AN ASSESSMENT OF AIR SERVICE ACCESSIBILITY IN U.S. METROPOLITAN REGIONS, 2007-2012

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Executive Summary

Regional accessibility to air transportation is often of interest to airport executives, politicians, and the general public due to the positive economic impacts of frequent commercial airline service. However, measuring access to air service can be challenging, particularly for regions with multiple airports. While many models exist to measure airline network connectivity at individual airports, there is limited literature on the geographic aggregation of these metrics to assess regional accessibility.

In this paper, we propose a new methodology to construct U.S. regional airport catchment areas using U.S. Census Bureau Primary Statistical Areas (PSAs). Using a connectivity index that evaluates airports on the quantity and quality of available service, air service accessibility scores are computed on a regional level for 323 PSAs from 2007-2012. We find that most U.S. regions lost access to air service during the study period in the midst of domestic schedule rationalization and airline "capacity discipline." Accessibility scores for each PSA from 2007 to 2012 are available in an appendix.

On average, metropolitan regions in the United States lost about 11.6% of their accessibility to commercial air transportation between 2007 and 2012. Mid-sized regions of 500,000 - 5 million people lost the most access to air service—about 14.4% on average—aligning with past work that suggests that medium-sized communities have been harmed most by airline capacity discipline. In multi-airport regions, losses in service at primary airports outweighed some consolidation in service at larger hubs, leading to net losses in accessibility in most cases.

The results of the accessibility model can be used by regional planners, policy-makers, and airport officials to understand how various regions in the U.S. lost or gained access to air transportation as a result of the Great Recession and airline capacity strategies. Additionally, the proposed catchment area definition provides a useful framework for further discussion of the demographic and geographic determinants of successful commercial air service.

1. Introduction

Metropolitan regions in the United States rely on their airports to connect residents, businesses, governmental officials, and tourists to the rest of the country and the world. Frequent and well-connected commercial airline service is therefore valuable to communities of all sizes, since it encourages trade and the free movement of people, goods, capital, and ideas. Along with the intangible benefits of increased personal mobility, past research has also shown a relationship between accessibility to airline service and business location, suggesting a further economic value to high quality air transportation service (Stilwell 2013).

Given these benefits, having reasonable access to one or more airports with well-connected airline service is important to regions throughout the United States. Airports at which new nonstop service is added are often lauded by local residents and businesses; conversely, a cut in available service can often leave an airport and a region scrambling to replace the connectivity that has been lost. To wit, airports of all sizes often offer financial incentives directly to airlines in exchange for new service (Weatherill 2006; Smyth et al. 2012; Malina et al. 2012).

Measuring regional accessibility to air transportation has been the subject of an increasingly robust body of literature in recent years. Grubesic and Zook (2007), Yamaguchi (2007), Matisziw and Grubesic (2010), Jenkins (2011), Halpern and Bråthen (2011), Ryerson and Kim (2013), and others have created accessibility models to assess the quality of air service available in various geographic regions. Yet while assessing accessibility to airline service is fairly straightforward in regions with only a single airport, researchers have often struggled to represent accessibility in regions with multiple airports, or "multi-airport regions."

Indeed, some recent work (Fuellhart et al. 2013) has made the case that examining the individual airport level alone is inadequate to understand passenger choice and accessibility levels in multi-airport regions. As airlines removed service from smaller U.S. airports at a quicker pace than larger airports by keeping capacity growth low through a strategy referred to as "capacity discipline," these multi-airport regions have grown in importance (Wittman and Swelbar 2013). While many models exist to measure airline network connectivity at individual airports, there is limited literature on the geographic aggregation of these metrics to assess regional accessibility, particularly in regions with multiple airports.

Furthermore, it can be challenging to identify geographic airport catchment areas to properly assess the airports to which residents of a specific community have access. Defining airport catchment areas geographically can require some specialized knowledge of the region's demographic and economic characteristics, as well as the travel patterns of local residents. Choosing a simple distance-based radius around an airport is often used as a proxy for the airport's catchment area, but the size and shape of this radius may vary for communities in different regions based on residents' propensity to travel large distances to reach a nearby airport, the modes of transit available for airport access, and the geographic size of each metropolitan region.

Therefore, in any analysis of regional accessibility, a more robust definition of airport catchment areas is necessary. Maertens (2012) and Suau-Sanchez et al. (2014), in applications for Europe, suggest using land cover areas defined by governmental organizations to define airport catchment areas. Maertens (2012) uses Nomenclature of Units for Territorial Statistics 3 (NUTS 3) regions to define catchment areas, whereas Suau-Sanchez et al. (2014) use the CORINE land cover created by the European Environmental Agency. Such land covers are attractive because they are defined by local experts, can be heterogenous in shape, and can pass through or disregard political barriers (such as the boundaries between U.S. states).

In the United States, the U.S. Census Bureