shares. In 2019, Cape Air received $3.065 million to offer 24 nonstop round trips per week to O'Hare International Airport (ORD) and 12 nonstop round trips per week to St. Louis Lambert International Airport (STL) from Decatur Airport (DEC), with fares to Chicago starting at $59 one way and fares to St. Louis starting at $29 one way (DOT, 2017, 2019a; Cape Air, 2018). According to the DOT (2019a), Decatur Airport had 17,066 passengers (both directions) in 2019, corresponding to a $180 per-passenger subsidy. Despite Cape Air offering unusually low prices, tabulations of the Market Locator data reveal that only 7 percent of travelers flew from Decatur to either Chicago or St. Louis, while 21 percent of travelers drove 2 hours and 15 minutes to St. Louis, 27 percent of travelers drove 3 hours to Chicago, and 27 percent of travelers drove 1 hour to Central Illinois Regional

[17] As noted by Yirgu, Kim, and Ryerson (2021), business travelers are more inclined to purchase tickets directly from airlines rather than through third-party agents, meaning they are less likely to show up in the Market Locator data.
[18] The ability to link tickets with billing ZIP codes is only limited by the credit card processing company used for the transaction; otherwise, there are no selection criteria for determining which tickets can be linked with billing ZIP codes. The credit card processing companies generally do not process American Express cards, so there is a slight bias against business travelers to the extent business travelers are more likely to pay with American Express cards.
[19] Although the traveler's point of origin is typically within proximity to the purchaser's point of sale, this would not be the case if, for example, the purchaser and passenger were in different locations or, more frequently, if the traveler purchased one-way tickets individually.

Airport (BMI), a non-hub primary commercial service airport served by four major airlines. The remaining travelers drove to Springfield's Abraham Lincoln Capital Airport (SPI), Urbana–Champaign's Willard Airport (CMI), Indianapolis International Airport (IND), or Peoria International Airport (PIA).

Figure 3. Market Shares for Airports Chosen by Residents of Decatur



Source: Airlines Reporting Corporation.
Notes: See the notes to Figure 2. DEC is an EAS-subsidized airport in Decatur, Illinois. Market shares conditional on flying are shown as percentages after the airport codes. The dotted lines indicate travelers drove from Decatur to the indicated airport to take a departing flight. The dashed line indicates travelers flew from DEC to the indicated airport en route to a final destination.

The Market Locator data are also useful for determining who the primary users of an EAS-subsidized airport are, namely, residents of the community or nonresident visitors. Knowing the home location of an EAS airport's users is policy relevant because the purpose of EAS is to connect EAS community members to commercial air travel. To determine the residency status of EAS airport users, I draw geographical boundaries around the communities as shown in Appendix B—typically the Metropolitan or Micropolitan Statistical Area(s) encompassing the airport. Residents are then defined as passengers whose ZIP code is within the geographical region, and nonresidents are those whose ZIP code is outside the region. Overall, I find that nonresidents make up 57 percent of customers on EAS-subsidized flights. As shown in Appendix

Figure H1 and Appendix Table H2, several EAS communities are located very close to national parks, and airports in these communities likely serve as entry points for visitors; since *all* customers on EAS-subsidized flights, regardless of where they live, benefit from lower ticket prices, it is plausible that EAS serves to subsidizes tourism for these areas, which is not its statutory purpose. Yellowstone Airport, for example, is used almost exclusively by tourists likely visiting Yellowstone National Park, while residents of West Yellowstone overwhelmingly prefer to drive 1 hour and 30 minutes north to Bozeman Yellowstone International Airport.[20]

As will be explained in Section V.A, I use the Market Locator data to construct micromoments to be used for generalized method of moments estimation of the parameters of interest. I thus restrict the sample of Market Locator data in several ways. First, since several low-cost and ultra-low-cost carriers (including Southwest Airlines and Allegiant Air) generally do not have contracts with travel agencies or are not members of ARC, I do not observe travelers choosing products from these airlines.[21] I therefore restrict the set of airlines to the four legacy carriers: American Airlines, Delta Air Lines, United Air Lines, and US Airways.

Second, in order to identify substitution between airports, travelers living in an origin region must face a choice set containing at least two airports. I therefore restrict the origin regions under consideration to those among the top 40 busiest that contain at least two airports both served by a legacy carrier (see Appendix Table H1). These include Boston, Chicago, Cincinnati, Cleveland, Dallas, Detroit, Houston, Los Angeles, Miami, New York, Orlando, San Francisco, Tampa, and Washington, from which I drop Orlando Sanford International Airport (SFB), Chicago Rockford International Airport (RFD), and St. Pete–Clearwater International Airport (PIE) because these airports are not served by a legacy carrier.[22]

Lastly, I must specify each airport's catchment area in order to calculate market shares. Market shares are defined as a given product's share of the total potential trips from an origin area to a destination city. Appendix A shows airport locations and the constructed catchment areas for the 40 busiest origin regions, with darker shading corresponding to areas with higher population density. Appendix Table H1 shows the land area of each catchment area and the passenger-weighted average drive time to passengers' chosen

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[20] As noted by Grubesic and Wei (2013), Yellowstone Airport has the lowest subsidy rate among all EAS airports and a sparse local population base but has a much higher load factor than the national average, likely due to tourism. According to the National Park Service, approximately 1.73 million people used the west entrance to Yellowstone National Park in 2019.

[21] Southwest Airlines joined ARC in July 2019 and only shares data for corporate bookings made through its corporate-client wing SWABIZ.

[22] Although Southwest Airlines has *nearly* 100 percent market share at Chicago Midway International Airport (MDW), Dallas Love Field (DAL), and Hobby Airport (HOU), the fact that legacy carriers have *some* market share at these airports implies the micromoments can still identify the parameters under the generalized method of moments estimation framework.

airport. The market size is assumed to be the total population of the catchment area, or the number of potential passengers who consider air travel from an origin region to a destination city.[23]

B. OpenStreetMap

Driving times between ZIP code centroids were extracted from OpenStreetMap using the Open Source Routing Machine, a high-performance routing engine for shortest paths in road networks. The OpenStreetMap data have an advantage over geodesic distance data (*as the crow flies*), such as the National Bureau of Economic Research's ZIP Code Distance Database, because they properly account for vehicle mode, speed limits, and the nonlinear nature of road networks, although they do not account for delays caused by traffic. Travel time is based on speed limits for different road types.

C. Airline Origin and Destination Survey

Product characteristics and market shares were constructed using the DOT's Airline Origin and Destination Survey (DB1B), a 10 percent quarterly sample of airline tickets from US carriers that contains detailed itinerary information such as fares, layovers, and carrier identity. As noted in Section V.A, the DB1B data is used to construct macromoments to be used for generalized method of moments estimation of the parameters of interest. I consider flights departing from the 40 busiest origin regions and arriving at the 100 busiest destinations for every quarter from 2013 to 2019, excluding origins in Hawaii, Alaska, and Puerto Rico. Appendix Table H1 lists the 40 origin regions under consideration and the 76 airports contained within them, as well as populations of the constructed catchment areas (see Appendix A). I determine which airports belong in which regions largely based on the recommendations of Brueckner, Lee, and Singer (2014).

I clean the DB1B sample following standard sample cleaning procedures from the literature:[24] I drop all itineraries with more than one connection and collapse all coupons with a layover into a single observation, regardless of the layover airport; the prices for such products (indirect flights) are computed as the passenger-weighted average price. I drop all itineraries that start and end at different airports (i.e., are not round trips), are not economy class for all coupons, and are not flown on the same airline for all coupons. I drop all itineraries with a fare of less than $11.20 (the September 11 Security Fee for a round-

[23] Roughly speaking, market size is "some number of potential passengers who consider air travel" (Berry, Carnall, and Spiller, 2006, p. 189). Although somewhat arbitrary, Berry, Carnall, and Spiller (2006, p. 189) note that the use of the geometric mean of the origin and destination city populations as a measure of market size has "both empirical and (weak) theoretical precedent in the literature on travel demand." Population of the origin region is a reasonable measure of market size in my context because my sample of aggregate data is constructed using round-trip tickets, and passengers who desire to fly from an origin to a destination and back are much more likely to be residents of the origin region as opposed to residents of the destination city.

[24] My sample cleaning procedure closely follows the cleaning procedure described by Severin Borenstein (http://faculty.haas.berkeley.edu/borenste/airdata.html).

trip ticket), such as those booked entirely with airline loyalty points, or greater than $2,500. In addition, I only consider flights whose ticketing carrier is a reporting carrier, defined as a carrier with more than 0.5 percent of total domestic scheduled service passenger revenues; these include American Airlines, Delta Air Lines, United Air Lines, US Airways, Southwest Airlines, JetBlue Airways, Alaska Airlines, AirTran Airways, Virgin America, Allegiant Air, Frontier Airlines, Spirit Airlines, and Sun Country Airlines.[25]

D. Airline On-Time Performance

Additional product characteristics such as flight frequency, extra flight time, and layover times were constructed using the DOT's Airline On-Time Performance data. Layover times are computed by assuming passengers choose the itinerary with the shortest possible layover longer than a minimum connection time of 30 minutes, which is the industry standard for US domestic flights.

E. Zip-Codes.com

Detailed ZIP code demographics were obtained from zip-codes.com's ZIP Code Database (Business edition). Several useful demographics included in the database are population (used to construct market size), racial and gender composition, average home value, median household income, median age, and congressional district. The data are compiled by zip-codes.com using data from the US Postal Service, US Census Bureau, Office of Management and Budget, and various private sources.

Figure 4 shows the distribution of median household income for EAS communities alongside the distribution of median household income for all Core-Based Statistical Areas (CBSAs), where a region's median household income is computed as the weighted average of median household incomes across ZIP codes contained in the region. The median of the distribution for EAS communities is $52,500 compared to $64,250 for all CBSAs, implying EAS communities generally have lower incomes compared to the nation as a whole. Combining the demographic data with Market Locator data, Figure 5 shows the distribution of median household income for users of EAS airports broken down by EAS community residency status. Residents flying out of an EAS airport tend to have lower incomes than nonresidents flying into an EAS airport—medians of the distributions $53,400 and $62,800, respectively. Thus, not only do the majority of EAS funds go toward subsidizing nonresidents of the EAS community, but these nonresidents also tend to have higher incomes than residents.

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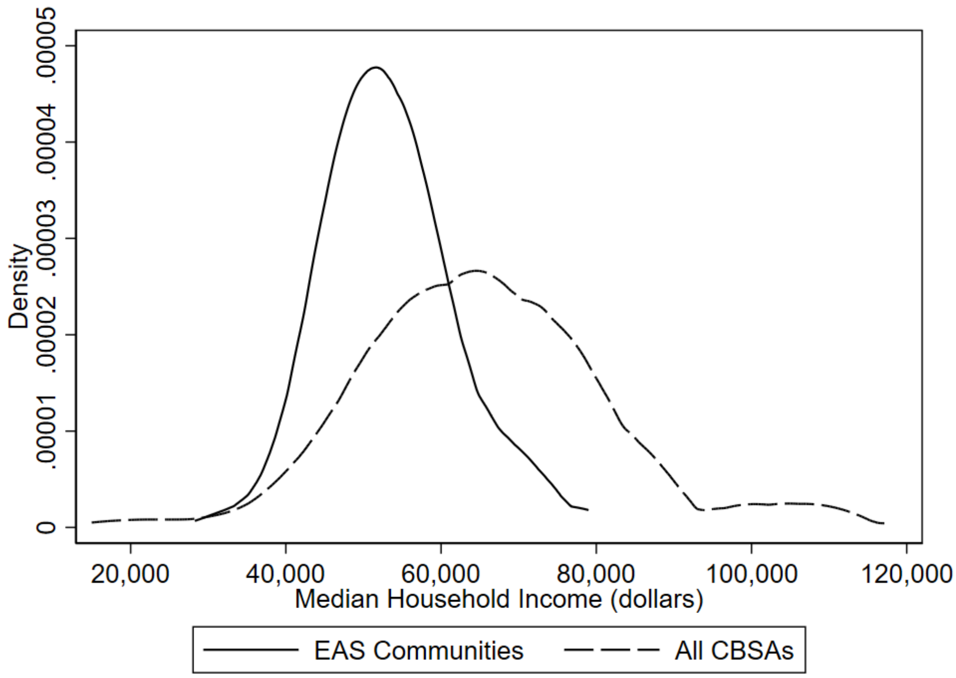
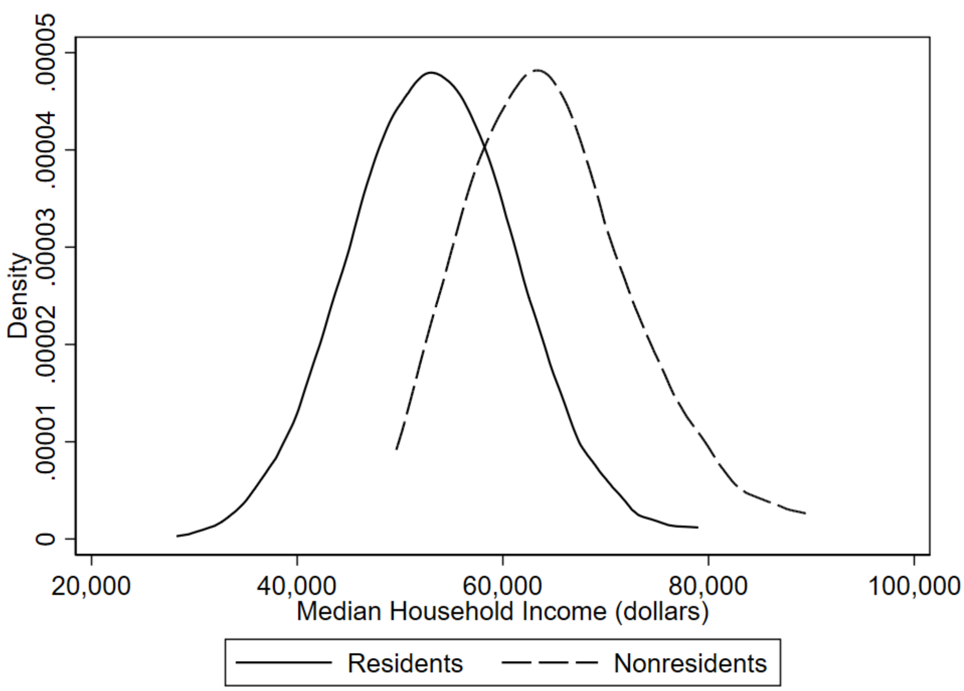
[25] I exclude Hawaiian Airlines because it primarily serves Hawaii, which I exclude from my set of origin regions. AirTran Airways merged with Southwest Airlines in May 2011 but was coded separately until January 2015. US Airways merged with American Airlines in December 2013 but was coded separately until October 2015. Virgin America merged with Alaska Airlines in April 2016 but was coded separately until April 2018. I classify large regional carriers under their corresponding marketing carrier.

Figure 4. Distributions of Income for EAS Communities and All CBSAs



Source: zip-codes.com.
Note: The densities are constructed using an Epanechnikov kernel with a bandwidth of $5,000.

Figure 5. Distributions of Income for Resident and Nonresident EAS Airport Users



Sources: Airlines Reporting Corporation; zip-codes.com.
Notes: Median household income is based on the ZIP codes of passengers from Market Locator for 2013–19. The densities are constructed using an Epanechnikov kernel with a bandwidth of $5,000.

F. American Community Survey

The American Community Survey (ACS) was used to construct income distributions at the ZIP code level, as explained in Appendix E. The ACS contains information about the number of households living in each Census block group with income in each of 16 income buckets ranging from $0 to $200,000 and above. These data were used to construct income distributions at the ZIP code level using a block group to ZIP code crosswalk obtained from the Missouri Census Data Center. The crosswalk, which provides the share of the population of each block group that lives in each ZIP code, was used to allocate the number of households in each block group into each ZIP code. Once block group populations were allocated to ZIP codes, the total number of households in each ZIP code and income bucket was computed. Finally, the number of households in each ZIP code and income bucket were converted to population shares by dividing by the total population of the origin region.

Table 1. Summary Statistics for the Estimation Samples

Variable	Mean	Standard deviation	Source
Fare (dollars)	186.69	66.87	DB1B
Direct	184.23	66.22	DB1B
Indirect	228.60	63.91	DB1B
Drive time (minutes)	38.4	21.1	Market Locator
Multi-airport region	38.3	21.6	Market Locator
Single-airport region	38.6	20.2	Market Locator
Extra time (minutes)	148	40	DB1B, On-Time
Layover time	83	32	DB1B, On-Time
Flight time	65	25	DB1B, On-Time
Number of daily flights	5.5	3.8	DB1B, On-Time
Direct flight distance (miles)	1,048	632	DB1B
Products per market	8.6	5.2	DB1B
Multi-airport region	11.1	5.6	DB1B
Single-airport region	5.3	1.9	DB1B
Share direct	0.945		DB1B
Share living in multi-airport region	0.657		Market Locator
Share of commercial enplanements	0.862		FAA

Notes: All statistics are passenger-weighted over quarterly data from 2013 to 2019 and are for one way. Drive time is to passengers' chosen origin. Extra time variables are for indirect flights. Layover time excludes layovers longer than 4 hours. Share of commercial enplanements is for 2019. See Section IV.A for the definition of products and markets. See Section IV.B for a description of several of the product characteristics listed. See Section III.A for the list of multi-airport regions.

IV. MODEL

In this section, I specify a nested logit model of consumer demand for airline products that closely resembles the canonical models of Berry, Carnall, and Spiller (1996, 2006) and Berry and Jia (2010). The nested logit model is a workhorse model used in many studies of the airline industry and, as noted by Berry and Jia (2010), is a parsimonious way to capture the correlation of tastes for different product attributes that can be evaluated analytically. The key innovation that I make to the canonical nested logit model for air travel demand is to allow consumers to choose between airports they could fly from and to include driving time from one's home to the airport in the traveler's utility function.

A. Demand Model

In each time period (quarter) and for each region, I assume all potential travelers living in a particular region decide whether to fly to a particular destination and, conditional on choosing to fly, which product to purchase. The utility for consumer i from choosing product j in market t is assumed to take the following form:

$$u_{ijt} = \alpha_i p_{jt} + \mathbf{x}'_{jt}\boldsymbol{\beta}_i + \xi_{jt} + \tau d_{ijt} + \eta_{it} + \lambda\varepsilon_{ijt}$$

where p_{jt} is the price of product j, $\mathbf{x}_{jt}$ is a vector of observed product characteristics, ξ_{jt} is the unobserved quality of j, and d_{ijt} is the driving time from consumer i's home to the departing airport of product j. The coefficient τ represents the marginal utility from driving to the airport and the coefficients α_i and $\boldsymbol{\beta}_i$ represent the marginal utilities from airfare and other product characteristics, respectively, where the subscripts i indicate that the coefficients are allowed to differ by individual.

The term ε_{ijt} represents consumer i's idiosyncratic taste for product j and is assumed to be independently and identically distributed type-I extreme value across consumers and products. The term η_{it} represents consumer i's idiosyncratic taste for airline products and is assumed to be distributed such that the composite error term $\eta_{it} + \lambda\varepsilon_{ijt}$ with $\lambda \in (0,1)$ gives rise to the nested logit model with two nests.[26] The first nest contains all airline products, and the second nest contains only the outside option, which can be thought of as not flying to a particular destination during a quarter. To facilitate identification, the utility of the outside good is normalized to $u_{i0t} = \varepsilon_{i0t}$.

Individuals i can purchase products j that belong to one and only one market t, which I define as an origin–destination pair at a point in time. While most studies of the airline industry define a market to be

[26] Cardell (1997) describes the precise distributional assumptions necessary to give rise to such a model. Specifically, the distribution of η_{it} is defined to be the unique distribution parameterized by λ that has the property that $\eta_{it} + \lambda\varepsilon_{ijt}$ is distributed type-I extreme value when ε_{ijt} is also distributed type-I extreme value.

either an *airport pair* (products flying between two specific airports) or a *city pair* (products flying between any of the airports within two cities)—see Brueckner, Lee, and Singer (2014)—I want to consider the possibility that travelers might drive to an airport from beyond a city's boundaries. I thus construct broad geographical areas around airports that could reasonably be considered substitutes and refer to such areas as *origin regions*.[27] I assume all products departing from airports within the same origin region and flying to the same destination airport are within the same market. Formally, I define a *market* as a directional region-to-airport pair at a point in time.[28] A *product* is defined as the airline, origin airport, and service type (direct and connecting) that gets passengers from one origin region to a destination airport. All flights from one airport to another with at most one layover that are operated by the same airline are thus considered the same product.[29]

B. Model Specification

All product characteristics in $\mathbf{x}_{jt}$ are assumed to be exogenous. These include variations on several variables commonly found in the literature.[30] I include an indicator for whether a product is a direct flight, since utility should increase if there are fewer connections. I include flight frequency, defined as a product's average number of daily departures, since consumers prefer to have flights offered at different times throughout the day for more flexibility when booking. I include a variable for origin presence, defined as the number of destinations served by an airline out of the origin airport, to capture the fact that consumers may be loyal to certain airlines and prefer to depart from airports where it is easier to accumulate frequent flier miles.[31] Airlines with a larger origin presence at an airport may also offer more convenient flight schedules, which benefits consumers.

I include a variable for direct flight distance, defined as the minimum distance (in miles) for a direct flight between the origin region and destination airport, to capture the fact that flights compete with the

[27] Appendix A shows the 40 constructed origin regions used in the estimation, and Appendix Table H1 shows their land areas.

[28] Markets are *directional* in the sense that flights between airports are distinguished by their direction of travel. For example, flights from New York City to Chicago are a different market than flights from Chicago to New York City.

[29] I do not distinguish connecting flights by the airport at which the layover occurs, and I drop all flights with more than one connection. Berry and Jia (2010) consider products with more than one connection. Unlike Berry and Jia (2010), I do not consider fares or fare bins in the product definition and instead use the average price weighted by the number of passengers as a product characteristic.

[30] This literature includes, among others, Berry (1990), Berry, Carnall, and Spiller (2006), Berry and Jia (2010), Ciliberto and Williams (2014), McWeeny (2019), and Ciliberto, Murry, and Tamer (2021).

[31] Borenstein (1989), Berry (1990), Morrison and Winston (1989), Evans and Kessides (1993), Berry, Carnall, and Spiller (2006), and Ciliberto, Murry, and Tamer (2021) emphasize that a larger origin presence increases the value of frequent flier programs and other airline marketing programs.

outside option (including cars, buses, and trains), which become worse substitutes as distance increases; so utility should increase with distance when there is an outside option.[32]

Following Berry and Jia (2010), I include a dummy that equals 1 if the destination is a popular vacation destination (Hawaii, Florida, Puerto Rico, St. Thomas, Las Vegas, or New Orleans), which helps to fit the relatively high traffic volume to these destinations that cannot be explained by the other observed product characteristics.[33] Unobserved factors of demand that affect all markets at a particular point in time, such as seasonality, macroeconomic fluctuations, or major world events, are controlled for using year and quarter fixed effects, which help to explain the choice between flying and not flying. Unobserved factors that make a particular airline more attractive, such as baggage fees, availability of in-flight entertainment, and friendliness of the crew, are controlled for using airline fixed effects. Unobserved factors that make a particular airport more attractive, such as parking fees, congestion, and the availability of lounges or food options, are controlled for using origin airport fixed effects.

The model incorporates heterogeneity in preferences for certain product characteristics, as indicated by the i subscripts on α_i and $\boldsymbol{\beta}_i$. Specifically, I allow heterogeneity in preferences by income for price, specified as

$$\alpha_i = \bar{\alpha} + \alpha^{\text{inc}}\,\text{inc}_i$$

and for service type (direct or connecting), specified as

$$\beta_{i,\text{direct}} = \bar{\beta}_{\text{direct}} + \beta_{\text{direct}}^{\text{inc}}\,\text{inc}_i$$

where inc_i is the income of consumer i and $\beta_x^{\text{inc}} = 0$ for all other characteristics in $\mathbf{x}_{jt}$ besides the direct flight indicator, $x_{jt,\text{direct}}$.[34] As shown by Berry and Jia (2010) and McWeeny (2019), higher-income consumers are less sensitive to price compared to lower-income consumers, so it is reasonable to include a heterogeneous coefficient on price by income. It is also plausible that higher-income consumers would have different preferences for service type compared to lower-income consumers, and that service type would

[32] Previous papers have opted to indirectly incorporate nonlinear preferences for flight time by including a quadratic term for flight distance. Berry and Jia (2010, p. 21) argue that air travel demand is inverse U-shaped in distance: "As distance increases further, travel becomes less pleasant, and demand starts to decrease." They hence include both flight distance and flight distance squared to capture the curvature of demand. Ciliberto and Williams (2014, p. 770) note that "for longer distances air travel becomes relatively more attractive but all forms of travel are less attractive," so they include distance, distance squared, and a "measure of the indirectness of a carrier's service" in their utility function. McWeeny (2019) includes direct flight distance, direct flight distance squared, extra flight distance, and extra flight distance squared in his utility function.

[33] Berry, Carnall, and Spiller (2006) capture the attractiveness of a particular destination by including a variable for the temperature difference between the origin and destination in January.

[34] Alternatively, let ι_{direct} denote a vector with length equal to the number of exogenous characteristics in $\mathbf{x}_{jt}$ that equals 1 in the position of the direct flight indicator and equals 0 in all other positions. Then $\boldsymbol{\beta}_i \equiv \bar{\boldsymbol{\beta}} + (\boldsymbol{\beta}^{\text{inc}}\,\text{inc}_i) \circ \iota_{\text{direct}}$, where $\circ$ denotes the elementwise Hadamard product.

be correlated with price, so it is important to also allow income heterogeneity in preferences for service type in order to identify ceteris paribus sensitivity to price.

V. MOMENTS, ESTIMATION, AND IDENTIFICATION

I estimate the model using the generalized method of moments (Hansen, 1982), closely following Berry, Levinsohn, and Pakes (2004) and Petrin (2002). I use three types of moments to estimate the model parameters. First, I set predicted market shares equal to observed market shares, which, as shown by Berry (1994), allows me to identify unobserved product quality. Second, I make an orthogonality assumption about the relationship between unobserved product quality and a set of instruments, which I use to construct macromoments using market-level data. Third, I construct micromoments by interacting driving times with observed choices using the individual-level data. Appendix F details how I construct the moments and provides other estimation details, including how I compute standard errors. After explaining how the moments are constructed, I explain how the moments identify the parameters.

A. Moments

The first set of moments equate market shares predicted by the model with observed market shares. As shown by Berry (1994) and others, the distributional assumptions of the composite error term give rise to a closed-form expression for the model-predicted market share (see Appendix F). Let s_{jt} denote the model-predicted market shares, let S_{jt} denote the market shares observed in the data, and let $\mathbf{s}$ and $\boldsymbol{S}$ denote the vectors of s_{jt} and S_{jt}, respectively, for all products $j = 1, \dots, J_t$ and markets $t = 1, \dots, T$. The first set of moments are constructed by setting $\mathbf{s} = \boldsymbol{S}$.

The second set of moments are referred to as macromoments because they are constructed using market-level data, where the unit of observation is product j. I assume that the unobserved product quality ξ_{jt} is uncorrelated with a set of instruments. Since price p_{jt} is possibly correlated with unobserved product quality—consumers may be willing to pay a higher price for higher quality that is not observed by the researcher—I assume the instruments are correlated with price but uncorrelated with a product's quality. Formally, let $\mathbf{z}_{jt}$ be a set of exogenous instruments. The moment conditions are $E[\mathbf{z}'_{jt}\xi_{jt}] = \mathbf{0}$ and the macromoments $\mathbf{m}_1$ are defined as the sample analog of $E[\mathbf{z}'_{jt}\xi_{jt}]$.

The third set of moments are referred to as micromoments because they are constructed using individual-level data, where the unit of observation is individual i purchasing a product j. Specifically, I compute the micromoments using a random sample of 10,000 individuals from the Market Locator data living in origin regions with two or more airports each served by legacy carriers (see Section III.A). I form the moments by equating model-predicted conditional purchase probabilities with data on whether or not an individual purchased a product. Let $y_{ijt} = 1$ if individual i purchased product j in market t and $y_{ijt} = 0$ otherwise. Let $\bar{s}_{ijt}$ denote the probability that individual i purchases product j in market t conditional on purchasing an airline product. The moment condition is $E\left[\left(y_{ijt} - \bar{s}_{ijt}\right)d_{ijt}\right] = 0$ and the micromoments $\mathbf{m}_2$ are defined as the sample analog of $E\left[\left(y_{ijt} - \bar{s}_{ijt}\right)d_{ijt}\right]$.

B. Estimation

Let $\boldsymbol{\theta}$ denote the parameters to be estimated. To reduce the dimensionality of the generalized method of moments nonlinear parameter search, I follow Conlon and Gortmaker (2020) by rewriting the utility specification as

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + \nu_{ijt}$$

where

$$\delta_{jt} = \bar{\alpha} p_{jt} + \mathbf{x}_{jt}' \overline{\boldsymbol{\beta}} + \xi_{jt}$$

$$\mu_{ijt} = \tau d_{ijt} + \alpha^{\text{inc}}\left(\text{inc}_i \times p_{jt}\right) + \beta_{\text{direct}}^{\text{inc}}\left(\text{inc}_i \times x_{jt,\text{direct}}\right)$$

$$\nu_{ijt} = \eta_{it} + \lambda \varepsilon_{ijt}$$

Let $\boldsymbol{\theta}_1 \equiv \left(\bar{\alpha}, \overline{\boldsymbol{\beta}}\right)$, $\boldsymbol{\theta}_2 \equiv \left(\lambda, \tau, \alpha^{\text{inc}}, \beta_{\text{direct}}^{\text{inc}}\right)$, and $\boldsymbol{\theta} \equiv (\boldsymbol{\theta}_1, \boldsymbol{\theta}_2)$. Grigolon and Verboven (2014) show how δ_{jt} can be recovered for a given value of $\boldsymbol{\theta}_2$ using a modified contraction mapping algorithm introduced by Berry, Levinsohn, and Pakes (1995) (see Appendix F). By partitioning the utility specification in this way, the parameters $\boldsymbol{\theta}_1$ can be consistently estimated via two-stage least squares estimator $\widehat{\boldsymbol{\theta}}_1$ using the instruments $\mathbf{z}_{jt}$, and the generalized method of moments estimator only has to perform a nonlinear search over the parameters $\boldsymbol{\theta}_2$.

Following Berry, Levinsohn, and Pakes (2004) and Petrin (2002), I stack the moments $\mathbf{m} \equiv (\mathbf{m}_1, \mathbf{m}_2)$ to form the generalized method of moments objective function $\mathbf{m}'\,\mathbf{W}\,\mathbf{m}$, where $\mathbf{W}$ is a matrix that assigns weights to the moments. The estimator $\widehat{\boldsymbol{\theta}}_2$ searches for parameter values that minimize the objective function up to some convergence tolerance. Appendix F explains how the matrix $\mathbf{W}$ is constructed so that $\widehat{\boldsymbol{\theta}}_2$ is an efficient estimator.

C. Identification

To identify $\boldsymbol{\theta}_1 \equiv \left(\bar{\alpha}, \overline{\boldsymbol{\beta}}\right)$, recall that $\delta_{jt} = \bar{\alpha} p_{jt} + \mathbf{x}_j' \overline{\boldsymbol{\beta}} + \xi_{jt}$. The term ξ_{jt} represents desirable characteristics of product j that are unobserved to the researcher, which, given the limitations of the data, might include ticket restrictions (such as refundability) and departure time, among others.[35] Product j's price p_{jt} is singled out from the other (exogenous) product characteristics in $\mathbf{x}_{jt}$ to emphasize that special care must be taken to account for endogeneity: Travelers are willing to pay a higher p_{jt} for better characteristics ξ_{jt} that are observed by the traveler and the airline but not by the researcher. I allow for arbitrary correlation between ξ_{jt} and p_{jt} and instrument for p_{jt}, as explained below.

There are two unobserved variables in this equation: δ_{jt} and ξ_{jt}. As explained in Appendix F, I use a contraction mapping algorithm described by Grigolon and Verboven (2014) to recover δ_{jt} for any value of $\boldsymbol{\theta}_2$, which allows $\boldsymbol{\theta}_1$ to be estimated using two-stage least squares, where ξ_{jt} is treated as the residual. Recall that price p_{jt} is potentially endogenous because product quality ξ_{jt} may be correlated with price and is observed by consumers when making purchases, yet is unobserved by the researcher. Thus, a consistent estimator of $\boldsymbol{\theta}_1$ requires valid instruments $\mathbf{z}_{jt}$ that are correlated with a product's price but uncorrelated with a product's unobserved quality.

Following Berry, Levinsohn, and Pakes (1995) and the large subsequent literature, I form instruments by exploiting rival product attributes and the competitiveness of the market environment, as products with closer substitutes should have lower prices, all else equal. The validity of the instruments relies on the admittedly strong but standard assumption in the literature that market structure is exogenous with respect to product-level unobserved quality.[36] As noted by Berry and Jia (2010), this assumption is reasonable in the short run, since market entry decisions involve substantial fixed costs, such as acquiring gate access, optimizing flight schedules, obtaining aircraft and crew members, and advertising to customers. In addition, the fact that capacity reduction is costly and that carriers are generally cautious about serving new markets suggests that the number of carriers is likely to be determined by long-term considerations and uncorrelated with temporal demand shocks.

In addition to the exogenous product characteristics $\mathbf{x}_{jt}$, I construct several sets of instruments to aid in the identification of p_{jt}. Following Murry (2017), I include the squared difference of each product's exogenous characteristics (origin presence, extra time, and flight frequency) from the mean of the characteristic for competitors in the market. Following Ciliberto, Murry, and Tamer (2021), I include the exogenous characteristics (origin presence, extra time, flight frequency) of all competitors in a market, as the authors argue these instruments capture greater variation in the competitive environment than

[35] As noted by Berry and Jia (2010), in practice not all products are available at every point of time. For example, discount fares, which typically require advanced purchase, tend to disappear first. The term ξ_{jt} can therefore include a ticket's availability, where ξ_{jt} is higher for products that are always available or have fewer restrictions and lower for products that are less obtainable or with more restrictions.

[36] Ciliberto, Murry, and Tamer (2021) relax the assumption of exogenous market structure.

instruments constructed by summing or averaged characteristics of products within a market.[37] I also include the share of products in a market that are direct flights, since markets with more direct flights may be more competitive. I include the number of products in each market, as this instrument will be useful for identifying λ (as explained below). Lastly, following Berry and Jia (2010), I include interactions of each product's exogenous characteristics (origin presence, direct flight distance, extra time, and flight frequency).

To identify $\boldsymbol{\theta}_2 \equiv \left(\lambda, \tau, \alpha^{\text{inc}}, \beta_{\text{direct}}^{\text{inc}}\right)$, I use the same set of instruments $\mathbf{z}_{jt}$ described above and interact them with the estimated residuals $\hat{\xi}_{jt} = \delta_{jt} - \hat{\hat{\alpha}} p_{jt} - \mathbf{x}_{jt}' \hat{\hat{\boldsymbol{\beta}}}$, where $\hat{\boldsymbol{\theta}}_1 \equiv \left(\hat{\hat{\alpha}}, \hat{\hat{\boldsymbol{\beta}}}\right)$ is the two-stage least squares estimator. Since the instruments $\mathbf{z}_{jt}$ are arguably uncorrelated with unobserved product quality ξ_{jt}, an orthogonality argument implies that the sample analog of $E\left[\mathbf{z}_{jt}' \hat{\xi}_{jt}\right] = \mathbf{0}$, which is the basis for forming the macromoments. As noted by Berry and Jia (2010), λ is identified by variation in the market share of the airline products relative to the outside option as the number of products varies, and a common choice of instrument is the number of products in each market. The income-specific preference parameters α^{inc} and $\beta_{\text{direct}}^{\text{inc}}$ are identified by covariation between travelers' incomes and the attributes of purchased products. The micromoments, which are constructed using detailed information on travelers' home ZIP code relative to their chosen airport, are particularly useful for identifying τ, the preference parameter for driving.[38]

VI. ESTIMATION RESULTS

In this section, I present the estimation results and post-estimation checks of model fit and identification.

A. Results

Table 2 presents the estimation results using quarterly data from 2013–19. All estimated coefficients are statistically significant and have the expected signs. Travelers dislike higher prices and longer driving times, but higher-income travelers are less sensitive to price. Travelers benefit from the ability to travel to faraway cities though they prefer to take the most direct route, with higher-income travelers having a stronger preference for direct flights. Travelers also prefer airline–airport pairs that make it easier to accumulate frequent flier miles and who offer more daily flights. To interpret the estimated coefficients from Table 2, it is useful to convert the units into monetary terms, which is done by dividing the coefficient

[37] If a carrier does not serve a market, then the value of the instrument enters as a large negative number.
[38] Recall that the micromoments were constructed using data from the legacy carriers American Airlines, Delta Air Lines, United Airlines, and US Airways. Notably, Southwest Airlines is excluded. This restriction does not introduce bias under the generalized method of moments estimation framework as long as we are willing to assume that travelers' preferences for driving are independent of their choice of airline.

of interest by the price coefficient estimate adjusted for income. For example, the implied willingness to pay for a direct flight relative to an indirect flight, all else equal, is $50 for households making $50,000 per year and $88 for households making $100,000 per year, implying preference for direct flights increases with income.

Table 2. Model Coefficient Estimates

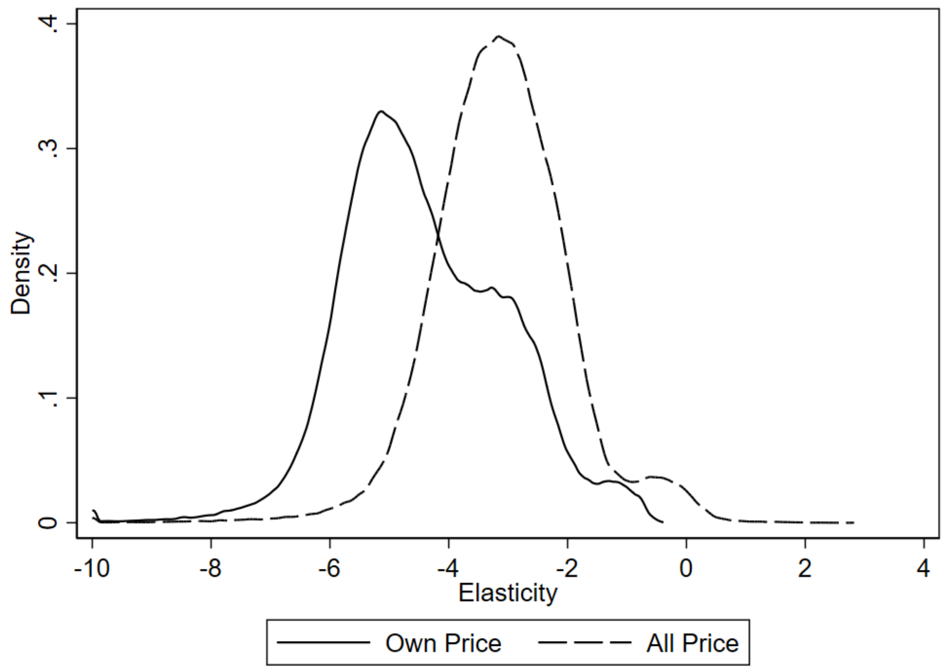
	(1)
Driving time (hours)	–1.686
	(0.132)
Price ($100)	–2.669
	(0.014)
Price ($100) × income ($100,000)	0.838
	(0.111)
Direct flight	0.644
	(0.010)
Direct flight × income ($100,000)	0.970
	(0.066)
Direct distance (1,000 miles)	0.696
	(0.008)
Extra time (hours)	–0.183
	(0.003)
Origin presence (100 destinations)	0.285
	(0.006)
Number of daily flights	0.125
	(0.001)
Vacation destination	0.360
	(0.005)
Nesting parameter	0.658
	(0.003)
No. of products	346,199
No. of markets	53,912

Notes: The coefficients are estimated using data from 2013–19 described in the text. Standard errors are shown in parentheses.

Converting the coefficient on driving time to monetary terms yields an estimate of the marginal value of travel time savings (VTTS) of $75 per hour for households making $50,000 per year and $92 per hour for households making $100,000 per year. The estimate for high-income households ($92 per hour) is reasonably close to the VTTS for business travelers computed using the DOT’s (2016) methodology ($88 per hour), and the estimate for middle-income households ($75) reasonably close to the VTTS for leisure travelers computed using the DOT's (2016) methodology ($75) (see Appendix D).[39] My estimates of VTTS are therefore reasonable and consistent with both the recent literature and current DOT (2016) methodology.

Figure 6 shows the distributions of own-price elasticity (i.e., percentage change in market share from a percentage change in own price) and all-price elasticity (i.e., percentage change in market share from a percentage change in price of all products). The median of the own-price elasticities is –4.41 and the median of the all-price elasticities is –3.12.[40] Figure 7 shows average own-price elasticities for each of the 16 income groups. As expected, own-price elasticity of demand decreases with income, implying higher-income travelers are less price sensitive.

Figure 6. Distributions of Own- and All-Price Elasticities of Demand



Notes: Own-price elasticity of demand is the percentage change in market share for a product from a 1 percent change in a product's own price. All-price elasticity of demand is the percentage change in market share for a product from a 1 percent change in all products' prices. The densities are constructed using an Epanechnikov kernel with a bandwidth of 0.05.

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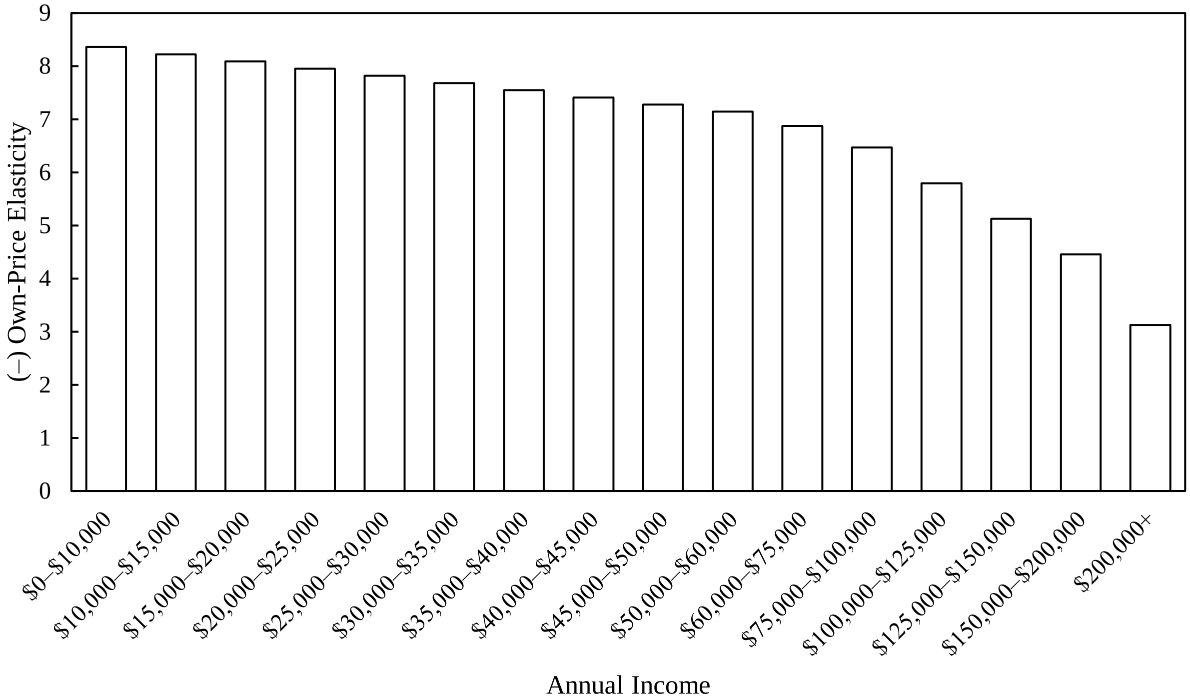
[39] The DOT's (2016) methodology for computing the VTTS for leisure travelers is admittedly arbitrary. Specifically, the DOT (2016) assumes the VTTS for leisure travelers is equal to ½ hourly median income. Using high-frequency GPS data linking drivers to their choice of gas station, Dorsey, Langer, and McRae (2022) estimate the VTTS as 89 percent of hourly median income. Using large-scale field experiments for Lyft riders, Goldszmidt et al. (2020) estimate the VTTS as 100 percent of hourly median income. Zamparini and Reggiani (2007) report that the mean VTTS from a meta-analysis of 90 studies was 83 percent of hourly median earnings.

[40] IATA (2008) estimates an own-price elasticity of demand for short-haul, intra–North America markets as –1.65. McWeeny (2019) finds that a model that does not account for driving time to alternative airports understates own-price elasticities of demand by about 42 percent. Applying McWeeny's (2019) adjustment to IATA's (2008) estimate would suggest an own-price elasticity of demand for short-haul, intra–North America markets of –2.87. The elasticities I estimate are at the product level, which are expected to be larger than estimates at the market level.

Figure 7. Own-Price Elasticity of Demand by Income



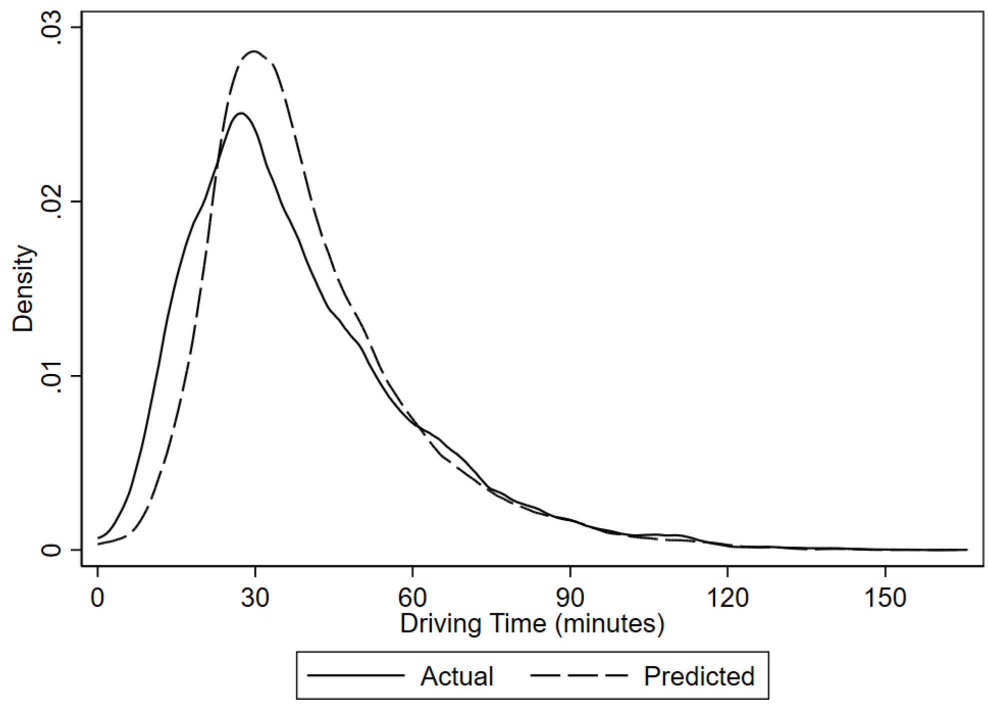
Note: Own-price elasticity of demand is the average over all products for each of the 16 income groups shown on the horizontal axis.

B. Model Fit and Post-Estimation Checks

Figure 8 shows the empirical distribution of driving times from the Market Locator data alongside the model-predicted distribution of driving times. The model does a good job of fitting the data: The distributions are similar in shape and the median driving times are very close, 33 minutes (actual) versus 36 minutes (predicted).

To assess the role of each set of moments in identifying the parameters, I compute Honoré, Jørgensen, and de Paula's (2020) ε_4 measure of moment informativeness, which measures the relative change in the asymptotic variance of the estimator from the removal of a set of moments. A large relative change in the asymptotic variance of a parameter's estimator suggests the removed moments were informative for identifying said parameter. I categorize the moments into five groups: (1) six interactions between four (continuous) exogenous product characteristics (direct flight distance, extra time, origin presence, number of daily flights) interacted with the estimated residual $\hat{\xi}_{jt}$; (2) squared differences from the average among competitors for three (continuous) exogenous product characteristics (extra time, origin presence, number of daily flights) interacted with the estimated residual $\hat{\xi}_{jt}$; (3) three (continuous) exogenous product characteristics (extra time, origin presence, number of daily flights) for 11 competitors interacted with the estimated residual $\hat{\xi}_{jt}$; (4) the number of products in each market and share of products that are direct flights interacted with the estimated residual $\hat{\xi}_{jt}$; (5) the sum over all individuals and all products of the difference between a purchase indicator y_{ijt} and the model-predicted purchase probability conditional on purchase $\bar{s}_{ijt}$ interacted with driving time d_{ijt} (i.e., micromoments).

Figure 8. Actual and Predicted Distributions of Driving Times to the Airport



Sources: Airlines Reporting Corporation; Open Source Routing Machine.
Notes: Driving time is computed for a random sample of 10,000 passengers from Market Locator for 2013–19. Actual driving time comes from the data. Predicted driving time is $\sum_j \left[y_{ijt} - \bar{s}_{ijt}\left(\widehat{\boldsymbol{\theta}}_2\right)\right] d_{ijt}$. The densities are constructed using an Epanechnikov kernel with a bandwidth of 2.5 minutes.

Table 3 shows Honoré, Jørgensen, and de Paula's (2020) ε_4 measure of moment informativeness for the five groups of moments described above on the estimated parameters for mean price sensitivity ($\bar{\alpha}$), the nesting parameter (λ), drive time sensitivity (τ), and income-specific price sensitivity (α^{inc}). The results confirm the identification intuition explained in Section V.C. The most informative moments for identifying mean and income-specific price sensitivity are those derived from Ciliberto, Murry, and Tamer's (2021) instruments. Identification of drive time sensitivity is driven almost entirely from the micromoments calculated using the Market Locator data, while these micromoments have almost influence on identifying any other parameters. Identification of the nesting parameter is driven by the moments that include the number of products in each market as an instrument, which validates the standard practice in the literature.

Table 3. Moment Informativeness

Moments	Mean price sensitivity	Nesting parameter	Drive time sensitivity	Income-specific price sensitivity
1	0.595	0.522	0.054	1.537
2	0.177	0.227	0.012	0.353
3	**9.584**	0.629	0.053	**2.680**
4	2.544	**2.331**	0.074	0.136
5	0.000	0.024	**24.630**	0.000

Notes: Moment informativeness is calculated using Honoré, Jørgensen, and de Paula's (2020) ε_4 measure. Moments listed in the first column correspond to the five groups explained in the text. The **bolded** cell in each column indicates the most informative moment for identifying the column parameter.

VII. COUNTERFACTUAL ANALYSIS OF ESSENTIAL AIR SERVICE

In this section, I use my estimated model to perform a counterfactual policy experiment to determine the consumer surplus that community members derive from EAS-subsidized commercial service at their community airports. To do so, I analyze a policy environment in which all EAS subsidies are ended. As noted in Appendix Table H3, most airports that have lost EAS eligibility no longer have commercial service, so it is reasonable to assume that ending EAS subsidies would result in an end to commercial service. However, it is possible that ending EAS subsidies would *not* end all commercial service—such as at Hagerstown Regional Airport (HGR), which lost EAS eligibility in 2018 but still has commercial service offered by Allegiant Air—in which case my counterfactual analysis would *over*estimate the value of EAS-subsidized commercial service at an airport. Importantly, my counterfactual analysis does not assume that all activity at the airport would be eliminated, only that subsidized commercial service would end; an airport may provide benefits beyond commercial service—such as the ability to fly private planes into and out of the community—and as shown in Appendix Table H3, all formerly eligible EAS airports still support general aviation.

A. Data Construction

I use the Market Locator data to link customers' choice of product with their home ZIP code. Generally, when EAS community members are observed flying from an airport that is not their local airport, I assume that they drove there. (Appendix G gives more details about the construction of the data used for the counterfactual policy experiment.) I use the same notions of *products* and *markets* that were used in the estimation; namely, a *market* is an origin region to destination airport pair, where in this case the origin region is an EAS community. Appendix B shows constructed catchment areas for the 107 EAS airports under consideration along with an array of alternative nearby airports. To avoid complications arising due to airports changing carriers over time, I restrict my counterfactual policy analysis to using data from 2019.

At least two relevant institutional details are worth mentioning. First, EAS-eligible airports are typically only served by one subsidized carrier at a time flying to one or two hubs.[41,42] Second, prices on EAS-subsidized flights generally exhibit little to no variability within a contract period. Thus, rather than using DB1B to compute average prices for EAS-originating flights from a sample of itineraries, I extract prices directly from the subsidized carriers' EAS proposals to the DOT (listed in Appendix Table H4), which usually include the airlines' expected average fares.

EAS community members can be thought of as having two basic choices to access commercial air travel: via driving a short distance to their local airport for an indirect flight to their final destination, or via driving a (potentially substantially) longer distance to an alternative airport for a direct flight to their final destination.[43] An EAS community member's choice set could include several nearby airports within driving distance, such as those shown in Appendix B. I restrict the set of alternative airports to those within a 5-hour drive from the EAS community with non-trivial market shares. Market size is assumed to be the population of the catchment areas shown in Appendix B.

B. Methodology

The basic idea of the counterfactual policy analysis is to compare the consumer surplus that EAS community members derive from two alternative choice sets, one that includes the option to fly on an EAS-subsidized flight and one that does not. I calculate the change in consumer surplus from the removal of EAS-originating products as the compensating variation using the log-sum approach (de Jong et al., 2007; Small and Rosen, 1981). As shown by Kling and Thomson (1996), the distributional assumption on the composite structural error term implies

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[41] Starting in May 2021, SkyWest, the largest regional carrier, began offering subsidized service from Yellowstone Airport under two different brands, Delta Connection and United Express (DOT, 2021a). Previously, SkyWest only offered service from Yellowstone Airport under the Delta Connection brand (DOT, 2019b).

[42] Starting in June 2021, United Airlines offered service from Joplin Regional Airport to three hubs: O'Hare International Airport, Denver International Airport, and George Bush Intercontinental Airport (DOT, 2021b; *Joplin Globe* staff, 2021). United dropped its flight to Houston in late 2021 and filed to withdraw service at Joplin completely in early 2022, citing pilot shortages, though the DOT ordered United to continue service at Joplin until a replacement carrier was found (DOT, 2022a; *Joplin Globe* staff, 2022; Woodin, 2022).

[43] For computational simplicity, I assume the driving time to the local airport for all members of an EAS community is 0. I only consider direct flights from non-EAS airports to ensure consistent comparison of products within the modeling framework. For example, the modeling framework does not allow for flights with more than one connection. Only about 10 percent of EAS community members make more than one stop en route to their final destination.

$$E(CS_{it}) = -\frac{1}{\alpha_i}\ln\left\{1 + \left[\sum_j \exp\left(\frac{\delta_{jt} + \mu_{ijt}}{\lambda}\right)\right]^{\lambda}\right\} + C$$

where the sum is taken over all products $j = 1, \dots, J_t$ in market t, excluding the outside option; and C is an unrecoverable constant.

To ascertain the consumer surplus derived from EAS-subsidized commercial service, I compute expected consumer surplus under two choice scenarios: The true scenario where consumers have access to all products—including those originating from EAS airports—and the counterfactual scenario where consumers do not have access to commercial service departing from the EAS airport. Let CS_{1it} denote consumer surplus from the true scenario and let CS_{2it} denote consumer surplus from the counterfactual scenario. The surplus that consumer i places on EAS-subsidized commercial service is the difference between the expected value of these two quantities: $\Delta E(CS_{it}) = E(CS_{1it}) - E(CS_{2it})$. A community's aggregate consumer surplus from having access to EAS-subsidized commercial service is found by aggregating $\Delta E(CS_{it})$ over all community members i and markets t.

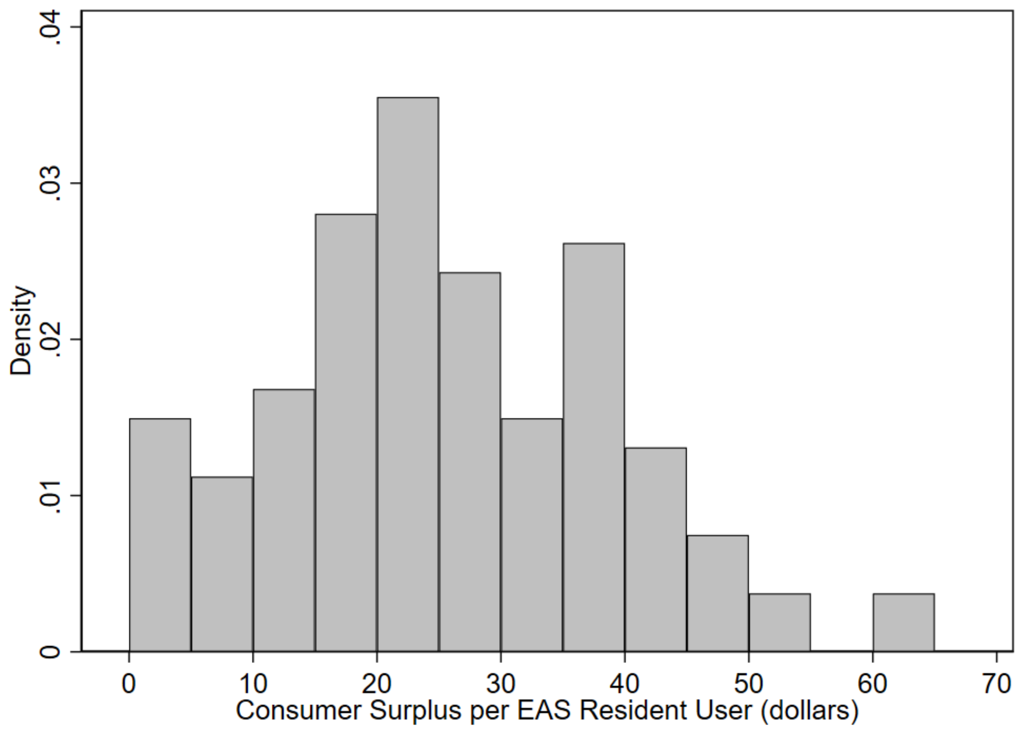
C. Counterfactual Results

I compute each EAS community's aggregate expected consumer surplus from EAS-subsidized commercial service using the above equation. As noted previously, it is plausible that removing EAS subsidies for many EAS airports would not result in the termination of all commercial service, and might actually result in increased service to the extent EAS subsidies act as entry barriers to competitors. Thus, the counterfactual analysis likely overestimates the consumer surplus derived from EAS subsidies.

I find that the aggregate consumer surplus that community members derive from EAS-subsidized commercial service at all 107 airports under consideration is about \$16 million in 2019, a paltry amount compared to EAS's cost of roughly \$290 million in 2019. From an aggregate cost–benefit perspective, it is clear that EAS does not provide nearly enough benefits to communities to justify its costs. Figure 9 shows the distribution of consumer surplus derived from EAS-subsidized commercial service per EAS community member who uses the airport. On average, users of EAS airports who live in the community each derive about \$24 in consumer surplus from subsidized commercial service at the community airport, compared to a median per-passenger subsidy of \$141.

Table 4 summarizes the top 10 and bottom 10 EAS communities in terms of estimated net consumer surplus (estimated benefits less the subsidy cost). The top 10 communities have several features in common. First, their community airports are all among the busiest EAS airports, with 9 among the top 15 in terms of annual enplanements. Second, they all have arguably negligible per-passenger subsidy rates, averaging less than $20 per passenger, which suggests subsidies are likely not needed to sustain commercial service. Third, they are all served by legacy carriers. Fourth, several are served by more than one airline or by one airline but without the use of subsidies, including Grand Island, Cody, West Yellowstone, Joplin, and Sioux City.

Figure 9. Distribution of Consumer Surplus per EAS Resident User



Notes: Consumer surplus for each community is calculated using the methodology described in the text. Consumer surplus per EAS resident user is calculated by dividing consumer surplus by the share of EAS airport users who are deemed residents based on their home ZIP code multiplied by total enplanements at the airport in 2019.

Anecdotal evidence suggests Joplin Regional Airport and Sioux Gateway Airport are two of the most competitive EAS-eligible airports. From 2010 to 2018, American Airlines provided subsidized service from Joplin to O'Hare International Airport and Dallas/Fort Worth International Airport. But not wanting to be undercut by United—which also maintains a hub at O'Hare—American agreed to continue *unsubsidized* service from 2018 to 2020, until the COVID-19 pandemic made maintaining unsubsidized service unsustainable. American proceeded to pull out of Joplin in 2020, at which point United secured the vacated EAS contract, agreeing to provide subsidized service from Joplin to three of its hubs: Denver International Airport, O'Hare International Airport, and Houston George Bush Intercontinental Airport. An almost identical story played out at Sioux Gateway Airport: From 2011 to 2016, American provided subsidized service from Sioux City to O'Hare and Dallas/Fort Worth, but fearing competition from United, American agreed to provide *unsubsidized* service from 2016 to 2020, when American pulled out due to the COVID-

19 pandemic and United quickly secured the EAS contract at Sioux Gateway Airport. This anecdotal evidence is suggestive of rent-seeking behavior, as American apparently used its EAS contract at Joplin and Sioux City to stifle competition, and United now appears to be doing the same.

Table 4. Top 10 and Bottom 10 EAS Communities Ranked by Net Consumer Surplus

Community	Airline	Price	Per-passenger subsidy	Total consumer surplus (millions)	Total subsidy (millions)	Miles to nearest hub	Miles to nearest airport
Top 10 in terms of net consumer surplus							
Joplin, MO	American	$102	$0.00	$0.727	$0.000	154	66
Sioux City, IA	American	$124	$0.00	$0.689	$0.000	189	89
Grand Island, NE	American	$135	$2.76	$0.469	$0.389	138	94
Cody, WY	United	$101	$10.31	$0.708	$0.850	449	107
Butte, MT	Delta	$105	$16.99	$0.336	$0.882	415	78
Garden City, KS	American	$110	$17.43	$0.291	$0.874	300	200
West Yellowstone, MT	Delta	$115	$36.14	$0.000	$0.650	332	91
Aberdeen, SD	Delta	$103	$23.50	$0.400	$1.390	270	175
Bemidji, MN	Delta	$99	$21.20	$0.257	$1.310	213	122
Pellston, MI	Delta	$96	$23.18	$0.173	$1.347	267	84
Bottom 10 in terms of net consumer surplus							
Macon, GA	Contour	$89	$137.00	$0.046	$4.688	82	82
Presque Isle, ME	United	$143	$180.50	$0.260	$4.781	358	157
Page, AZ	Contour	$129	$52.90	$0.014	$4.399	282	134
Clovis, NM	Boutique	$97	$401.23	$0.035	$4.281	409	101
Sidney, MT	Cape Air	$40	$208.21	$0.052	$4.248	658	172
Greenbrier, WV	United	$79	$155.33	$0.102	$3.994	230	79
Tupelo, MS	Contour	$49	$128.74	$0.076	$3.932	94	62
Devils Lake, ND	United	$120	$284.49	$0.133	$3.935	402	84
Liberal, KS	United	$79	$174.44	$0.076	$3.748	356	176
Watertown, NY	American	$93	$87.72	$0.360	$3.950	277	66

Sources: US Department of Transportation; OpenStreetMap.

Notes: Consumer surplus for each community is calculated using the methodology described in the text. Miles to the nearest hub is to the nearest medium or large hub. Miles to the nearest airport is miles to the nearest commercial airport, including small hubs and non-hubs.

As additional evidence of a competitive environment, consider that 3 of the top 10 communities in terms of net consumer surplus are served by one subsidized airline *and* one or more unsubsidized airlines. Central Nebraska Regional Airport in Grand Island is served by both a subsidized airline (American Airlines) and an unsubsidized airline (Allegiant Air), which has been providing unsubsidized service from Grand Island to Harry Reid International Airport and Phoenix–Mesa Gateway Airport since 2008. Yellowstone Regional Airport, located less than an hour's drive from the east entrance of Yellowstone

National Park in Cody, is an attractive destination during the summer tourism season. In the summer months, both United and Delta provide unsubsidized service to and from Yellowstone Regional Airport; but during the non-summer months, only United provides (subsidized) service. Similarly, Yellowstone Airport is located on the Montana–Wyoming border near the west entrance of Yellowstone National Park and is also served by United and Delta (both subsidized), who received a waiver from the usual service requirements in order to provide twice the number of weekly round trips during the summer months compared to the non-summer months.

Several of the bottom 10 communities in terms of net consumer surplus (4 of the bottom 5), shown in the bottom panel of Table 4, are served by non-legacy carriers that offer scheduled passenger service only through EAS contracts. These non-legacy carriers typically offer much lower prices and receive much higher per-passenger subsidies compared to the legacy carriers. Overall, prices for the non-legacy carriers serving EAS communities average $67 one way, compared to $95 for the legacy carriers, and per-passenger subsidies for the non-legacy carriers average $318 compared to $80 for the legacy carriers. The non-legacy carriers tend to serve less popular routes using smaller aircraft, but the routes they serve are no more isolated in terms of distance to the nearest medium or large hub compared to routes served by the legacy carriers.

For example, Boutique Air—whose slogan is “fly private for the cost of commercial”—offers essentially private, EAS-subsidized flights on 9-seat Pilatus PC-12s from Cavern City Air Terminal in Carlsbad, New Mexico, to Dallas/Fort Worth International Airport for a price of $91; yet less than 2 percent of travelers from Carlsbad choose this option, while 36 percent choose to drive 1.25 hours to Roswell Air Center and 23 percent choose to drive 2.75 hours to El Paso International Airport. These discrepancies suggest there are differences in unobserved quality between legacy and non-legacy carriers such that EAS community members would much rather drive a considerable distance to a hub than fly on a heavily subsidized, essentially private flight from their local airport.

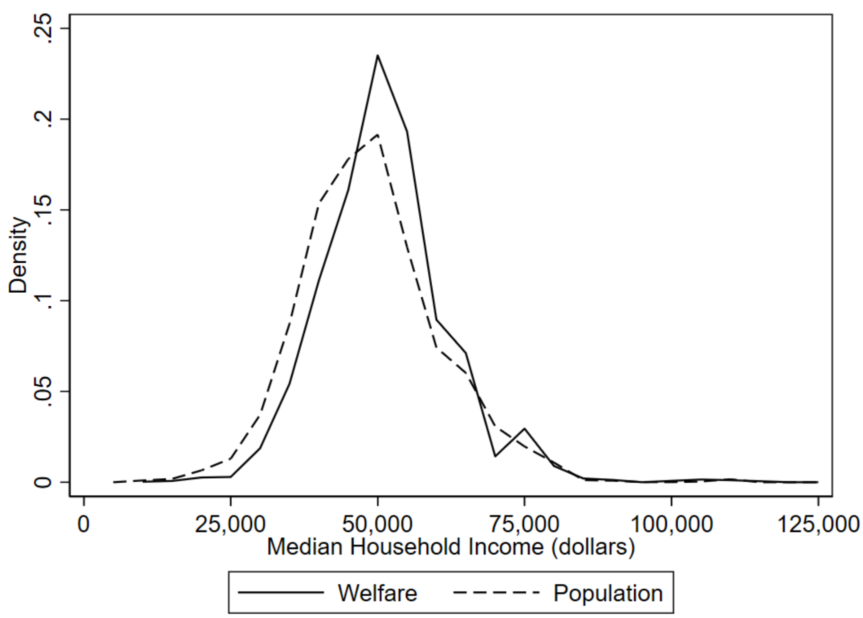
The bottom 10 airports in terms of net consumer surplus are also characterized by very high subsidy rates (all exceeding $3.75 million per year) and low utilization. Prescott Regional Airport, Chippewa Valley Regional Airport, and Middle Georgia Regional Airport are particularly egregious examples, as all three communities are located about 90 minutes from major international airports—Phoenix Sky Harbor, Minneapolis–Saint Paul International Airport, and Hartsfield–Jackson Atlanta International Airport, respectively—yet only about 10 percent of travelers from Prescott choose a subsidized flight from Prescott Regional Airport compared to 80 percent choosing to drive to Phoenix; 10 percent of travelers from Eau Claire choose a subsidized flight from Chippewa Valley Regional Airport compared to 84 percent choosing to drive to Minneapolis; and 3 percent of travelers from Macon choose a subsidized flight from Middle Georgia Regional Airport compared to 94 percent choosing to drive to Atlanta. Middle Georgia Regional

Airport is also notable for requiring the 2nd-largest subsidy among all EAS communities, at $4.7 million in 2019. (Appendix Figure H3 shows the distribution of annual subsidy amounts for 2019.)

D. Distributional Implications

From a distributional perspective, policymakers might be interested to know whether EAS serves those it intends to and whether the benefits are evenly distributed among recipients. Figure 10 shows the distribution of consumer surplus by income compared to the population distribution by income. There are no discernable differences in the distributions, suggesting those in the community who benefit from EAS are representative of the community as a whole in terms of income. Figure 11 shows the distribution of consumer surplus by income for communities that are more than 210 miles from a medium or large hub compared to communities that are less than 210 miles from a medium or large hub. Again, the distributions are nearly identical, suggesting the distribution of consumer surplus by income is no different for community members who live far from a hub compared to those who live close to a hub.

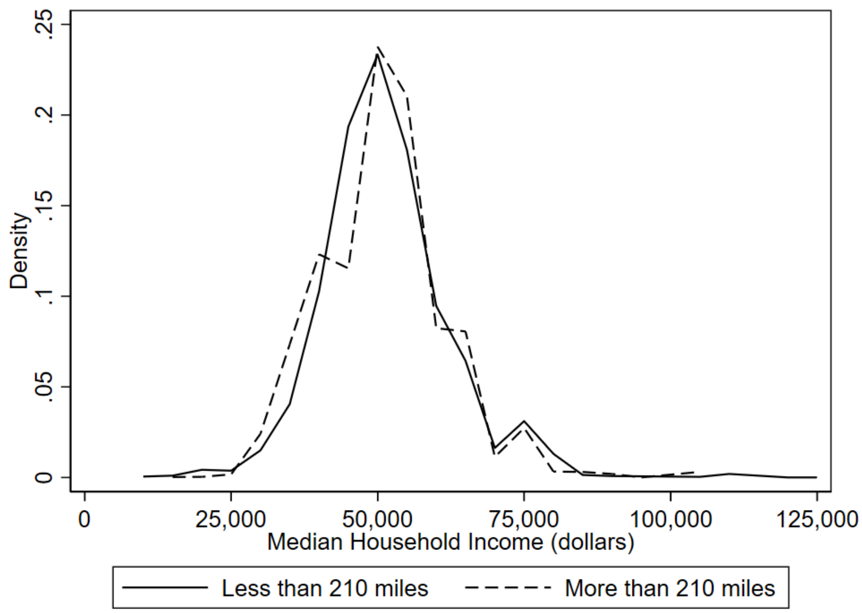
Figure 10. Distributions of Consumer Surplus and Population in EAS Communities by Income



Source: zip-codes.com.
Notes: Consumer surplus for each airport is calculated using the methodology described in the text. Median household income is for the ZIP code in which the traveler resides. The distributions are smoothed by grouping median household incomes into buckets of $5,000.

Figures 10 and 11 suggest that the benefits received by EAS community members do not differ substantially between communities along observable characteristics. Rather, distributional discrepancies likely arise because the main beneficiaries of the EAS programs are high-income tourists who visit the EAS communities. While it is beyond the scope of this paper to formally estimate the consumer surplus that tourists derive from EAS, back-of-the-envelope calculations can provide a sense of how much tourism is potentially generated by an EAS airport and its contribution to the local economy. Although it is not the statutory purpose of EAS to promote local tourism, policymakers representing districts with EAS-subsidized service often brag about the impact that the program has on their local economies.[44]

Figure 11. Distributions of Consumer Surplus in EAS Communities by Income and Distance from Hub



Source: zip-codes.com.
Notes: Consumer surplus for each community is calculated using the methodology described in the text. The solid line is for EAS communities located less than 210 miles from a medium or large hub. The dashed line is for EAS communities located more than 210 miles from a medium or large hub. Median household income is for the ZIP code in which the traveler resides. The distributions are smoothed by grouping median household incomes into buckets of $5,000.

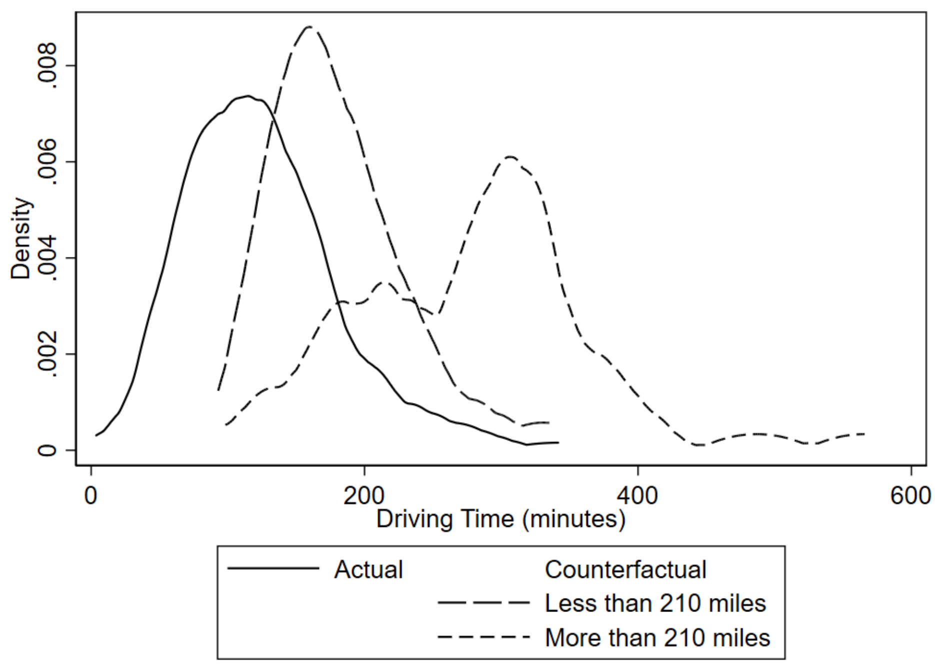
Appendix Table H2 shows 21 EAS airports that serve as gateways to 23 national parks. The table shows total annual visitors to the parks along with the total number of nonresidents using the nearby EAS airport. In every case, the number of visitors flying into the EAS airport is trivial compared to the parks' total annual visitors, suggesting a vast majority of visitors arrive at the parks by driving. Thus, even if the EAS communities nearby national parks were to lose subsidies and lose commercial service, the effect on regional tourism would likely be trivial.

Figure 12 shows the change in the distribution of driving time from the removal of the EAS option, shown separately for communities located less than 210 miles from a hub and communities located more than 210 miles from a hub. The median of the actual distribution of driving time 116 minutes. The

[44] Elise Stefanik, for example, who in 2021 represented five EAS communities in upstate New York, boasts that EAS "attracts travelers to our region, while boosting small businesses and tourist areas" (Stefanik, 2021).

counterfactual distributions of driving time are constructed by removing products originating at EAS-subsidized airports from community members' choice sets.[45] The counterfactual distribution of driving time is clearly bimodal: The median of the distribution for communities located less than 210 miles from a hub is 168 minutes and the median of the distribution for communities located more than 210 miles from a hub is 297 minutes. The bimodal nature of the counterfactual distribution suggests that, even though isolated communities have alternative options (see Figure 2 and Appendix B), these alternative airports are less accessible or less attractive compared to alternative airports nearby less isolated communities.

Figure 12. Actual and Counterfactual Distributions of Driving Time for EAS Communities



Sources: Federal Aviation Administration; Airlines Reporting Corporation; OpenStreetMap.
Notes: The distributions are constructed by taking the average driving time weighted by product shares for each of the 107 EAS communities. The counterfactual distributions are constructed by removing products originating from EAS-subsidized airports. Counterfactual distributions are shown separately for EAS communities located less than and more than 210 miles from a medium or large hub. The densities are constructed using an Epanechnikov kernel with a bandwidth of 20 minutes.

[45] The distributions are constructed conditional on flying. The model predicts that about 20 percent of passengers switched to an alternative product under the counterfactual scenario while about 80 percent switched to the outside option.

VIII. CONCLUSIONS

The aviation industry has completely transformed in the almost half century after the great airline deregulation experiment. Yet despite the major changes to passenger aviation around the country, Essential Air Service, a remnant of the pre-deregulation era designed to be temporary and transitional, has persisted.[46] I have presented evidence in this paper that suggests EAS is a regressive program that provides very little value to the communities it is meant to serve.

Several broad conclusions can be drawn from the counterfactual policy analysis. First, the costs of maintaining subsidized service at all EAS-eligible communities are considerably higher than the benefits residents derive: In aggregate, the EAS program cost $290 million in 2019 yet EAS community members received only $16 million in consumer surplus. Second, there were no discernable differences in the distributions of consumer surplus among EAS communities by income or distance to the nearest hub, suggesting EAS does not disproportionately benefit high-income people within EAS communities. Third, airports that provide the largest benefits to EAS communities are primarily served by legacy airlines with per-passenger subsidy rates so low as to be negligible, while airports that provide the lowest benefits to EAS communities are served by a mixture of legacy and non-legacy carriers that require high per-passenger subsidies. Fourth, EAS airports that provide the most benefit to their communities tend to have features of a competitive environment, such as competition between multiple airlines and legacy carriers providing unsubsidized service in order to keep competitors out.

At least two novel insights can be drawn from simple tabulations of the proprietary Market Locator data linking airline passenger purchases to their home ZIP code. First, travelers in nearly every EAS community not only *have* other options available to them when it comes to accessing commercial air travel, they also *prefer* those options—with many choosing to drive several hours to a larger airport rather than to take a subsidized flight from their local airport—although communities located farther from a medium or large hub face greater barriers to accessing commercial air travel. Second, EAS community members are not the primary users of EAS airports nor the main beneficiaries of EAS subsidies, as tourists and other visitors make up 57 percent EAS airport users and have about 18 percent higher incomes than residents on average. Thus, EAS does a poor job of targeting its intended beneficiaries (i.e., members of the community), and instead serves to subsidize well-off outsiders to visit national parks and other points of interest where EAS communities happen to be located.

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[46] EAS is a classic example of a government program with concentrated benefits and diffuse costs, which may explain why EAS has continued to persist. Hall, Ross, and Yencha (2015) find that higher EAS subsidies are associated with airports located in districts with congressional representatives on the Transportation Committee, which handle renewal of the EAS program, and the Ways and Means Committee, which has jurisdiction over the Airport and Airway Trust Fund from which EAS is funded. Appendix Figure H2 shows the political leanings of EAS communities based on the Cook Political Report's Partisan Voting Index.

While this paper provides novel insights into the airline industry, it is not without its limitations. First, I only considered the implications of airport substitution on demand. Jointly estimating a model of supply could provide a fuller picture of the implications of rent-seeking and airport substitution, particularly as it relates to antitrust and merger analyses. Future work should investigate the implications of airport substitution and market definition for merger analyses. Second, I assumed airlines' network structures were exogenous with respect to product-level unobserved quality, though recent work by Ciliberto, Murry, and Tamer (2021) has attempted to relax this assumption. Third, I only considered the benefit of EAS to members of EAS-eligible communities and did not formally model the choice behavior or quantify the benefit of EAS to travelers living outside of EAS communities.

Policymakers should consider whether Essential Air Service is still essential in the 21st century. The airline industry has dramatically changed since deregulation in 1978, and the EAS program has not evolved with the times. Congress could continue to limit the scope of the program by enacting more stringent eligibility requirements. Two simple reforms Congress could enact would be to include distance to small hubs in addition to medium and large hubs when determining EAS eligibility, and to increase the minimum allowable distance to a hub beyond 70 miles. Such reforms would do a better job of targeting communities that actually face significant barriers to commercial air travel. Eliminating EAS entirely has the potential to benefit the communities it is meant to serve and would move the US closer to realizing the full societal benefits of airline deregulation.

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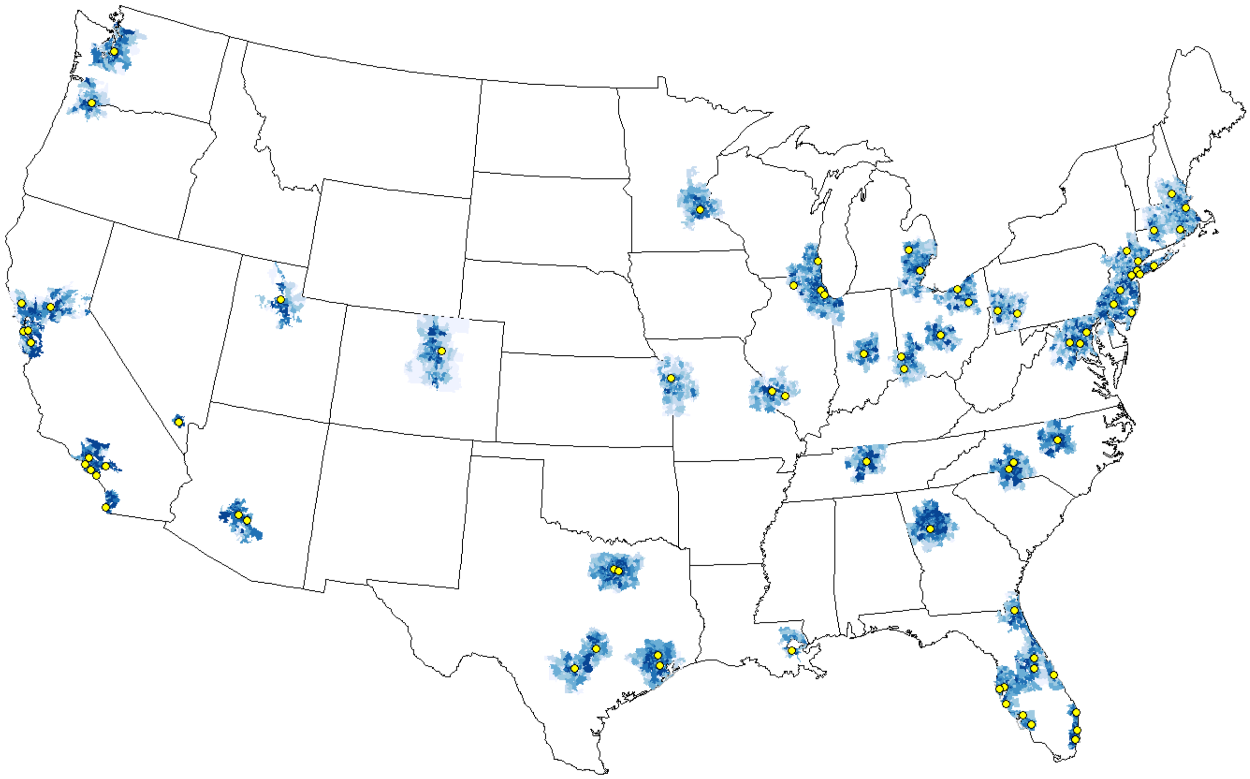
Appendix A. Catchment Areas and Population Densities for Estimation Regions

Appendix Figure A1. Estimation Regions and Airports on One Map

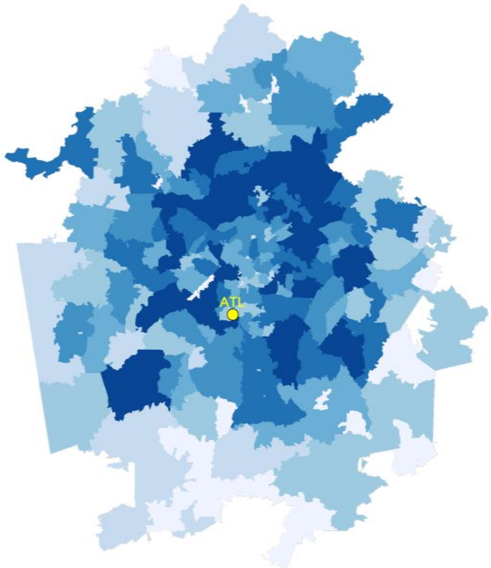


Source: zip-codes.com.

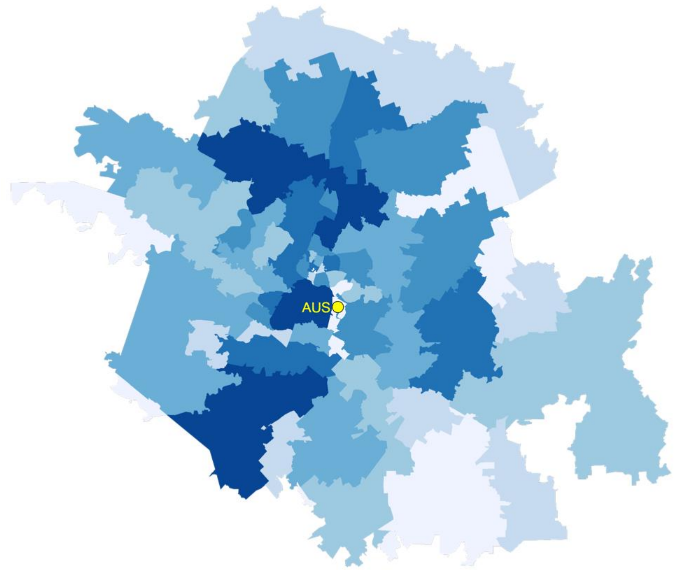
Notes: Each colored area represents an origin region, each geographical unit within the regions represents a ZIP code, and darker shading represents higher population density. The dots represent airports that serve residents of the regions.

Appendix Figure A2. Estimation Regions and Airports Separated by Region

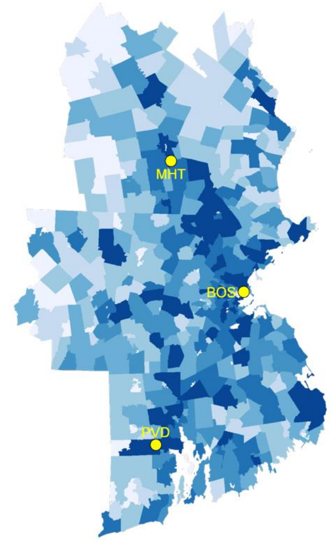
Atlanta



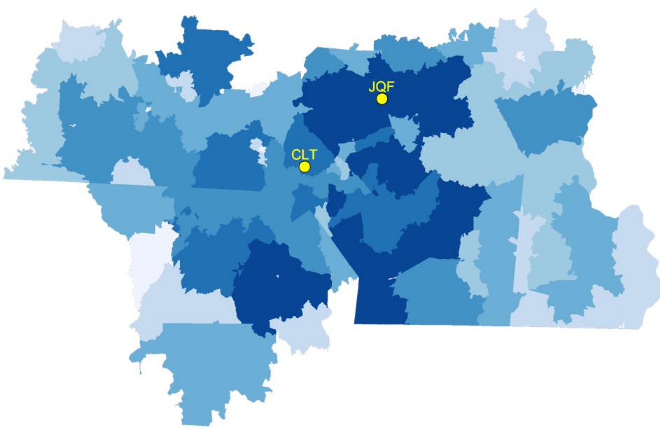
Austin



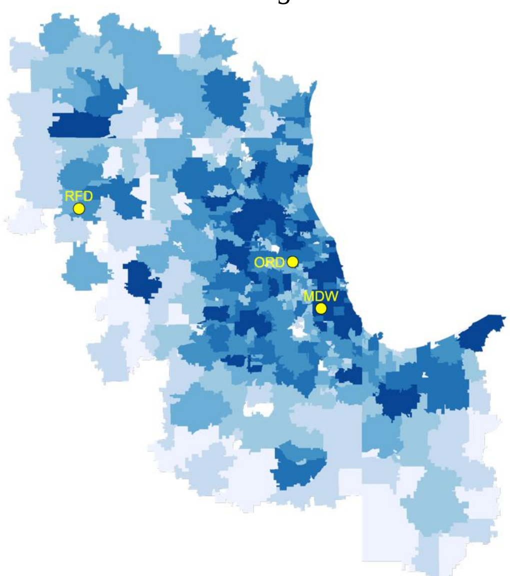
Boston



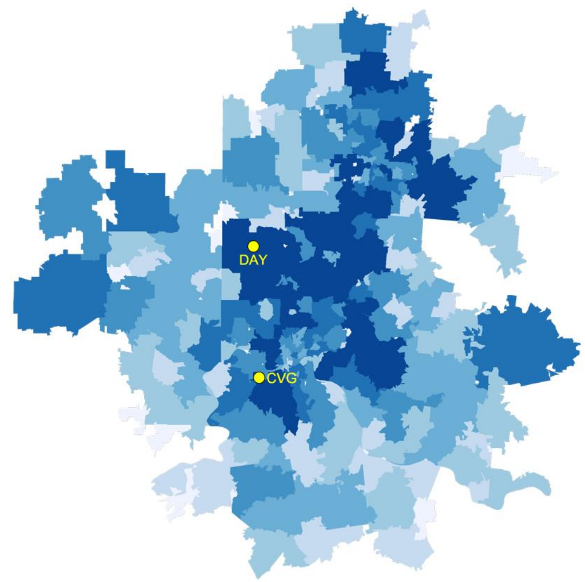
Charlotte



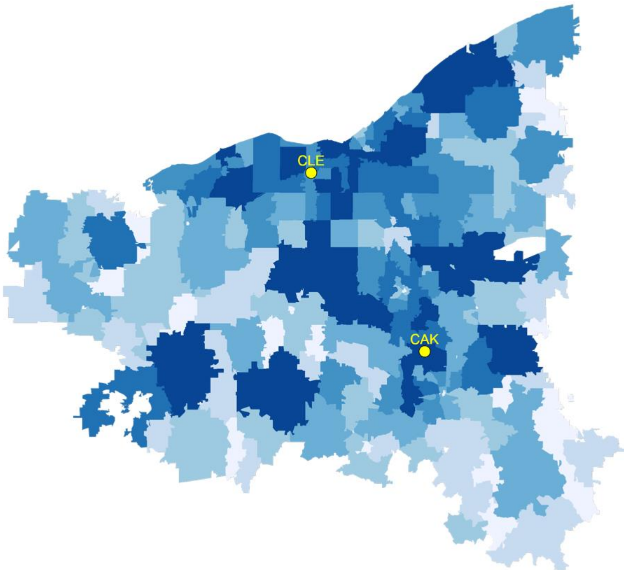
Chicago



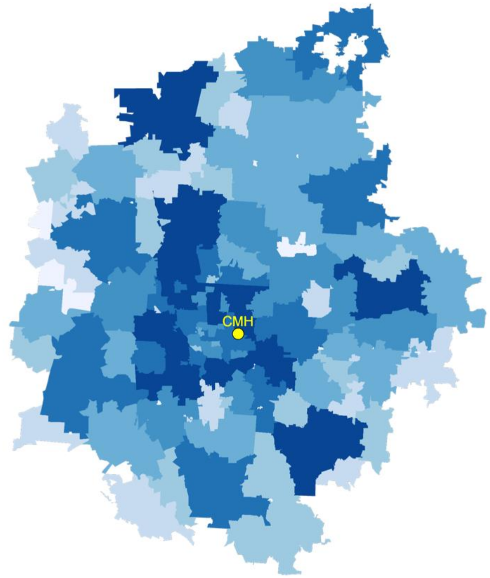
Cincinnati



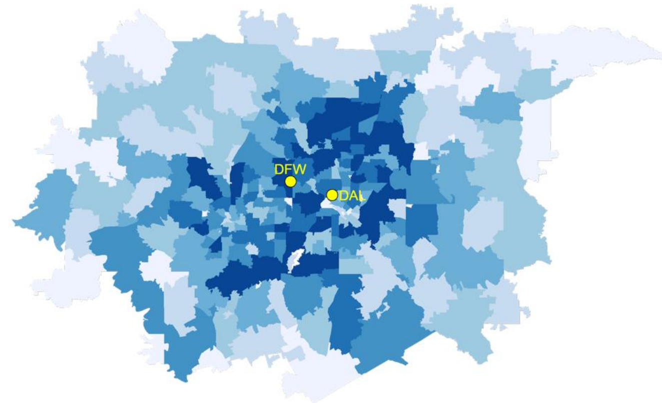
Cleveland



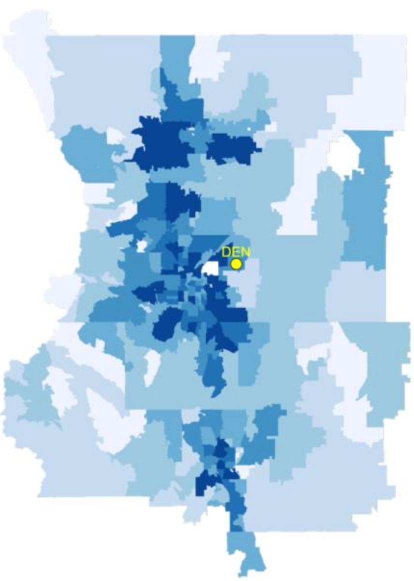
Columbus



Dallas



Denver



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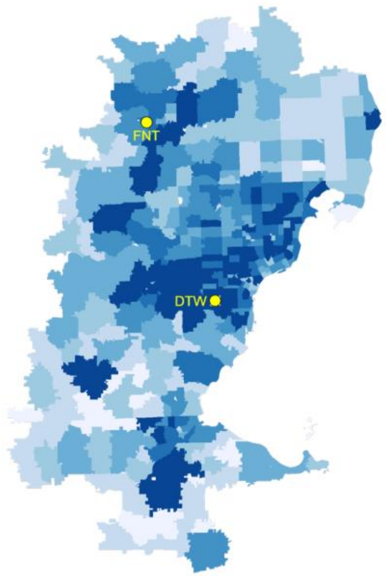

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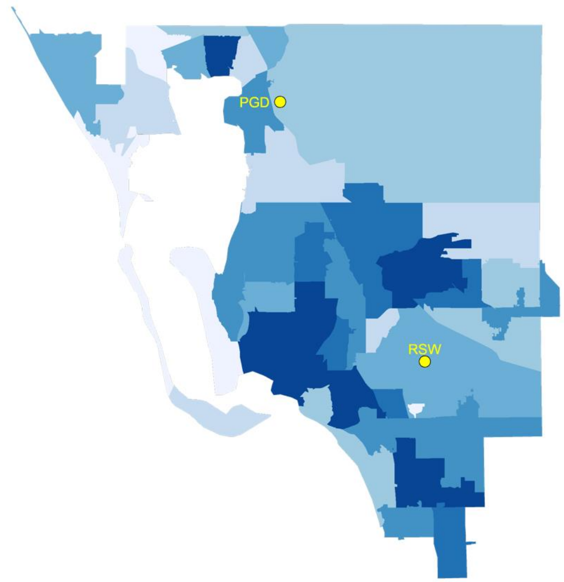
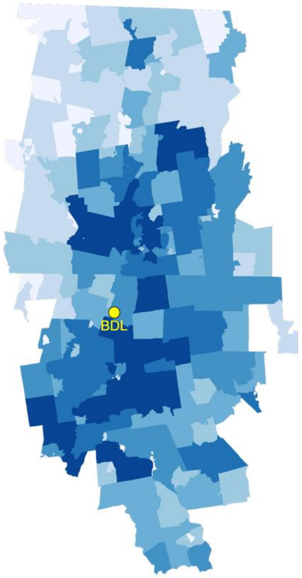


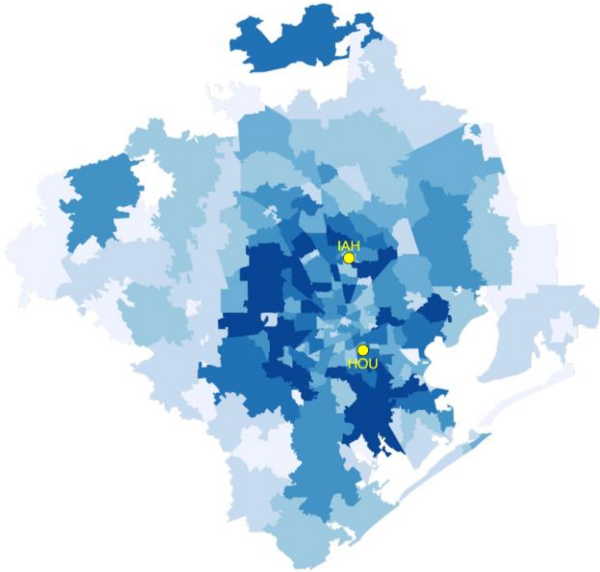
Hartford

Houston

Indianapolis



Jacksonville



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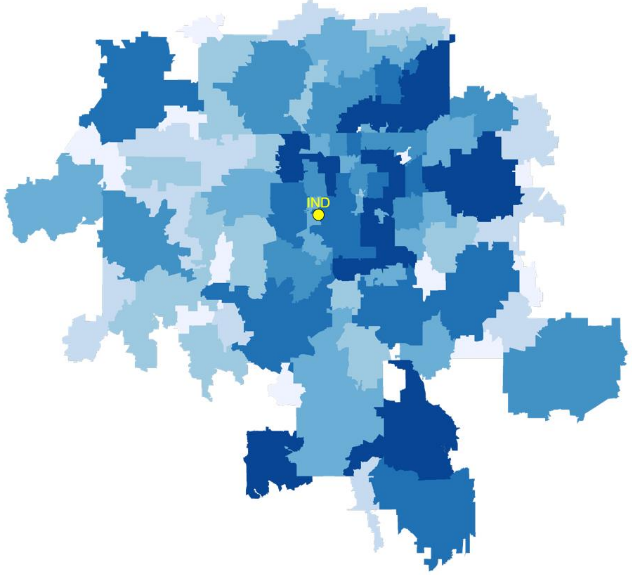
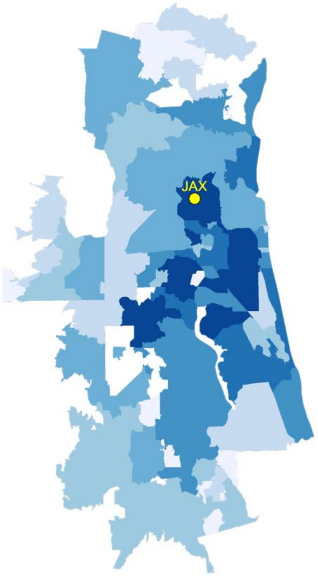


Las Vegas



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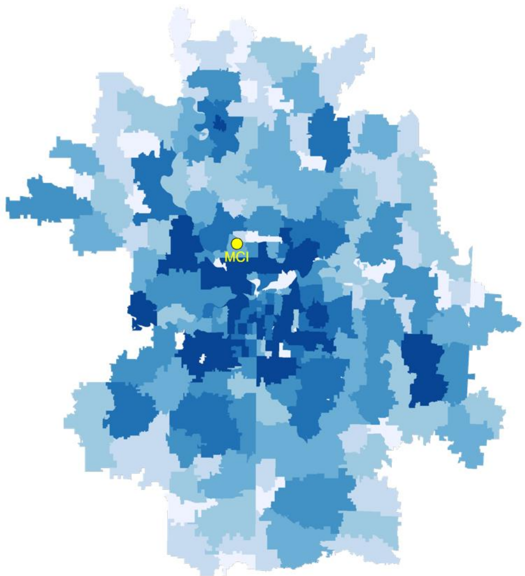
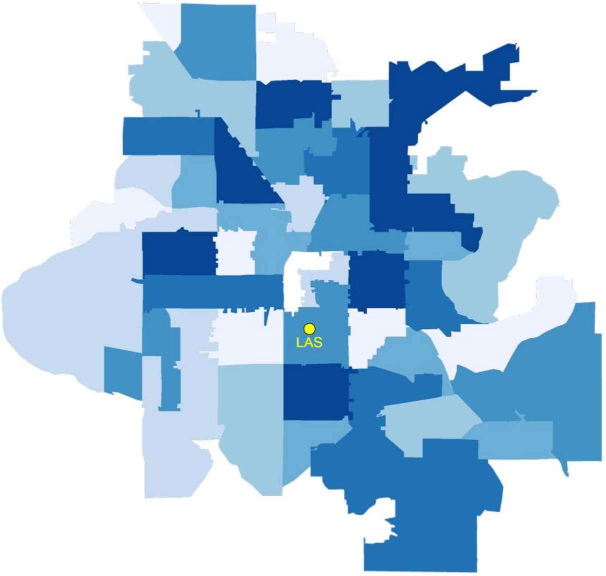
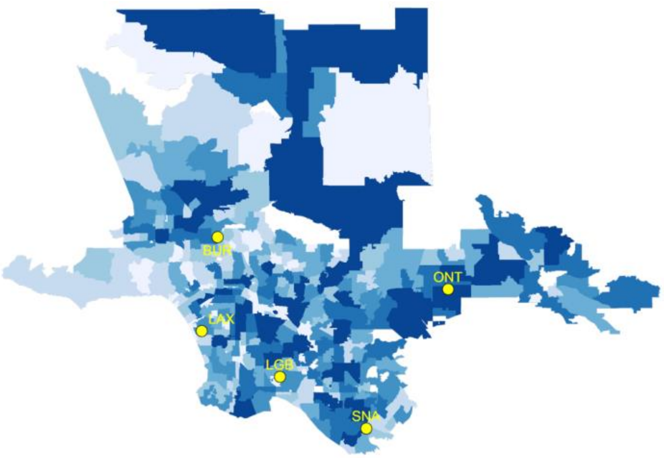


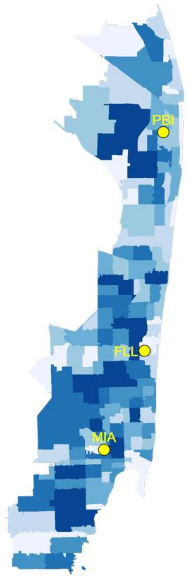
Miami

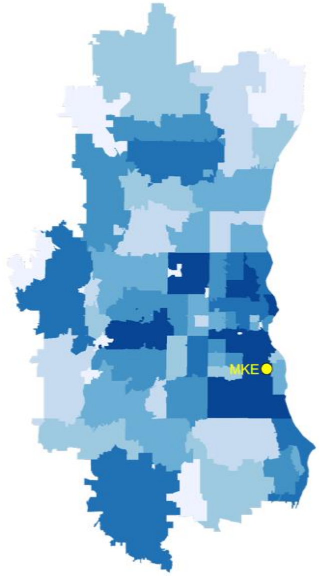
Milwaukee

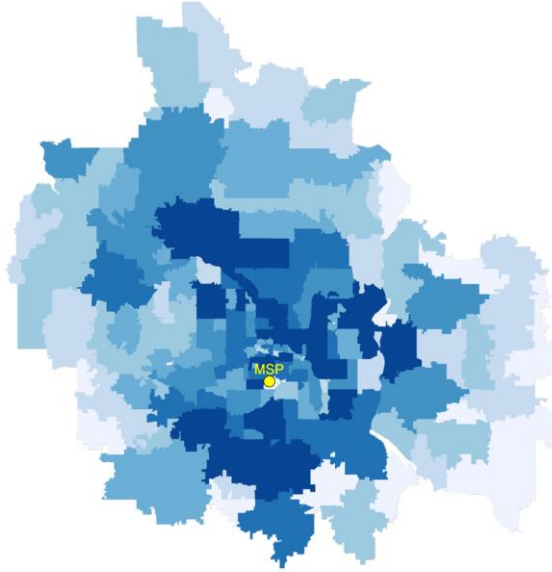


Minneapolis

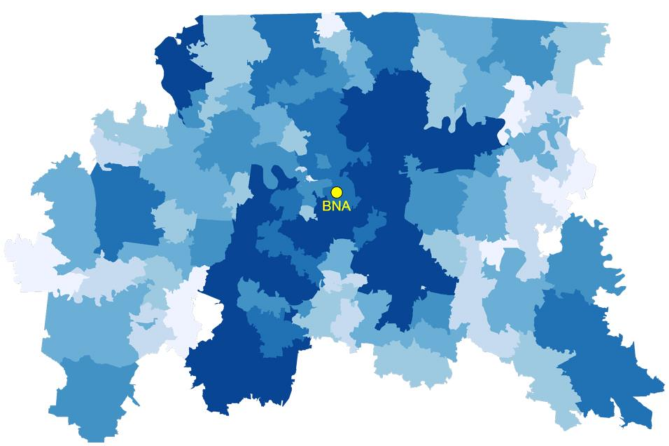


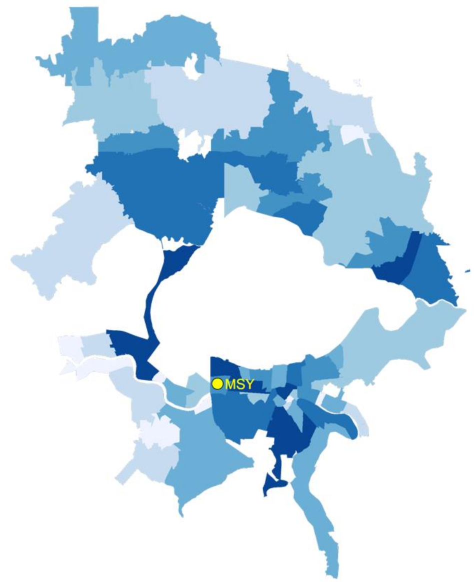




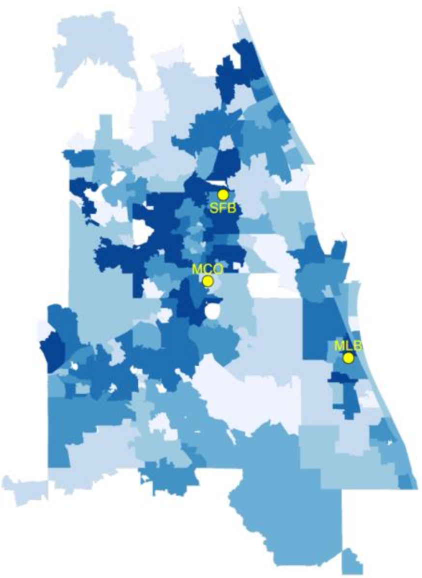


Nashville *New Orleans* *New York*





Orlando *Philadelphia* *Phoenix*



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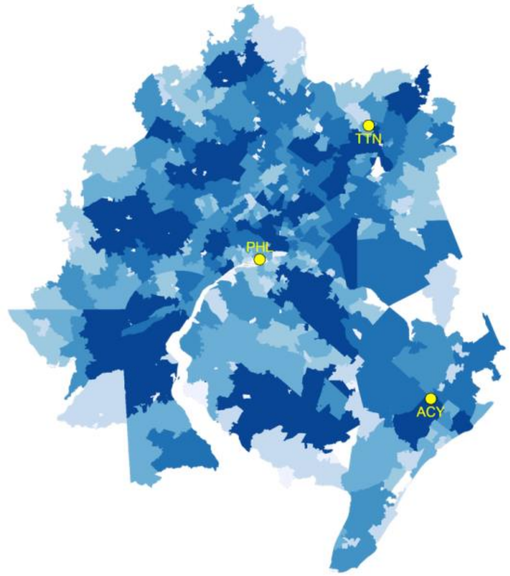
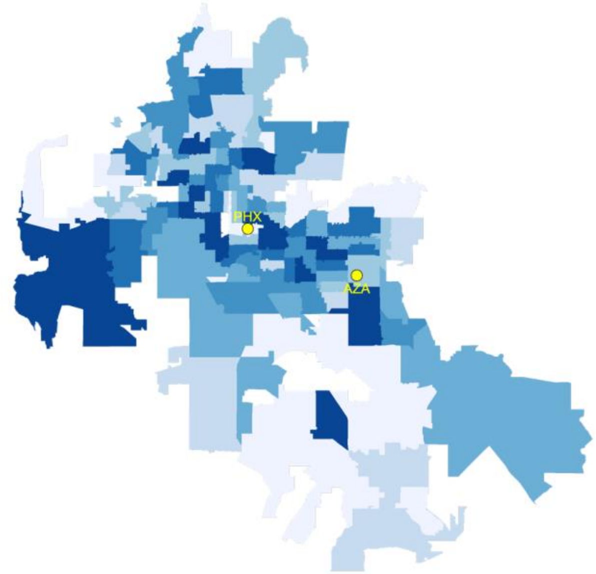
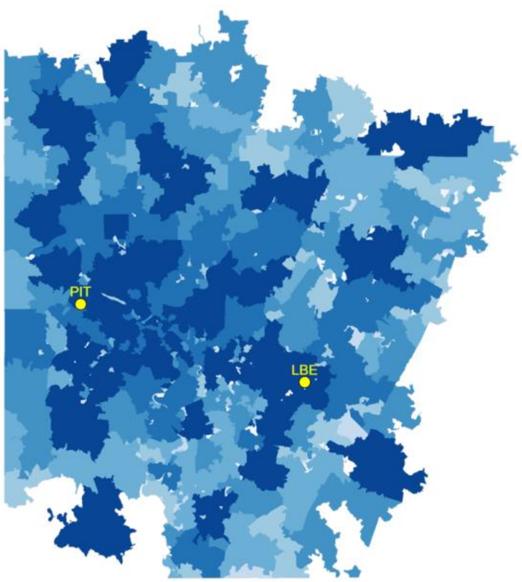


Portland



Raleigh/Durham



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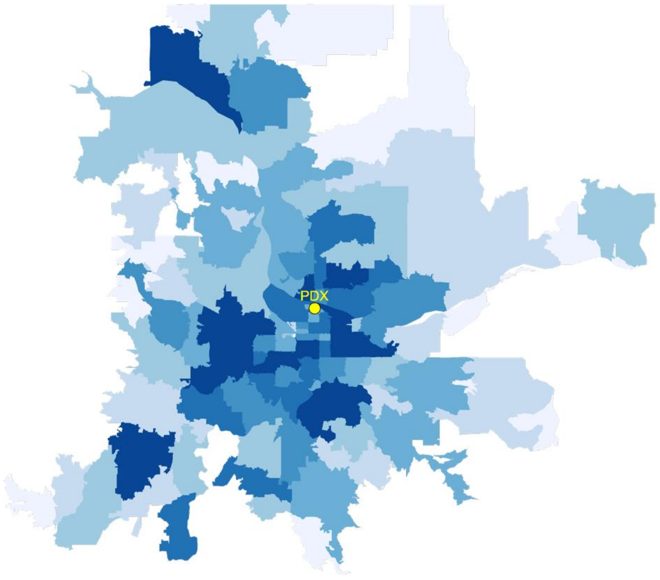
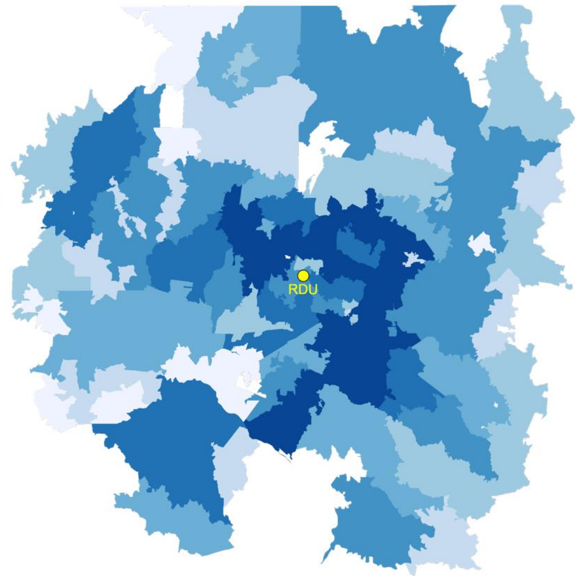


Salt Lake City



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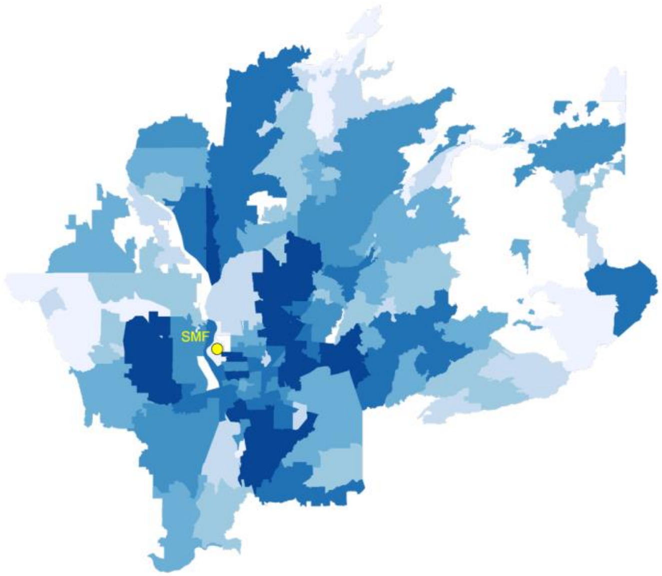

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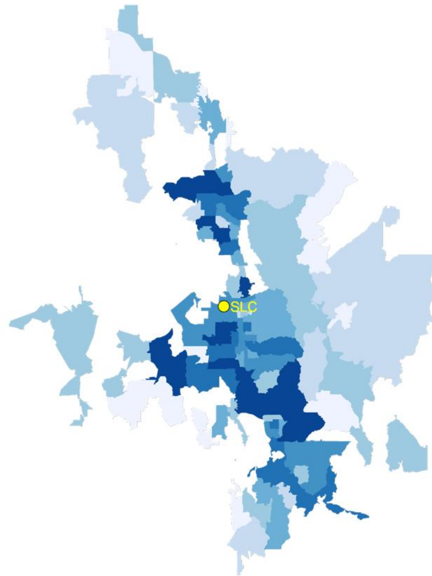

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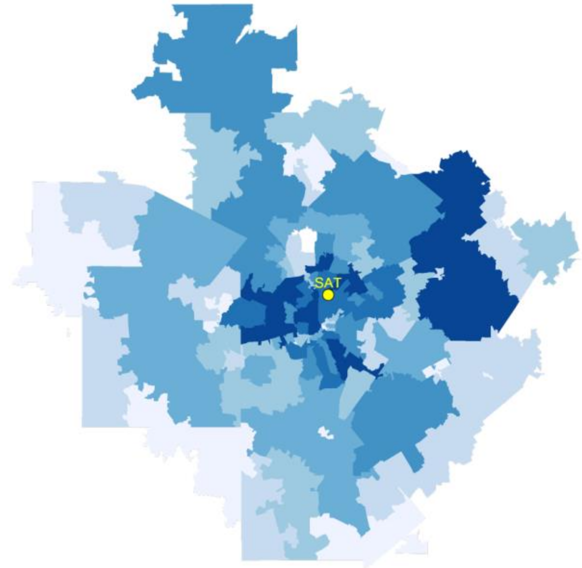

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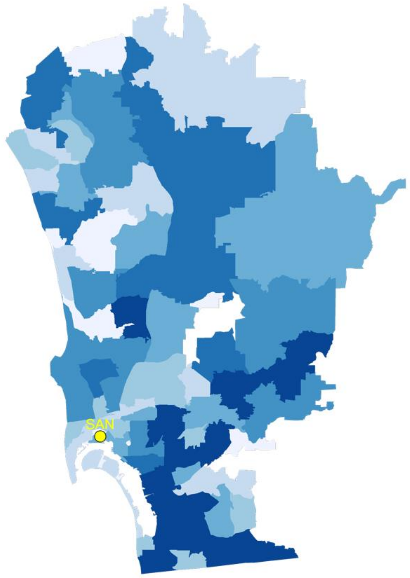

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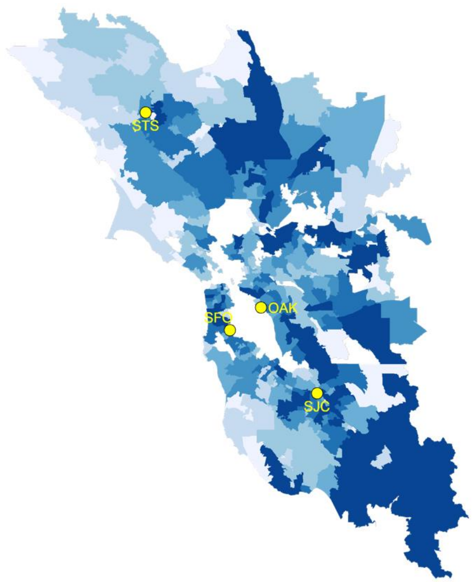
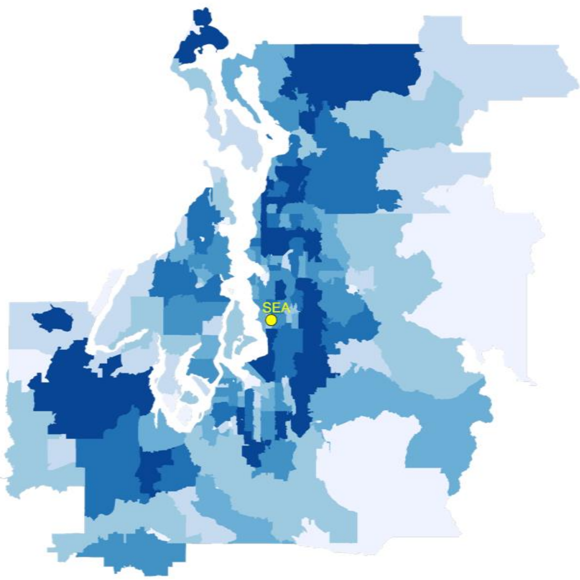
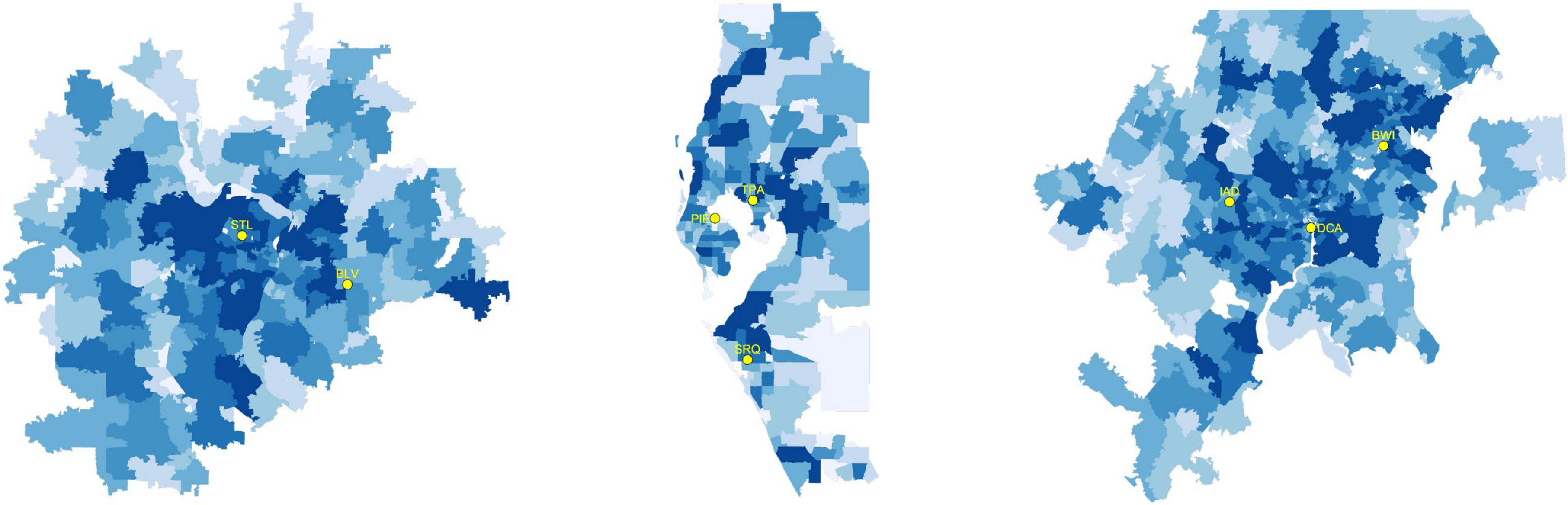


Tampa



Washington

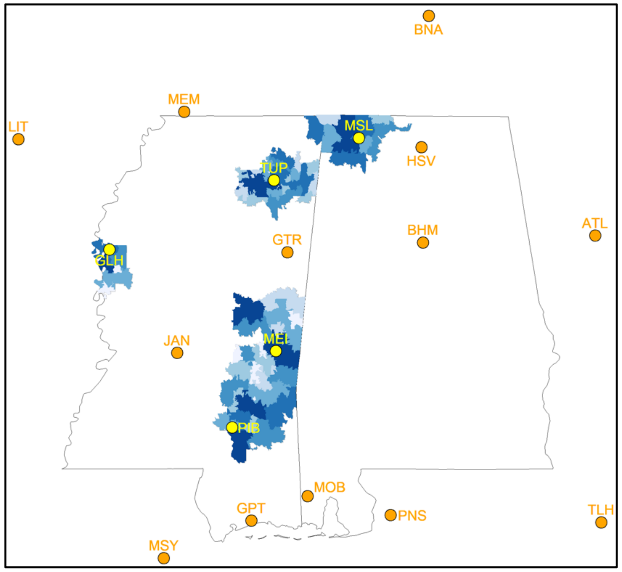


Source: zip-codes.com.

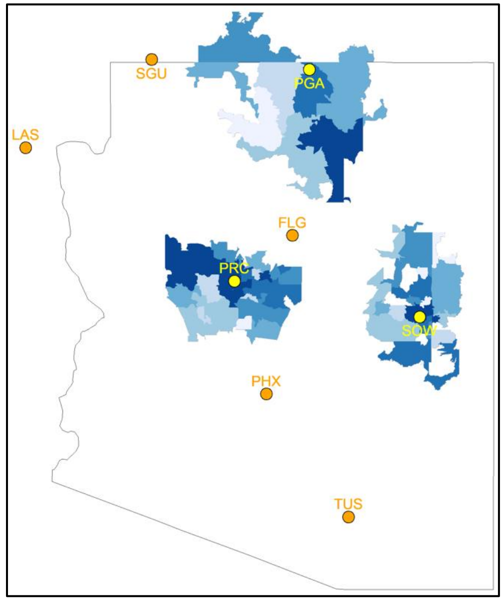
Notes: Each panel represents an origin region, each geographical unit within the regions represents a ZIP code, and darker shading represents higher population density. The dots represent airports that serve residents of the regions.

Appendix B. Catchment Areas, Population Densities, and Nearby Airports for EAS Regions

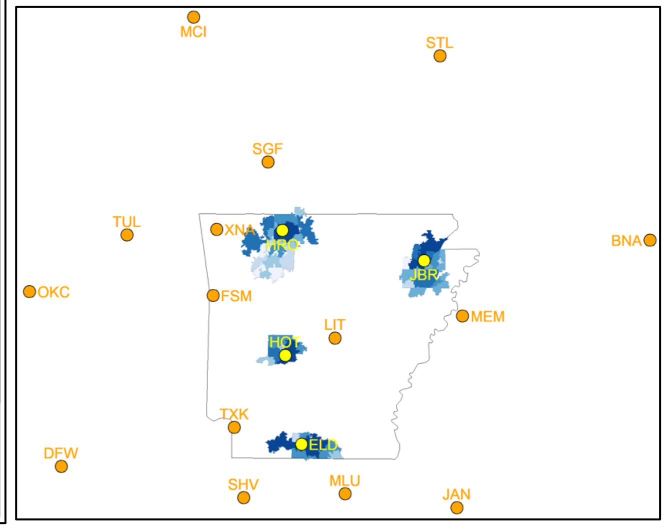
Alabama / Mississippi



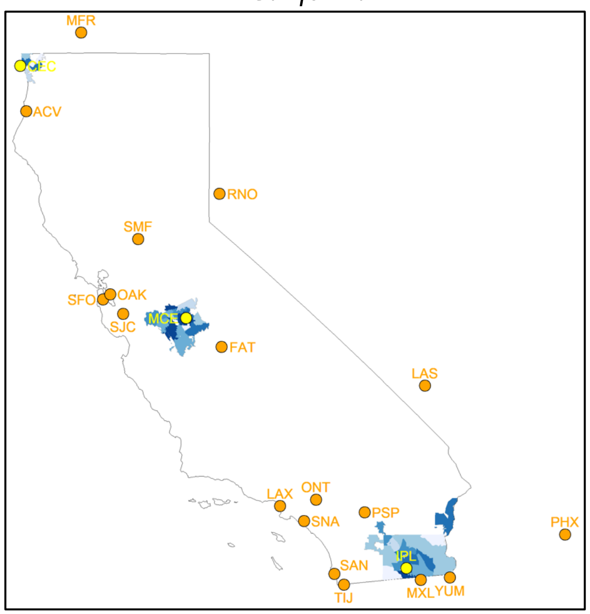
Arizona



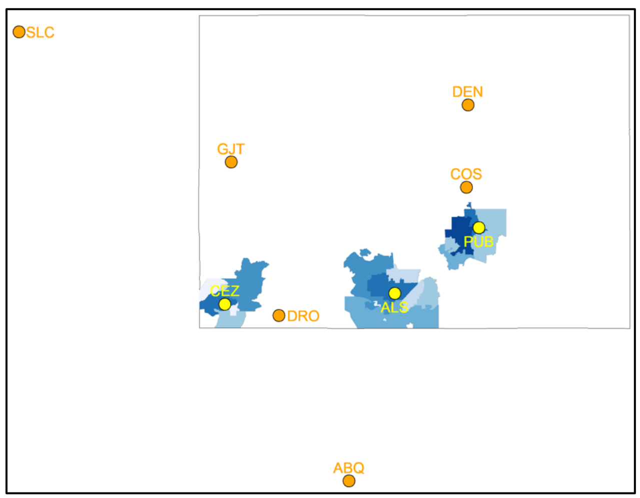
Arkansas



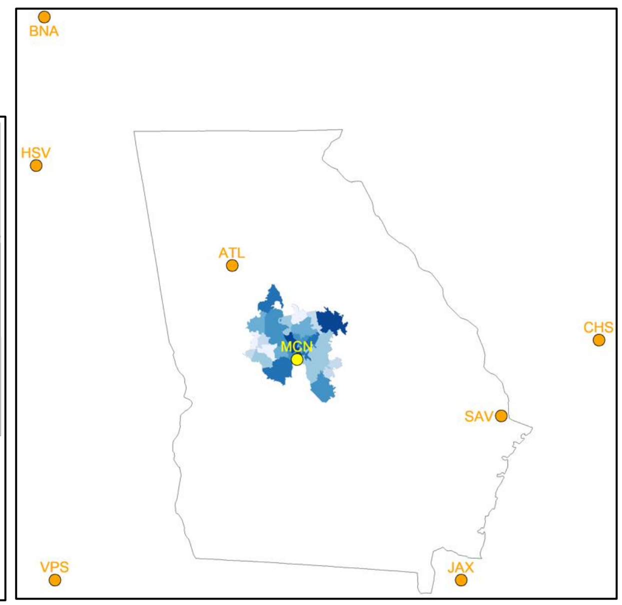
California



Colorado



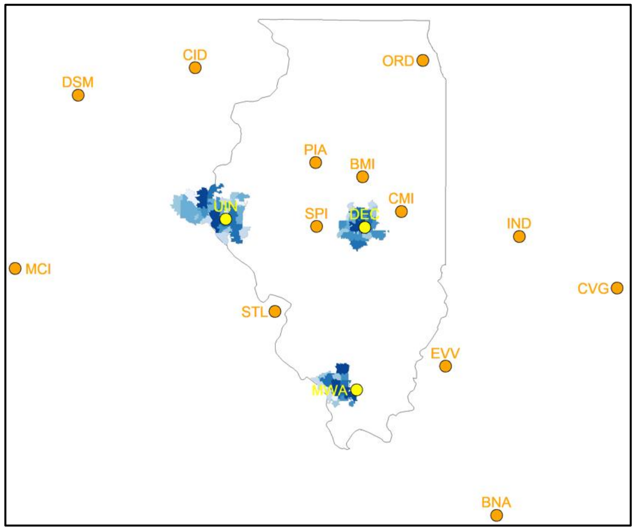
Georgia



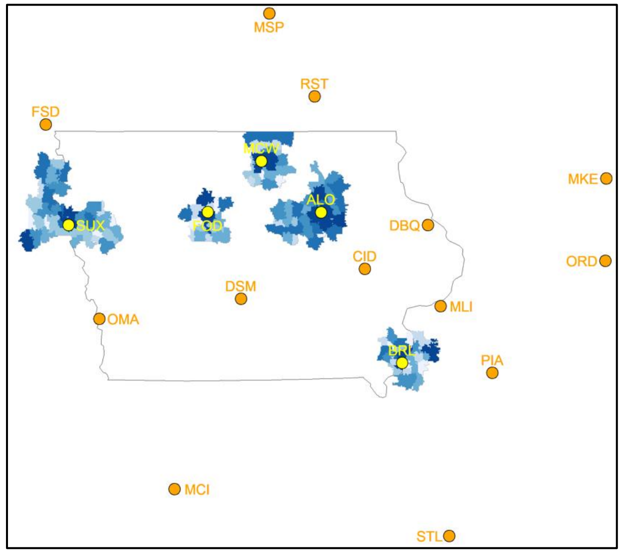
Illinois

Iowa

Kansas

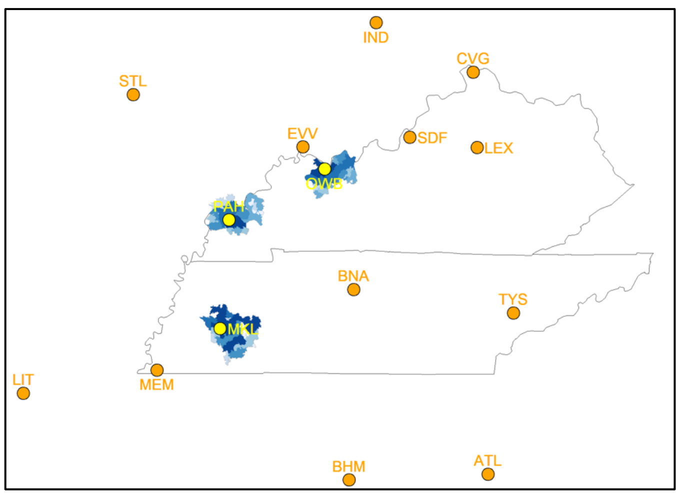


Kentucky / Tennessee

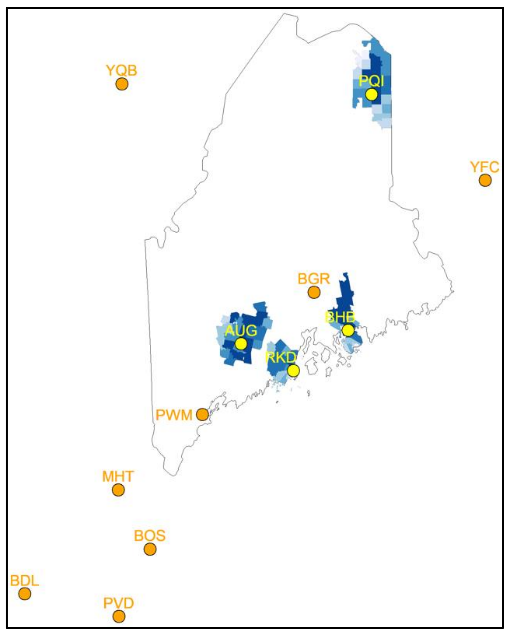


Maine

Michigan / Wisconsin



Minnesota



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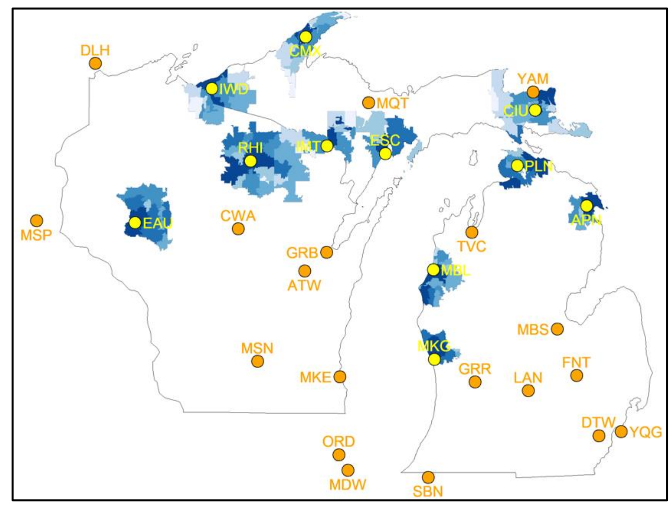
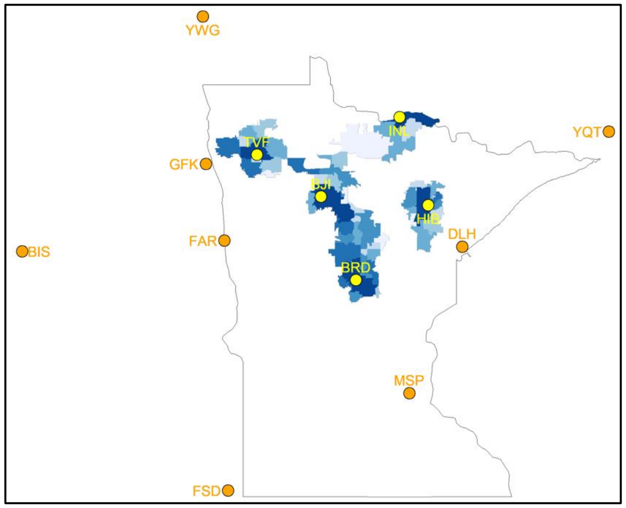


Montana / Wyoming



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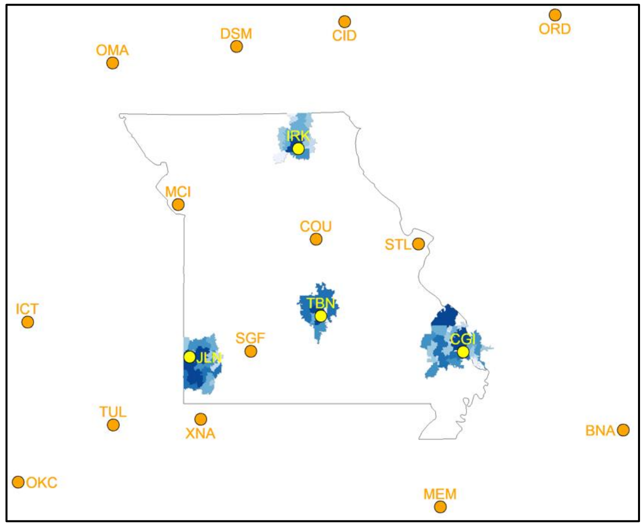
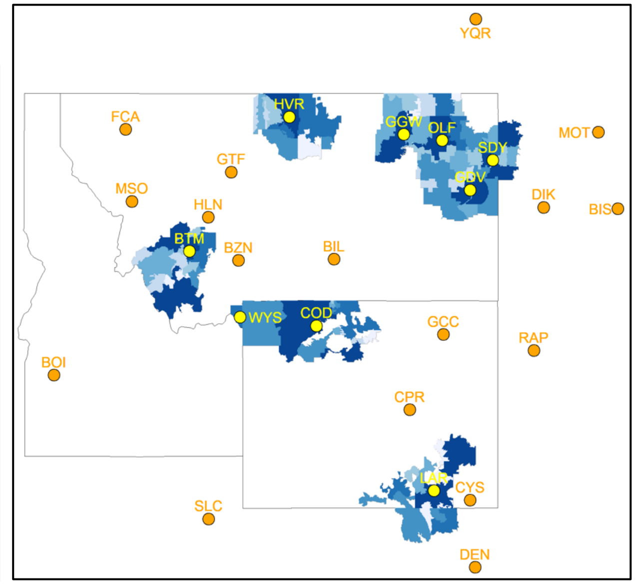
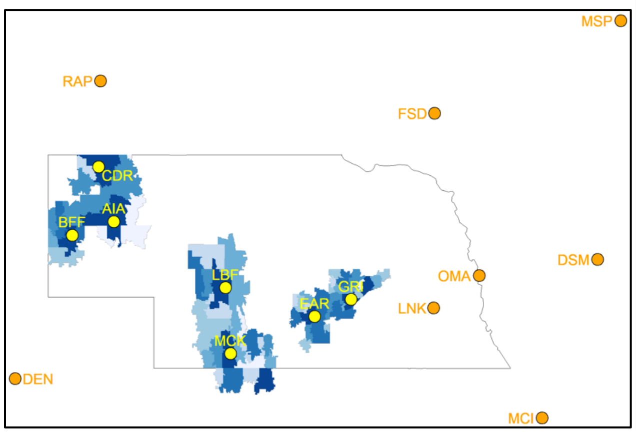
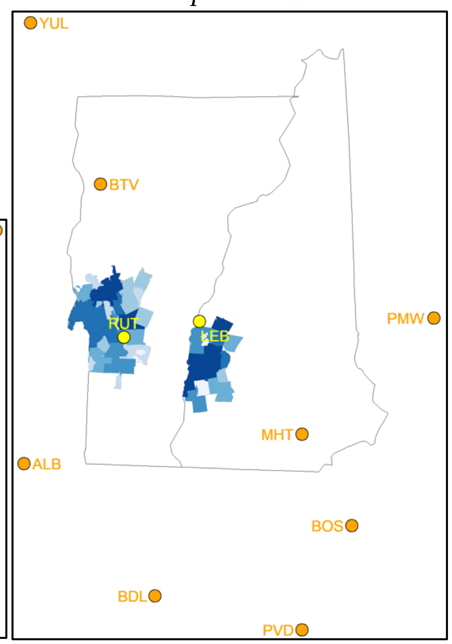


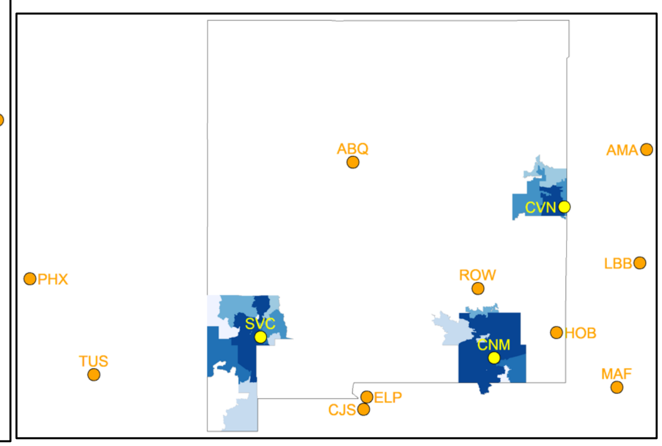
New Hampshire / Vermont



New Mexico



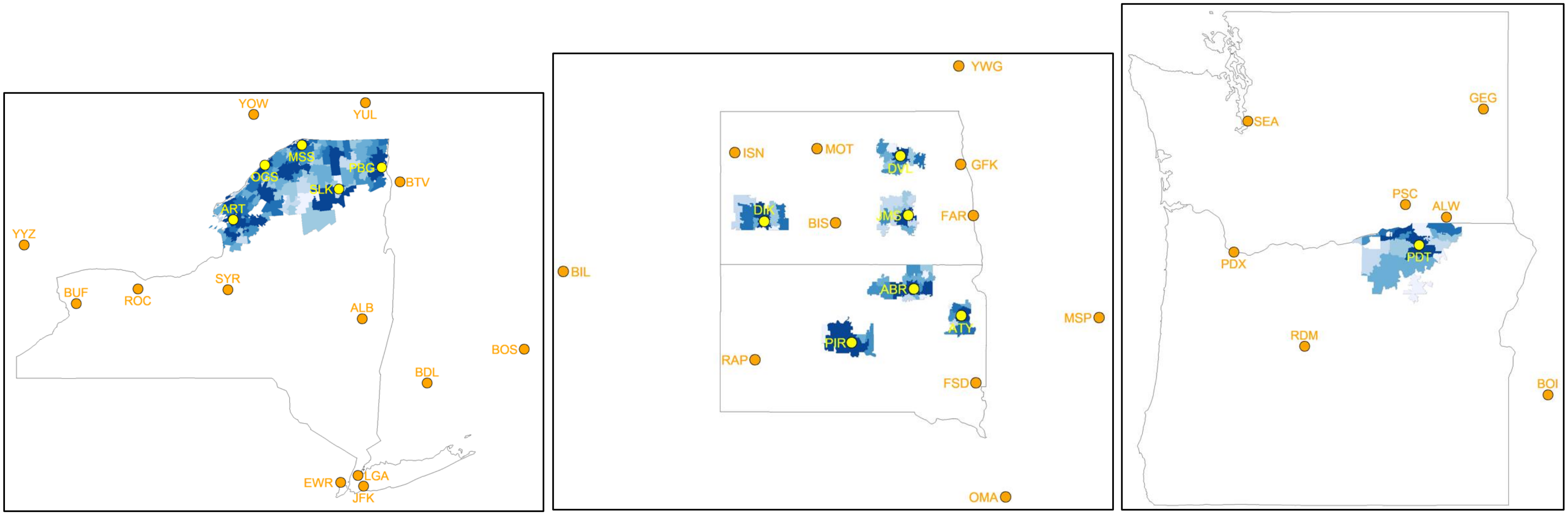




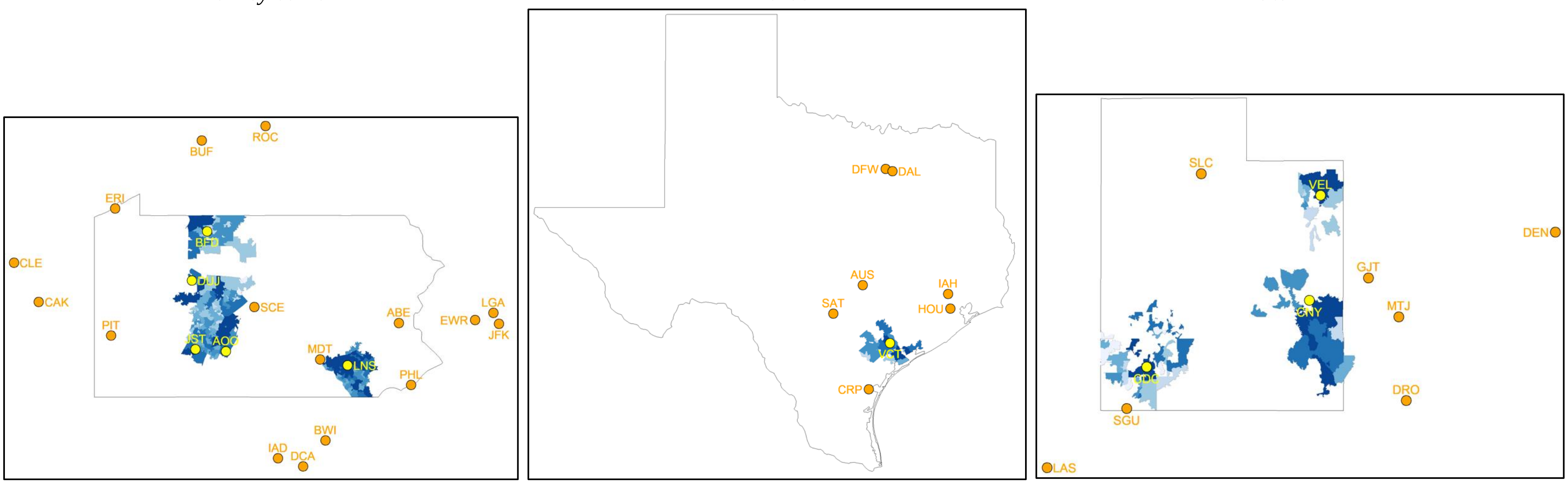
New York

North Dakota / South Dakota

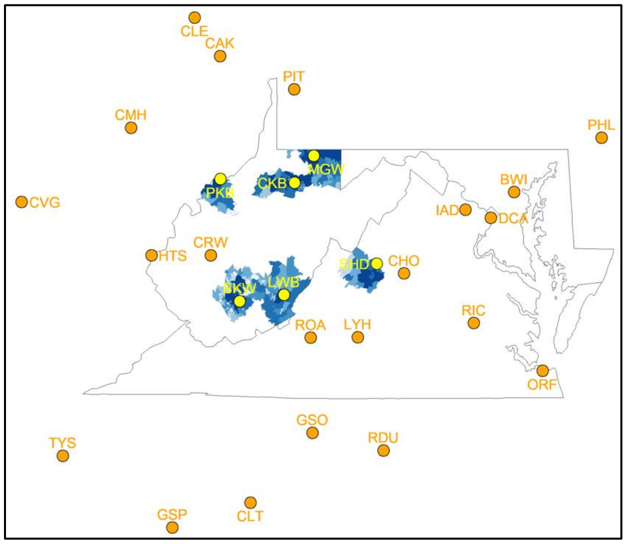
Oregon



Pennsylvania *Texas* *Utah*



Virginia / West Virginia



Sources: Airlines Reporting Corporation; zip-codes.com.

Notes: Each panel shows a cluster of EAS communities, which are made up of ZIP codes, where darker shading corresponds to higher population density. The yellow dots are airports receiving EAS-subsidized service. The orange dots are a sampling of airports used by residents of the EAS communities shown in each panel.

Appendix C. Legal Statutes Governing EAS Eligibility

See Tang (2018) for a primer on the EAS program, its legal history, and eligibility rules. EAS typically subsidizes one airline to provide two to four round trips per day, six days per week, from an EAS community to a larger hub, as codified by 49 *U.S.C.* § 41732. Since the passage of the FAA Modernization and Reform Act in 2012, except for Alaska and Hawaii, communities are only eligible for EAS if they received subsidies in fiscal year 2011, and no new communities can enter the program even if they were formerly eligible.

The Related Agencies Appropriations Act of 2000 prohibits subsidies to carriers for service provided to communities located fewer than 70 miles from the nearest medium or large hub airport. A large hub receives more than 1 percent of annual commercial enplanements (approximately 10 million or more passenger boardings per year), a medium hub receives between 0.25 and 1 percent of total enplanements (approximately 3 million or more passenger boardings per year), a small hub receives between 0.05 and 0.25 percent of total commercial enplanements (approximately 500,000 or more passenger boardings per year), and a non-hub primary airport receives between 10,000 passengers and 0.05 percent of total commercial enplanements. The Consolidated Appropriations Act of 2014, Continued Appropriations Resolution of 2015, and Consolidated Appropriations Act of 2018 require EAS airports located less than 40 miles from a small hub to have a cost-sharing agreement with the DOT. Hub classification can change each year based on changing passenger volumes; see DOT (2021). Although EAS eligibility is based on a community's distance to the *nearest medium or large hub*, airlines that receive EAS contracts are not required to fly passengers to the *nearest* hub nor to a *medium or large hub*.

According to the DOT (2014), its longstanding practice is to measure distance to a hub as the shortest driving distance from the "center of the EAS community" to the "entrance of the nearest large or medium hub airport" as determined by the Federal Highway Administration. More precisely, according to Grubesic and Matisziw (2011), based on phone conversations with the DOT, distance to a hub is typically measured from the location of a community's city hall to the property boundary of an airport using the shortest network path. The Vision 100—Century of Aviation Reauthorization Act of 2003 directs the DOT to consult with state governors to determine the "most commonly used route" between the community and the nearest large or medium hub to establish eligibility.

The Related Agencies Appropriations Act of 2000 prohibits EAS for communities that require a per-passenger subsidy rate in excess of $200, unless the community is located more than 210 miles from the nearest large or medium hub; and the Airport and Airway Extension Act of 2011 prohibits EAS for communities that require per-passenger subsidy rates in excess of $1,000, regardless of distance from the nearest hub. Subsidy cutoffs are calculated by dividing the annual subsidy by the annual passengers generated (outbound plus inbound), and compliance is evaluated at the end of each fiscal year; see DOT (2019). The FAA Modernization and Reform Act of 2012 requires carriers serving EAS communities to maintain an average of 10 or more enplanements per day, but also gives the DOT discretion to grant temporary waivers to communities that do not meet the per-passenger subsidy or daily enplanements rules; see DOT (2014).

Airlines compete for EAS contracts through a bidding process, and the DOT typically receives 1–3 proposals per airport every 1–3 years, when EAS contracts typically expire. By law, the DOT must take into account the views of the community when deciding which proposal to accept, as well as the carrier's service reliability and any arrangements it has with larger carriers at the hub. Notably, subsidy cost is *not* among the factors the DOT is required by law to consider when evaluating bids, and if more than one carrier proposes to offer service then local officials are under no obligation to favor the proposal that entails the lowest cost to the federal government. 49 *U.S.C.* 41733(c)(1) states that the DOT *shall* consider the following five factors when making a carrier selection: (1) demonstrated reliability of the carrier in providing scheduled air service, (2) contractual and marketing arrangements the carrier has with a larger carrier at the hub, (3) interline agreements that the carrier has with a larger carrier at the hub, (4) preferences of the community, and (5) how the carrier proposes to market the service to members of the community. 49 *U.S.C.* 41733(c)(1)(D) instructs the DOT to give "substantial weight" to the views of the community. The Consolidated and Further Continuing Appropriations Act of 2015 (Pub. L. 113-235, 128 Stat. 2699) and subsequent Consolidated Appropriations Acts (Pub. L. 114-113, 129 Stat. 2837; Pub. L. 116-260, 134 Stat. 1827) state that the DOT *may* consider the relative subsidy requirements of the carriers when making a carrier selection, and the DOT has on occasion exercised this prerogative.

Appendix D. Value of Travel Time Savings Using Official DOT (2016) Methodology

Business Travelers

The calculation of the value of travel time savings (VTTS) for business travelers using the DOT's (2016) methodology with data from 2019 is as follows: The DOT (2016, p. 8) notes that "there is wide agreement that the VTTS for business travel should equal the gross hourly cost of employment, including payroll taxes and fringe benefits." According to the US Bureau of Labor Statistics' quarterly reports on employer costs for employee compensation (www.bls.gov/ect), average employee compensation was roughly $35 per hour in 2019. To adjust for the higher incomes of business air travelers compared to the median household, this value is multiplied by 2.5, which is the ratio of median household income for business air travelers from the National Household Travel Survey to the median household income from the US Census Bureau. So the VTTS for business air travelers is $87.50 (= $35 × 2.5) per hour.

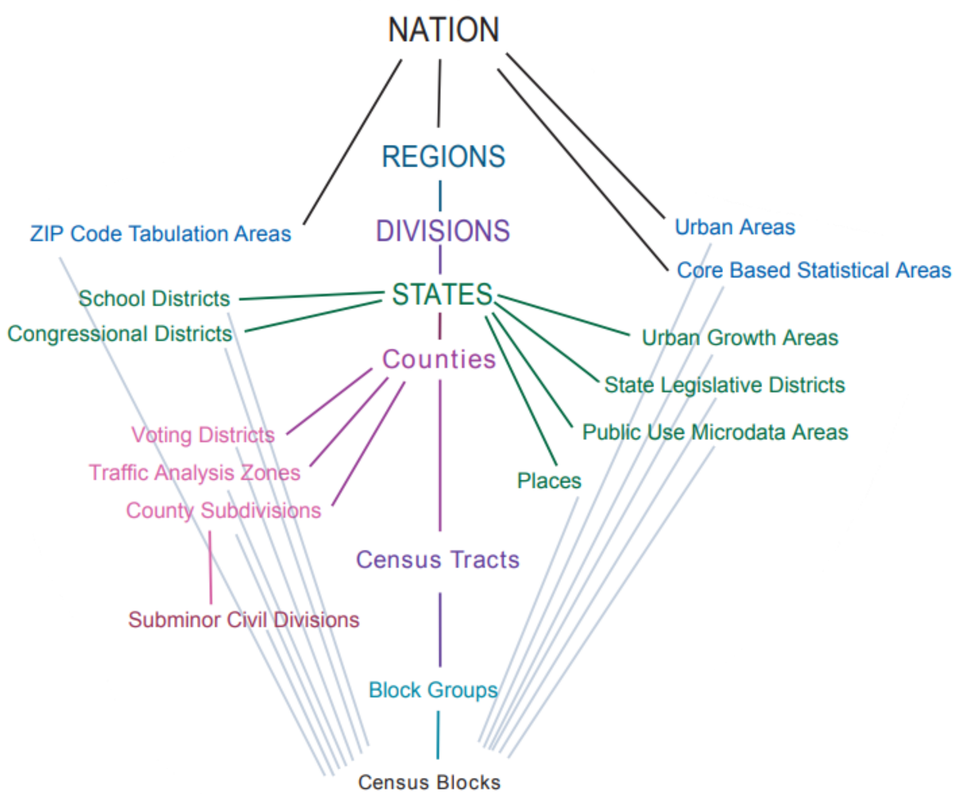
Leisure Travelers

The calculation of VTTS for leisure travelers using the DOT's (2016) methodology with data from 2019 is as follows: The DOT (2016, p. 5) notes that "leisure time is seen … as an object of consumption that can be substituted for other desirable objects according to individual preferences," hence "VTTS is estimated to be lower for personal than for business travel" (Mackie, Jara-Díaz, and Fowkes, 2001). Noting "the absence of a theoretically compelling hypothesis" (DOT, 2016, p. 8), for local personal travel, "VTTS is estimated at 50 percent of hourly median household income" (p. 11), following Small (1992); however, since "research has found evidence of a moderate rise in VTTS with trip distance" (p. 7), the DOT (2016) applies "a ratio of VTTS to hourly income of 70 percent" (p. 11), or a 20 percent premium. According to the US Census Bureau, median household income in 2019 was $68,700. Dividing by 2,080 (= 40 × 52) annual working hours yields income of $33 per hour. To adjust for the higher incomes of air travelers compared to the median household, this value is multiplied by 1.9, which is the ratio of median household income for leisure air travelers from the National Household Travel Survey to the median household income from the US Census Bureau. So the VTTS for leisure travelers is $44 (= $33 × 1.9 × [0.5 + 0.2]) per hour. Assuming VTTS is 100 percent of hourly median earnings, following Goldszmidt et al. (2020), the VTTS for leisure travelers is $75 (= $33 × 1.9 × [1 + 0.2]).

Appendix E. Construction of Income Distributions at the ZIP Code Level

Income distributions at the ZIP code level were constructed by building up from smaller geographic entities, specifically, Census block groups, following a procedure similar to Langer and Lemoine (2022). Appendix Figure E1 shows the US Census Bureau's standard hierarchy of Census geographic entities. The smallest geographic entity at which the Census Bureau publicly releases income information is the block group level. I am interested in constructing income distributions at the ZIP code level—or ZIP Code Tabulation Area (ZCTA), the Census Bureau's equivalent to the US Postal Service concept—which do not perfectly nest with block groups. In other words, ZCTAs can overlap multiple block groups and vice versa.

Appendix Figure E1. Standard Hierarchy of Census Geographic Entities



Source: US Census Bureau.
Note: Lines connect entities that perfectly nest.

The American Community Survey (ACS) contains information about the number of households living in each Census block group with income in each of 16 income buckets ranging from \$0 to \$200,000 and above. The 16 income buckets are: \$0–\$10,000; \$10,000–\$15,000; \$15,000–\$20,000; \$20,000–\$25,000; \$25,000–\$30,000; \$30,000–\$35,000; \$35,000–\$40,000; \$40,000–\$45,000; \$45,000–\$50,000; \$50,000–

\$60,000; \$60,000–\$75,000; \$75,000–\$100,000; \$100,000–\$125,000; \$125,000–\$150,000; \$150,000–\$200,000; \$200,000 and above.

A block group to ZCTA crosswalk was obtained from the Missouri Census Data Center. The crosswalk, which provides the share of the population of each block group that lives in each ZCTA, was used to allocate the number of households in each block group into each ZCTA. (This allocation implicitly assumes a uniform distribution of households by income within block groups.) Once block group populations are allocated to ZCTAs, the total number of households in each ZCTA and income bucket are computed. These ZCTA and income bucket pairs are known as "cells" and are denoted by the i subscript in the model exposition. Finally, the number of households in each ZCTA and income bucket are converted to population shares by dividing by the total population of the origin region (see Appendix Table H1). These shares are referred to as "population weights" w_i in Appendix F. For each region (see Appendix A), the total number of cells is equal to 16 times the number of ZCTAs in the region. Purchase probabilities for each product j are computed for each cell i, and market shares for product j are computed by aggregating over cells i in a region using population weights w_i (see Appendix F).

Appendix F. Estimation and Computational Details

Market Shares

Utility for individual i from purchasing product j from market t is

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + \nu_{ijt}$$

where

$$\delta_{jt} = \bar{\alpha} p_{jt} + \mathbf{x}_{jt}' \bar{\boldsymbol{\beta}} + \xi_{jt}$$

$$\mu_{ijt} = \tau d_{ijt} + \alpha^{\text{inc}}(\text{inc}_i \times p_{jt}) + \beta_{\text{direct}}^{\text{inc}}(\text{inc}_i \times x_{jt,\text{direct}})$$

$$\nu_{ijt} = \eta_{it} + \lambda \varepsilon_{ijt}$$

The composite error term $\nu_{ijt} = \eta_{it} + \lambda \varepsilon_{ijt}$ follows the necessary distribution to generate the nested logit model (Cardell, 1997). As shown by Berry (1994) and others, the probability that individual i purchases product j from market t can be written

$$s_{ijt} = \frac{\exp[(\delta_{jt} + \mu_{ijt})/\lambda]}{D_{it}} \cdot \frac{D_{it}^{\lambda}}{1 + D_{it}^{\lambda}}$$

where

$$D_{it} = \sum_{j'} \exp[(\delta_{j't} + \mu_{ij't})/\lambda]$$

is the inclusive value of the airline product nest, with the summation taken over all airline products j' in market t.

Market shares for product j are found by aggregating purchase probabilities over all the individuals in a market:

$$s_{jt} = \sum_{i} s_{ijt} \cdot w_i$$

where w_i is the population weight of each individual. For each origin region, w_i is equal to the number of households in an income bucket living in a ZIP code as a share of the total origin region population (see Appendix E), so the weights w_i sum to 1 for each region.

Contraction Mapping

Equate the model-predicted market shares s_{jt} to the observed market shares S_{jt}, $\mathbf{S} = \mathbf{s}(\boldsymbol{\delta}, \boldsymbol{\theta}_2)$, where $\mathbf{S} \equiv (S_{1,1} \cdots S_{J,T})$, $\boldsymbol{\delta} \equiv (\delta_{1,1} \cdots \delta_{J,T})$, and $\boldsymbol{\theta}_2 \equiv (\lambda, \tau, \alpha^{\text{inc}}, \beta_{\text{direct}}^{\text{inc}})$. As shown by Berry, Gandhi, and

Haile (2013), if $S_{jt} > 0$ for all $j = 0, 1, \ldots, J_t$ and for all $t = 1, \ldots, T$ then there is at most one $\boldsymbol{\delta}$ that satisfies the above equation, which is found by inverting the equation such that $\boldsymbol{\delta} = \mathbf{s}^{-1}(\mathbf{S}, \boldsymbol{\theta}_2)$. To compute $\boldsymbol{\delta}$ for a given value of the parameters $\boldsymbol{\theta}_2$, Grigolon and Verboven (2014) show that the modified mapping of Berry, Levinsohn, and Pakes (1995),

$$f : \boldsymbol{\delta} \hookleftarrow \boldsymbol{\delta} + \lambda[\ln \mathbf{S} - \ln \mathbf{s}(\boldsymbol{\delta}, \boldsymbol{\theta}_2)]$$

is a contraction for the nested logit model, so by the contraction mapping theorem there exists a unique fixed point $\boldsymbol{\delta}^*$ such that $f(\boldsymbol{\delta}^*) = \boldsymbol{\delta}^*$. As shown by Berry and Haile (2014), normalizing $E[\xi_{j_t}] = 0$ implies ξ_{jt} is identified for all products and for all markets.

A consistent estimator of ξ_{jt} is obtained by estimating the mean utility equation $\delta_{jt} = \bar{\alpha} p_{jt} + \mathbf{x}'_{jt}\overline{\boldsymbol{\beta}} + \xi_{jt}$ via two-stage least squares, where δ_{jt} is an element of the fixed point described above. The residual $\hat{\xi}_{jt} = \delta_{jt} - \hat{\bar{\alpha}} p_{jt} - x'_{jt}\hat{\overline{\boldsymbol{\beta}}}$ is a consistent estimator of ξ_{jt}, where $\widehat{\boldsymbol{\theta}}_1 \equiv \left(\hat{\bar{\alpha}}, \hat{\overline{\boldsymbol{\beta}}}\right)$ is the two-stage least squares estimator.

Macromoments

Let $\mathbf{z}_{jt}$ be the set of K exogenous instruments. The moment conditions are $E\left[\mathbf{z}'_{jt}\xi_{jt}\right] = \mathbf{0}$. Since $\hat{\xi}_{jt} \xrightarrow{p} \xi_{jt}$ then by the law of large numbers

$$\frac{1}{J}\sum_j \mathbf{z}'_{jt}\hat{\xi}_{jt} \xrightarrow{p} E\left[\mathbf{z}'_{jt}\xi_{jt}\right]$$

where the summation is taken over all products and markets. Define $\mathbf{g}_{1jt}(\boldsymbol{\theta}_2) \equiv \mathbf{z}'_{jt}\hat{\xi}_{jt}$ and the moment

$$\mathbf{m}_1(\boldsymbol{\theta}) \equiv \frac{1}{J}\sum_j \mathbf{g}_{1jt}(\boldsymbol{\theta}_2)$$

where the summation is taken over all products and all markets. Note that the dimension of $\mathbf{m}_1(\boldsymbol{\theta}_2)$ is $K \times 1$. The moment condition is satisfied because $\mathbf{m}_1(\boldsymbol{\theta}_2) \xrightarrow{p} \mathbf{0}$.

Micromoments

Let $y_{ijt} = 1$ if individual i purchased product j in market t and $y_{ijt} = 0$ otherwise. Let $\bar{s}_{ijt}$ denote the probability that individual i purchases product j in market t conditional on purchasing an airline product:

$$\bar{s}_{ijt} = \frac{s_{ijt}}{\sum_{j'} s_{ij't}}$$

where j' refers to all products in market t, including product j, but excluding the outside option. The moment conditions are $E\left[\left(y_{ijt} - \bar{s}_{ijt}\right)d_{ijt}\right] = 0$, where the expectation is taken over individuals and products within a market. Define $\mathbf{g}_{2ijt}(\boldsymbol{\theta}_2) \equiv \left(y_{ijt} - \bar{s}_{ijt}\right)d_{ijt}$ and the moment

$$\mathbf{m}_2(\boldsymbol{\theta}_2) \equiv \frac{1}{I}\sum_i \frac{1}{J}\sum_j \mathbf{g}_{2ijt}(\boldsymbol{\theta}_2)$$

where the summation is taken over all individuals, products, and markets. Note that the dimension of $\mathbf{m}_2(\boldsymbol{\theta}_2)$ is 1×1. The moment condition is satisfied because $\mathbf{m}_2(\boldsymbol{\theta}_2) \xrightarrow{p} \mathbf{0}$.

Efficient GMM Estimation and Standard Errors

To estimate the parameters $\boldsymbol{\theta}_2 = \left(\lambda, \tau, \alpha^{\text{inc}}, \beta^{\text{inc}}_{\text{direct}}\right)$, stack the moments $\mathbf{m}_1(\boldsymbol{\theta}_2)$ and $\mathbf{m}_2(\boldsymbol{\theta}_2)$ to form

$$\mathbf{m}(\boldsymbol{\theta}_2) = \begin{bmatrix} \mathbf{m}_1(\boldsymbol{\theta}_2) \\ \mathbf{m}_2(\boldsymbol{\theta}_2) \end{bmatrix}$$

Note that the dimension of $\mathbf{m}(\boldsymbol{\theta}_2)$ is $(K+1) \times 1$ and that $\mathbf{m}(\boldsymbol{\theta}_2) \xrightarrow{p} \mathbf{0}$, satisfying the moment condition. Form the objective function as

$$G(\boldsymbol{\theta}_2) = \mathbf{m}(\boldsymbol{\theta}_2)'\,\mathbf{W}\,\mathbf{m}(\boldsymbol{\theta}_2)$$

where $\mathbf{W}$ is a $(K+1) \times (K+1)$ matrix that assigns weights to the moments. The estimator $\widehat{\boldsymbol{\theta}}_2$ searches for parameter values that minimize the objective function up to some convergence tolerance:

$$\widehat{\boldsymbol{\theta}}_2 = \underset{\boldsymbol{\theta}_2}{\operatorname{argmin}}\, \mathbf{m}(\boldsymbol{\theta}_2)'\,\mathbf{W}\,\mathbf{m}(\boldsymbol{\theta}_2)$$

An efficient estimator of the parameters is found by using the optimal weight matrix $\mathbf{W} = \boldsymbol{\Omega}^{-1}$, where $\boldsymbol{\Omega} = \text{Var}\left[\mathbf{g}_{ijt}(\boldsymbol{\theta}_2)\right] = E\left[\mathbf{g}_{ijt}(\boldsymbol{\theta}_2)\mathbf{g}_{ijt}(\boldsymbol{\theta}_2)'\right]$ and

$$\mathbf{g}_{ijt}(\boldsymbol{\theta}_2) = \begin{bmatrix} \mathbf{g}_{1jt}(\boldsymbol{\theta}_2) \\ \mathbf{g}_{2ijt}(\boldsymbol{\theta}_2) \end{bmatrix}$$

The weight matrix $\mathbf{W} = \boldsymbol{\Omega}^{-1}$ is optimal because it assigns more weight to more precisely estimated moments. Since $\boldsymbol{\theta}_2$ is unknown, it is infeasible to compute $\boldsymbol{\Omega}$, so I employ the two-step procedure described by Hansen (1982) to construct a consistent estimator of $\boldsymbol{\Omega}^{-1}$ to use as the weight matrix. As noted by Petrin (2002), since the two sources of variance in $\mathbf{g}_{ijt}$ come from independent sampling processes, the optimal weight matrix is block-diagonal, with an upper block of dimension $K \times K$ corresponding to $\mathbf{g}_{1jt}$ and a lower block of dimension 1×1 corresponding to $\mathbf{g}_{2ijt}$. In the first step, a consistent estimator $\widetilde{\boldsymbol{\theta}}_2$ is found by setting the upper block equal to $(\mathbf{z}'\mathbf{z})^{-1}$, where $\mathbf{z} \equiv \left(\mathbf{z}'_{1,1}, \dots, \mathbf{z}'_{J,T}\right)$, and the lower block equal to the identity matrix. In the second step, I obtain an efficient estimator $\widehat{\boldsymbol{\theta}}_2$ using the following weight matrix in the second step:

$$\widehat{\mathbf{W}} = \begin{bmatrix} \widehat{\boldsymbol{\Omega}}_1 & 0 \\ 0 & \widehat{\boldsymbol{\Omega}}_2 \end{bmatrix}^{-1}$$

where $\widehat{\boldsymbol{\Omega}}_1 = \widehat{\text{Var}}\left[\mathbf{g}_{1jt}\left(\widetilde{\boldsymbol{\theta}}_2\right)\right]$ and $\widehat{\boldsymbol{\Omega}}_2 = \widehat{\text{Var}}\left[\mathbf{g}_{2ijt}\left(\widetilde{\boldsymbol{\theta}}_2\right)\right]$. I estimate the upper block as

$$\widehat{\boldsymbol{\Omega}}_1 = \hat{E}\left\{\left[\hat{\mathbf{g}}_{1jt}(\boldsymbol{\theta}_2)\right]^2\right\} = \frac{1}{J}\sum_j \left[\mathbf{z}_{jt}'\hat{\xi}_{jt}\left(\widetilde{\boldsymbol{\theta}}_2\right)\right]\left[\mathbf{z}_{jt}'\hat{\xi}_{jt}\left(\widetilde{\boldsymbol{\theta}}_2\right)\right]' = \mathbf{z}'\boldsymbol{\Omega}_{\hat{\boldsymbol{\xi}}}\,\mathbf{z}$$

where the summation is taken over all products and markets and $\boldsymbol{\Omega}_{\hat{\boldsymbol{\xi}}}$ is a $J \times J$ diagonal matrix with squared residuals $\hat{\xi}_{jt}^2$ on the diagonal. I estimate the lower block as:

$$\widehat{\boldsymbol{\Omega}}_2 = \hat{E}\left\{\left[\hat{\mathbf{g}}_{2ijt}(\boldsymbol{\theta}_2)\right]^2\right\} = \frac{1}{I}\sum_i \frac{1}{J}\sum_j \left\{\left[y_{ijt} - \bar{s}_{ijt}\left(\widetilde{\boldsymbol{\theta}}_2\right)\right]d_{ijt}\right\}^2$$

where the summation is taken over all individuals, products, and markets. Note that $\widehat{\mathbf{W}} \xrightarrow{p} \boldsymbol{\Omega}^{-1}$ so $\widehat{\mathbf{W}}$ is a consistent estimator of the optimal weight matrix.

Standard errors are computed numerically using the expressions for asymptotic variance from Hansen (1982), Berry, Levinsohn, and Pakes (1995), and Petrin (2002):

$$\text{SE}\left(\widehat{\boldsymbol{\theta}}_2\right) = \sqrt{\text{diag}\left(\widehat{\mathbf{V}}\right)}$$

where $\widehat{\mathbf{V}} = \left(\widehat{\boldsymbol{\Gamma}}'\widehat{\mathbf{W}}\widehat{\boldsymbol{\Gamma}}\right)^{-1}$ and

$$\widehat{\boldsymbol{\Gamma}} = \frac{\partial \mathbf{m}\left(\widehat{\boldsymbol{\theta}}_2\right)}{\partial \widehat{\boldsymbol{\theta}}_2}$$

Computational Details

The estimation procedure was coded in R following the recommendations of Conlon and Gortmaker (2020) and performed using the University of Arizona's High Performance Computing resources. I minimized the objective function using the gradient-based L-BFGS-B method and checked for consistency of results using different starting values and the simplex-based Nelder–Mead method. Following the recommendations of Raynaerts, Varadhan, and Nash (2012), I used Varadhan and Roland's (2008) squared polynomial extrapolation method for fixed point acceleration (SQUAREM) to accelerate the fixed point computation. Following the recommendations of Dubé, Fox, and Su (2012) and Conlon and Gortmaker (2020), the inner loop convergence tolerance was set to 10^{-13} so that the algorithm terminated when the norm between predicted and actual shares was as close to machine epsilon as possible without entering an infinite loop.

Appendix G. Data Construction for Counterfactuals

Market Shares

I use the Market Locator data to determine EAS community members' choice sets and products' market shares. Generally, when EAS community members are observed flying from an airport that is not their local airport, I assume that they drove there. However, a key feature of the Market Locator data requires special attention to ensure accurate construction of market shares. Specifically, the Market Locator data contain one record per *transaction*, which means that if a passenger books a round-trip ticket they would be counted once but if they book two one-way tickets they would be counted twice. (The Market Locator data pool one-way and round-trip flights.) This feature of the data is especially important for passengers whose local airport is served by a non-legacy carrier that does not have a codeshare agreement with a legacy carrier at the hub, since any passenger continuing through the hub would be counted twice, once at the EAS origin and once at the hub. (The legacy carriers are American Airlines, Delta Air Lines, and United Airlines, and a non-legacy carrier is any other airline with an EAS contract; see Appendix Table H4.)

To help ensure against double counting, I make the following assumption about passenger behavior: Passengers whose local EAS airport is served by a legacy carrier and who continue through the hub stay on the same carrier for the whole journey. This assumption is reasonable because, by design, legacy carriers fly to their own hubs to facilitate convenient connections on that same carrier to a final destination. Furthermore, flying on the same airline for the whole journey is convenient for passengers because they only need to purchase one ticket on one airline, rather than two tickets on two airlines. Convenient connections through the hub are an important consideration when selecting carriers to serve a community, as 49 *U.S.C.* 41733(c)(1)(B) instructs the DOT to consider contractual agreements that the applicant carrier has with a larger carrier at the hub in order to "ensure service beyond the hub." By assuming passengers flying on legacy carriers stay on the same carrier for the whole journey and do not book two one-way tickets, I can infer what share of passengers end their journey at the hub and what share of passengers continue through the hub. I find that, on average, ⅓ of passengers end their journey at the hub and ⅔ of passengers continue through the hub.

I then assume that passengers' pass-through behavior on legacy carriers is the same as passengers' pass-through behavior on non-legacy carriers. For example, suppose X passengers are observed flying on a non-legacy carrier to a hub airport and Y passengers are observed flying on any carrier from a hub airport to a final destination. Even though Y passengers living in an EAS region are observed at the hub airport, it would be wrong to assume all Y of them drove to the hub, since some share of the X passenger flying from the EAS airport continued on through the hub but purchased two one-way tickets. If Y passengers living in an EAS region are observed at the hub, I assume $Y - \frac{2}{3}X$ drove to the hub.

If a passenger lives in a region whose airport is served by a legacy carrier is observed at the carrier's hub, I assume all passengers observed at the hub drove there, which follows from the assumption that passengers flying on legacy carriers do not book two one-way tickets on the same carrier. If a passenger living in an EAS region is observed at an airport that is not the designated hub for the carrier, I assume all passengers observed at said airport drove there.

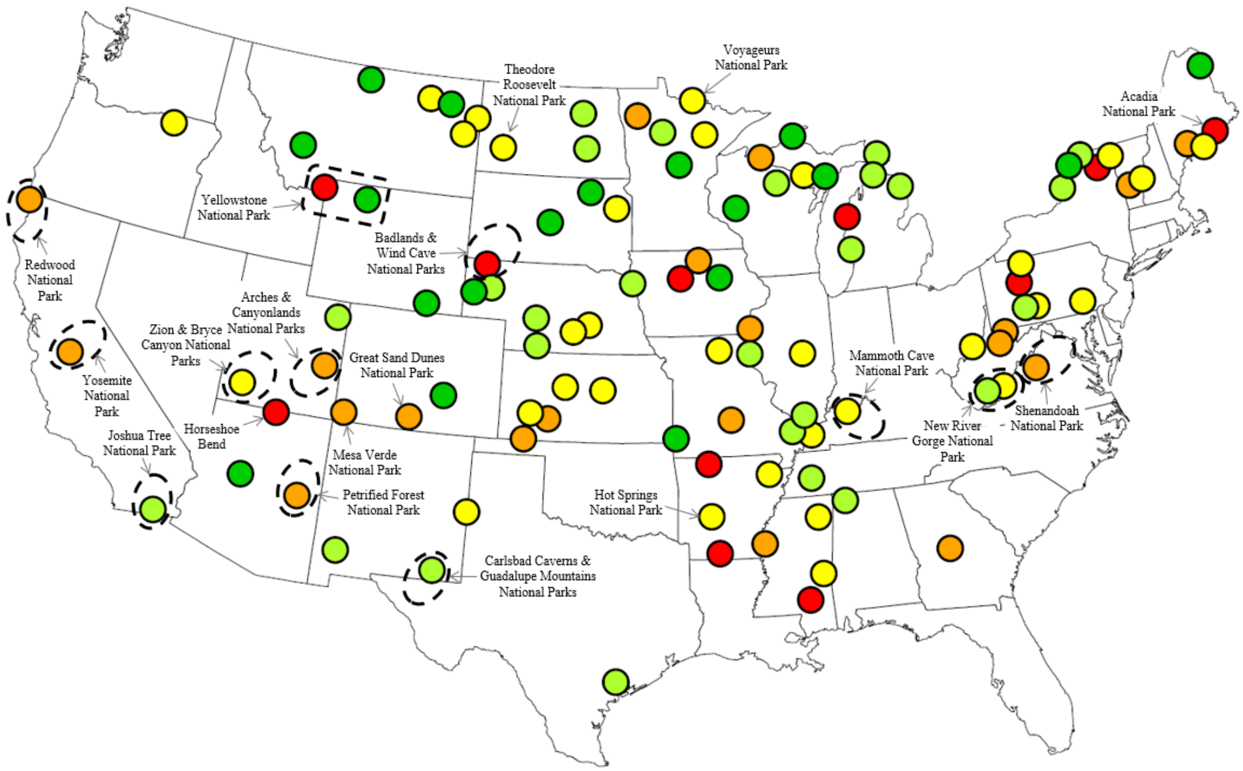
I must also make an assumption about which airports are reasonably close to the EAS community such that a passenger might feasibly drive to said airports instead of taking a flight from their local airport. To that end, I exclude origins that are more than a 5-hour drive from the EAS community. These cases could correspond to EAS community members who are returning home from a trip or are traveling between airports far from home, perhaps on business or vacation—for example, EAS community members island-hopping in Hawaii.

Prices

Given the low coverage in DB1B for EAS-originating flights and the institutional detail that EAS-originating flights tend to exhibit low price variability, I extract the average price for EAS-originating flights from carriers' EAS service proposals submitted to the DOT, sources for which are listed in Appendix Table H4. I use DB1B to construct average prices for the second leg of a journey departing a hub.

Appendix H. Supplemental Figures and Tables

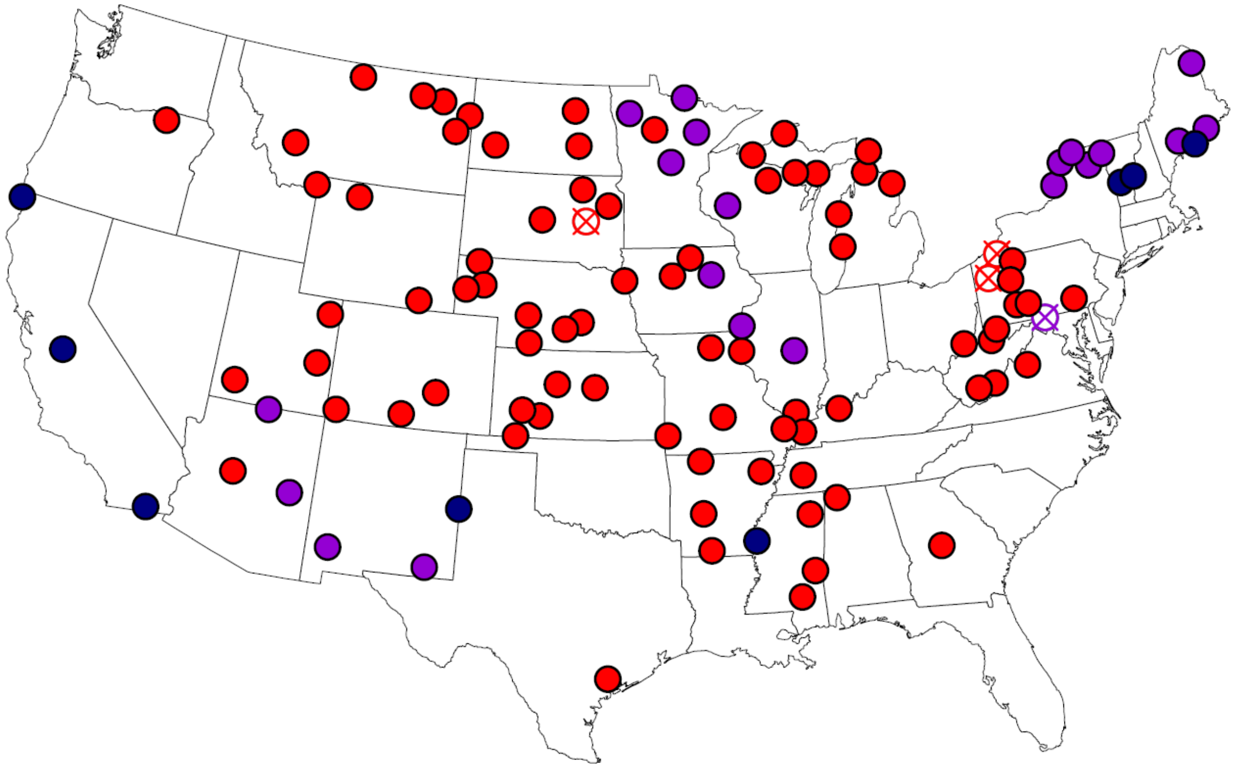
Appendix Figure H1. Share of EAS Airport Users Who Are Nonresidents and Proximity to National Parks



Source: Airlines Reporting Corporation.

Notes: Dark green, light green, yellow, orange, and red dots are EAS airports with nonresident passenger shares of less than 50 percent, 50–60 percent, 60–70 percent, 70–80 percent, and more than 80 percent, respectively. National Parks are encircled with dashed lines.

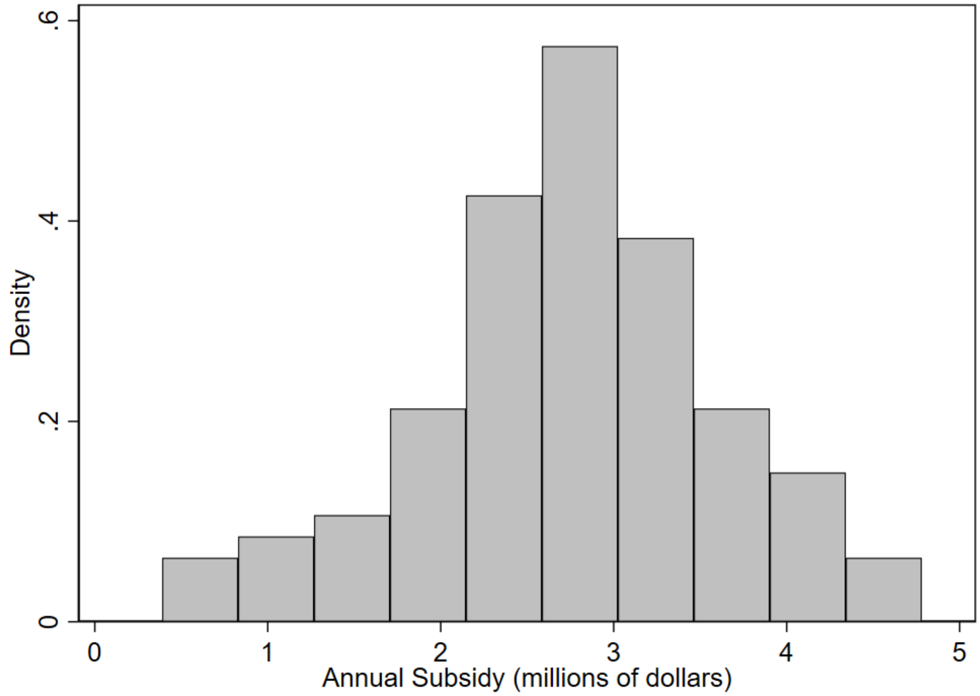
Appendix Figure H2. Political Leanings of EAS Communities



Sources: zip-codes.com; Cook Political Report.

Notes: Political leaning is calculated using the 2019 Cook Political Report's Partisan Voter Index. Red dots correspond to EAS communities with a Republican lean, blue dots correspond to EAS communities with a Democratic lean, and purple dots correspond to EAS communities considered swing districts.

Appendix Figure H3. Distribution of Annual Subsidy Amounts in 2019



Source: Federal Aviation Administration.
Note: American Airlines operated subsidy-free at Joplin and Sioux City in 2019, and these communities are excluded from this figure.

Appendix Table H1. Characteristics of Origin Regions Used in Estimation

Region	Airport codes	Population (thousands)	Income (dollars)	Land area (miles^2)	Drive time (minutes)
Atlanta	ATL	5,280	67,966	8,772	47
Austin	AUS	1,725	76,445	4,355	35
Boston	BOS*, MHT*, PVD*	7,608	83,386	8,812	39
Charlotte	CLT, JQF	2,413	62,053	6,669	31
Chicago	ORD*, MDW*, RFD	10,200	71,376	9,650	38
Cincinnati	CVG*, DAY*	2,935	62,024	5,862	44
Cleveland	CLE*, CAK*	3,429	57,919	5,462	37
Columbus	CMH	1,889	66,466	4,587	27
Dallas	DFW*, DAL*	6,372	71,408	8,808	34
Denver	DEN	4,036	75,992	17,734	50
Detroit	DTW*, FNT*	5,968	61,376	8,106	49
Fort Myers	RSW, PGD	778	54,460	1,442	44
Hartford	BDL	1,904	71,354	3,356	37
Houston	IAH*, HOU*	5,929	69,675	8,243	50
Indianapolis	IND	1,887	63,007	4,276	39
Jacksonville	JAX	1,395	60,928	3,290	41
Kansas City	MCI	2,203	67,085	9,967	48
Las Vegas	LAS	1,851	57,208	581	22
Los Angeles	LAX*, BUR*, LGB*, SNA*, ONT*	13,500	69,274	4,436	34
Miami	MIA*, FLL*, PBI*	5,496	58,162	1,652	29
Milwaukee	MKE	1,768	63,012	1,968	31
Minneapolis	MSP	3,342	79,901	7,294	34
Nashville	BNA	1,651	66,093	5,859	31
New Orleans	MSY	1,270	53,169	2,199	36
New York	LGA*, EWR*, JFK*, HPN*, ISP*, SWF*	20,500	82,651	8,848	39
Orlando	MCO*, SFB, MLB*	4,018	54,652	7,923	49
Philadelphia	PHL, TTN, ACY	7,020	73,662	6,465	44
Phoenix	PHX, AZA	4,023	63,926	4,689	34
Pittsburgh	PIT, LBE	2,537	59,743	6,464	41
Portland	PDX	2,327	71,720	5,482	34
Raleigh/Durham	RDU	1,920	68,084	5,221	26
Sacramento	SMF	2,417	70,656	6,099	42
Salt Lake City	SLC	2,253	74,060	6,074	39
San Antonio	SAT	2,135	60,798	6,857	27
San Diego	SAN	2,894	78,226	1,260	28
San Francisco	SFO*, OAK*, SJC*, STS*	7,425	102,982	7,054	39
Seattle	SEA	4,068	82,714	7,588	43
St. Louis	STL, BLV	2,783	65,365	7,708	32
Tampa	TPA*, PIE, SRQ*	3,556	56,300	3,626	40
Washington	DCA*, IAD*, BWI*	8,354	97,489	8,947	37

Sources: zip-codes.com; Airlines Reporting Corporation; OpenStreetMap.

Notes: Income is the population-weighted average of median household income by ZIP code. Drive time is the passenger-weighted average of drive time to passengers' chosen airport. Airports marked with * were used to construct the micromoments described in Section V.A.

Appendix Table H2. Proximity of EAS Communities to National Parks and Approximate Contributions to Total Park Visitors

Community	Airport code	Nearby national parks (driving time in minutes)	Total visitors in 2019 (millions)	Visitors arriving at EAS airport	EAS airport visitors as a share of total visitors
Cody, WY	COD	Yellowstone (30)	4.02	17,677	0.004
West Yellowstone, MT	WYS	Yellowstone (10)	4.02	8,961	0.002
Cedar City, UT	CDC	Zion (70), Bryce Canyon (90)	7.08	15,505	0.002
Merced, CA	MCE	Yosemite (90)	4.42	4,925	0.001
Bar Harbor, ME	BHB	Acadia (20)	3.40	10,088	0.003
El Centro, CA	IPL	Joshua Tree (105)	2.99	1,907	0.001
Moab, UT	CNY	Arches (20), Canyonlands (30)	2.39	12,271	0.005
Page, AZ	PGA	Horseshoe Bend (15)	2.20	36,765	0.011
Beckley, WV	BKW	New River Gorge (40)	1.70	885	0.001
Greenbrier, WV	LWB	New River Gorge (75)	1.70	8,723	0.005
Chadron, NE	CDR	Badlands (90), Wind Cave (70)	1.59	3,770	0.002
Hot Springs, AR	HOT	Hot Springs (10)	1.47	3,181	0.002
Staunton, VA	SHD	Shenandoah (30)	1.43	13,234	0.009
Dickinson, ND	DIK	Theodore Roosevelt (45)	0.69	15,990	0.023
Show Low, AZ	SOW	Petrified Forest (60)	0.64	3,331	0.005
Carlsbad, NM	CNM	Carlsbad Caverns (15), Guadalupe Mountains (40)	0.63	3,073	0.005
Cortez, CO	CEZ	Mesa Verde (20)	0.56	6,160	0.011
Owensboro, KY	OWB	Mammoth Cave (80)	0.55	12,524	0.023
Alamosa, CO	ALS	Great Sand Dunes (40)	0.53	7,213	0.014
Crescent City, CA	CEC	Redwood (15)	0.51	6,492	0.013
International Falls, MN	INL	Voyageurs (25)	0.23	11,504	0.050

Sources: Airlines Reporting Corporation; Federal Aviation Administration; National Park Service.

Notes: Driving time is from the EAS airport to the nearest national park entrance. For EAS airports located near more than one national park, total visitors is the sum of visitors to both parks. Visitors arriving at EAS airport is calculated by taking the share of EAS airport users who are deemed nonresidents based on their home ZIP code multiplied by total enplanements at the airport in 2019.

Appendix Table H3. Status of EAS Communities Terminated since 1989

Community	Airport code	Date EAS eligibility ended	Reason for losing eligibility	Airport classification	Status of commercial service
Franklin, PA	FKL	10/18/2019	Fewer than 10 daily enplanements	General aviation	No commercial service
Hagerstown, MD	HGR	10/18/2019	Fewer than 10 daily enplanements	Primary commercial	Allegiant Air provides scheduled air service to 3 destinations
Jamestown, NY	JHW	1/16/2018	Fewer than 10 daily enplanements	General aviation	No commercial service
Huron, SD	HON	9/30/2016	Exceeded $1,000 per passenger subsidy	General aviation	No commercial service
Worland, WY	WRL	9/30/2016	Exceeded $1,000 per passenger subsidy	General aviation	No commercial service
Great Bend, KS	GBD	5/20/2016	Exceeded $1,000 per passenger subsidy	General aviation	No commercial service
Kingman, AZ	IGM	5/1/2015	Exceeded $1,000 per passenger subsidy	General aviation	No commercial service
Athens, GA	AHN	9/30/2014	Fewer than 10 daily enplanements	General aviation	Received a $750,000 grant from the Small Community Air Service Development Program to attract commercial service
Lewistown, MT	LWT	7/16/2013	Exceeded $1,000 per passenger subsidy	General aviation	No commercial service
Miles City, MT	MLS	7/16/2013	Exceeded $1,000 per passenger subsidy	General aviation	No commercial service
Ely, NV	ELY	4/1/2013	Exceeded $1,000 per passenger subsidy	General aviation	No commercial service
Alamogordo, NM	ALM	4/1/2012	Exceeded $1,000 per passenger subsidy	General aviation	No commercial service
Brookings, SD	BKX	10/1/2009	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Enid, OK	WDG	9/1/2006	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Ephrata, WA	EPH	9/1/2006	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Ponca City, OK	PNC	9/1/2006	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Bluefield, WV	BLF	8/1/2006	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Brownwood, TX	BWD	3/13/2005	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Norfolk, NE	OFK	5/25/2004	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Topeka, KS	FOE	5/1/2003	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Oshkosh, WI	OSH	3/1/2003	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Gallup, NM	GUP	7/29/2002	Exceeded $200 per passenger subsidy	General aviation	Received a $3.5 million grant from the state of New Mexico’s Rural Air Service Enhancement Grant Program to attract commercial service

Utica, NY	UCA	6/30/2002	Exceeded $200 per passenger subsidy	General aviation	Airport closed in January 2007 and general aviation was transferred to Griffiss International Airport (RME)
Ottumwa, IA	OTM	10/1/2001	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Yankton, SD	YKN	4/30/2001	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Mattoon, IL	MTO	2/13/2001	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Goodland, KS	GLD	4/1/2000	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Lamar, CO	LAA	4/1/2000	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Fairmont, MN	FRM	1/6/2000	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Mt. Vernon, IL	MVN	10/30/1999	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Sterling, IL	SQI	4/12/1999	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Anniston, AL	ANB	6/1/1996	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Worthington, MN	OTG	11/27/1995	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Danville, IL	DNV	11/30/1994	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Elkins, WV	EKN	12/1/1993	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Gadsden, AL	GAD	12/1/1993	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Galesburg, IL	GBG	12/1/1993	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Hot Springs, VA	HSP	12/1/1993	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Laconia, NH	LCI	12/1/1993	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Paris, TX	PRX	12/1/1993	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Blythe, CA	BLH	1/1/1990	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Columbus, NE	OLU	1/1/1990	Exceeded $200 per passenger subsidy	General aviation	No commercial service
McAlester, OK	MLC	1/1/1990	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Sidney, NE	SNY	1/1/1990	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Winslow, AZ	INW	1/1/1990	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Coffeyville, KS	CFV	10/1/1989	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Hutchinson, KS	HUT	10/1/1989	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Janesville, WI	JVL	10/1/1989	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Kokomo, IN	OKK	10/1/1989	Exceeded $200 per passenger subsidy	General aviation	No commercial service
Lewiston, ME	LEW	10/1/1989	Exceeded $200 per passenger subsidy	Reliever	No commercial service
Moultrie, GA	MGR	10/1/1989	Exceeded $200 per passenger subsidy	General aviation	No commercial service

Source: Federal Aviation Administration.

Notes: Airport classification is based on the 2023–27 National Plan of Integrated Airport Systems. Status of commercial service is as of October 2022.

Appendix Table H4. Price Data for Subsidized Carriers in 2019

EAS airport code	Hub airport code(s)	Carrier (code)	Average fare ($)	Docket(s)	Notes
ABR	MSP	Delta Air Lines (DL)	103	DOT-OST-2011-0134-0037	
AIA	DEN	Boutique Air (4B) Key Lime Air (KG)	67	DOT-OST-2000-8322-0099 DOT-OST-2000-8322-0126	Boutique Air service to DEN ended May 31, 2019 and was replaced with Key Lime Air service to DEN.
ALO	ORD	American Airlines (AA)	88	DOT-OST-2011-0132-0043	
ALS	DEN	Boutique Air (4B)	89	DOT-OST-1997-2960-0179	
AOO	BWI/PIT	Southern Airways (9X)	45	DOT-OST-2002-11446-0184 DOT-OST-2002-11446-0171	
APN	DTW	Delta Air Lines (DL)	80	DOT-OST-2009-0300-0133	
ART	PHL	American Airlines (AA)	93	DOT-OST-2013-0188-0021	
ATY	DEN/ORD	United Airlines (UA)	95	DOT-OST-2001-10644-0170 DOT-OST-2001-10644-0173	Service to ORD was added September 1, 2019.
AUG	BOS	Cape Air (9K)	75	DOT-OST-1997-2784-0200	
BFD	PIT	Southern Airways (9X)	49	DOT-OST-1997-2523-0249 DOT-OST-2003-14528-0160	
BFF	DEN	United Airlines (UA)	69	DOT-OST-1999-5173-0108	
BHB	BOS	Cape Air (9K)	79	DOT-OST-2003-14783-0207	
BJI	MSP	Delta Air Lines (DL)	99	DOT-OST-2011-0134-0037	
BKW	CLT	Contour Airlines (LF)	68*	DOT-OST-2004-18715-0030	
BRD	MSP	Delta Air Lines (DL)	75	DOT-OST-2009-0304-0079	
BRL	STL/ORD	Air Choice One (3E)	54	DOT-OST-2006-23929-0075	
BTM	SLC	Delta Air Lines (DL)	105	DOT-OST-2011-0136-0037	
CDC	SLC	Delta Air Lines (DL)	69	DOT-OST-2003-16395-0087	
CDR	DEN	Boutique Air (4B)	70	DOT-OST-2000-8322-0099 DOT-OST-2000-8322-0126	
CEC	OAK	Contour Airlines (LF)	137*	DOT-OST-1997-2649-0087	
CEZ	DEN/PHX	Boutique Air (4B)	99	DOT-OST-1998-3508-0062	
CGI	ORD	United Airlines (UA)	87	DOT-OST-1996-1559-0088	
CIU	DTW/MSP	Delta Air Lines (DL)	103	DOT-OST-2009-0304-0079	
CKB	ORD/IAD	United Airlines (UA)	80	DOT-OST-2005-20736-0149	
CMX	ORD	United Airlines (UA)	108	DOT-OST-2009-0301-0037	
CNM	ABQ/DFW	Boutique Air (4B)	91	DOT-OST-2002-12802-0115 DOT-OST-2002-12802-0142	
CNY	DEN	United Airlines (UA)	82	DOT-OST-1997-2706-0160	

COD	DEN	United Airlines (UA)	101	DOT-OST-2011-0121-0068	United Airlines provides subsidized service during the off-peak season for visiting Yellowstone National Park, from October to May, and provides unsubsidized service during the peak season.
CVN	DFW	Boutique Air (4B)	97	DOT-OST-1996-1902-0113	
DDC	DEN	Boutique Air (4B)	59	DOT-OST-1998-3502-0100	
DEC	ORD/STL	Cape Air (9K)	77	DOT-OST-2006-23929-0075	
DIK	DEN	United Airlines (UA)	178	DOT-OST-1995-697-0118	
DUJ	PIT/BWI	Southern Airways (9X)	45	DOT-OST-2004-17617-0172	
DVL	DEN	United Airlines (UA)	120	DOT-OST-1997-2785-0215	
EAR	DEN	United Airlines (UA)	74	DOT-OST-1996-1715-0144	
EAU	ORD	United Airlines (UA)	93	DOT-OST-2009-0301-0037	
ELD	DFW/MEM	Southern Airways (9X)	56	DOT-OST-1997-2935-0345 DOT-OST-1997-2935-0388	
ESC	DTW	Delta Air Lines (DL)	95	DOT-OST-2003-15128-0143	
FOD	MSP/STL	Air Choice One (3E)	64	DOT-OST-2001-10684-0135	
GCK	DFW	American Airlines (AA)	110	DOT-OST-1998-3497-0092	
GDV	BIL	Cape Air (9K)	40	DOT-OST-1997-2605-0237	
GGW	BIL	Cape Air (9K)	40	DOT-OST-1997-2605-0237	
GLH	ATL/DFW	Boutique Air (4B)	99	DOT-OST-2008-0209-0137 DOT-OST-2008-0209-0140	Hub at BNA was changed to ATL on April 1, 2019.
GRI	DFW	American Airlines (AA)	135	DOT-OST-2002-13983-0135 DOT-OST-2002-13983-0139	
HIB	MSP	Delta Air Lines (DL)	79	DOT-OST-2003-15796-0075	
HOT	DFW	Southern Airways (9X)	57	DOT-OST-1997-2935-0345 DOT-OST-1997-2935-0388	
HRO	DFW/MEM	Southern Airways (9X)	63	DOT-OST-1997-2935-0345 DOT-OST-1997-2935-0388	
HVR	BIL	Cape Air (9K)	40	DOT-OST-1997-2605-0237	
HYS	DEN	United Airlines (UA)	99	DOT-OST-1998-3497-0092	
IMT	DTW/MSP	Delta Air Lines (DL)	93	DOT-OST-2009-0304-0079	
INL	MSP	Delta Air Lines (DL)	95	DOT-OST-2009-0304-0079	
IPL	LAX	Southern Airways (9X)	60*	DOT-OST-2008-0299-0118 DOT-OST-2008-0299-0113	Southern Airways acquired Mokulele Airlines in February 2019.
IRK	STL	Cape Air (9K)	41	DOT-OST-1997-2515-0087	
IWD	ORD/MSP	Air Choice One (3E)	69	DOT-OST-1996-1266-0185	
JBR	STL	Air Choice One (3E)	54	DOT-OST-1997-2935-0363	
JLN	DFW	American Airlines (AA)	102	DOT-OST-2006-23932-0078 DOT-OST-2006-23932-0091	
JMS	DEN	United Airlines (UA)	105	DOT-OST-1997-2785-0215	

JST	PIT/BWI	Boutique Air (4B)	48	DOT-OST-2002-11451-0163	
LAR	DEN	United Airlines (UA)	68	DOT-OST-1997-2958-0094	
LBF	DEN	United Airlines (UA)	69	DOT-OST-1999-5173-0108	
LBL	DEN	United Airlines (UA)	79	DOT-OST-1998-3502-0100	
LEB	BOS	Cape Air (9K)	54	DOT-OST-2003-14822-0072	
LNS	PIT/BWI	Southern Airways (9X)	63	DOT-OST-2002-11450-0145	
LWB	ORD/IAD	United Airlines (UA)	79	DOT-OST-2003-15553-0155	
MBL	MDW	Regional Sky (4P)	59	DOT-OST-1996-1711-0144 DOT-OST-1996-1711-0172	Fare estimate for Regional Sky flights is not available. Fare shown is from Cape Air proposal for flights beginning October 1, 2020.
MCE	LAX/OAK	Boutique Air (4B)	83	DOT-OST-1998-3521-0210	
MCK	DEN	Boutique Air (4B)	47	DOT-OST-1997-3005-0100	
MCN	BWI	Contour Airlines (LF)	89	DOT-OST-2004-18715-0032 DOT-OST-2007-28671-0111	
MCW	MSP/ORD	Air Choice One (3E)	64	DOT-OST-2001-10684-0135	
MEI	DFW/ORD	American Airlines (AA)	116	DOT-OST-2008-0112-0049	
MGW	PIT/BWI	Southern Airways (9X)	46	DOT-OST-2004-17617-0172	
MKG	ORD	United Airlines (UA)	73	DOT-OST-2009-0301-0037	
MKL	STL	Air Choice One (3E)	59	DOT-OST-2000-7857-0264	
MSL	ATL	Boutique Air (4B)	75	DOT-OST-2000-7856-0216	
MSS	BOS	Boutique Air (4B)	72	DOT-OST-1997-2842-0423	
MWA	STL	Cape Air (9K)	39	DOT-OST-2003-14492-0061	
OGS	BOS ORD/IAD	Cape Air (9K) United Airlines (UA)	49 101	DOT-OST-1997-2842-0220 DOT-OST-1997-2842-0423	Cape Air service to BOS via ALB ended March 30, 2019 and was replaced with United Airlines service to ORD/IAD.
OLF	BIL	Cape Air (9K)	40	DOT-OST-1997-2605-0237	
OWB	STL	Cape Air (9K)	41	DOT-OST-2000-7855-0141	
PAH	ORD	United Airlines (UA)	94	DOT-OST-2009-0301-0037	
PBG	IAD	United Airlines (UA)	105	DOT-OST-2000-8012-0149	
PDT	PDX	Boutique Air (4B)	86	DOT-OST-2004-19934-0109	
PGA	PHX/LAS	Contour Airlines (LF)	129*	DOT-OST-1997-2694-0231	
PIB	DFW/ORD	American Airlines (AA)	116	DOT-OST-2008-0112-0050	
PIR	DEN	United Airlines (UA)	90	DOT-OST-2001-10644-0170	
PKB	CLT	Contour Airlines (LF)	68*	DOT-OST-2004-18715-0030	
PLN	DTW	Delta Air Lines (DL)	96	DOT-OST-2011-0133-0041	
PQI	EWR	United Airlines (UA)	143	DOT-OST-2003-14783-0236	
PRC	DEN/LAX	United Airlines (UA)	87	DOT-OST-1996-1899-0266	
PUB	DEN	United Airlines (UA)	60	DOT-OST-1999-6589-0123	
RHI	MSP	Delta Air Lines (DL)	85	DOT-OST-2009-0304-0079	
RKD	BOS	Cape Air (9K)	83	DOT-OST-1997-2784-0200	
RUT	BOS	Cape Air (9K)	78	DOT-OST-2005-21681-0043	

SDY	BIL	Cape Air (9K)	40	DOT-OST-1997-2605-0237	
SHD	ORD/IAD	United Airlines (UA)	69	DOT-OST-2003-15553-0155	
SLK	BOS	Cape Air (9K)	95	DOT-OST-2000-8025-0152	
SLN	DEN/ORD	United Airlines (UA)	88	DOT-OST-2002-11376-0196	
SOW	PHX	Boutique Air (4B)	75	DOT-OST-1998-4409-0134	
SUX	ORD	American Airlines (AA)	124	DOT-OST-2011-0131-0109 DOT-OST-2011-0131-0115	
SVC	ABQ/PHX	Advanced Air (AN)	95	DOT-OST-1996-1903-0404	
TBN	STL	Contour Airlines (LF)	56	DOT-OST-1996-1167-0119 DOT-OST-1996-1167-0131 DOT-OST-1996-1167-0157 DOT-OST-1996-1167-0170	Served by: Cape Air under basic EAS until January 31, 2019; Contour Airlines under Alternate EAS until September 30, 2021; United Airlines under basic EAS until September 30, 2022; and Contour Airlines under basic EAS since October 1, 2022. Fare shown is from Contour Airlines proposal for service starting October 1, 2022, adjusted for inflation.
TUP	BNA	Contour Airlines (LF)	49	DOT-OST-2009-0305-0148 DOT-OST-2000-7856-0211	
TVF	MSP	Boutique Air (4B)	69	DOT-OST-2001-10642-0132	
UIN	ORD	United Airlines (UA)	75	DOT-OST-1996-1559-0088	
VCT	IAH/DFW	Boutique Air (4B)	63	DOT-OST-2005-20454-0100	
VEL	DEN	United Airlines (UA)	99	DOT-OST-1997-2706-0160	
WYS	SLC	Delta Air Lines (DL)	115	DOT-OST-2003-14626-0069	Delta Air Lines only provides subsidized service during the peak season for visiting Yellowstone National Park, from May to October. No service is provided during the non-summer months.

Source: Regulations.gov.

Notes: Contour Airlines provides public charter service under the Alternate Essential Air Service (49 *U.S.C.* 41745). Fares marked with * were not provided in the DOT proposal documentation and are from an Internet search in early September 2022 for a flight departing 2 weeks later, adjusted for inflation.

References for Appendices

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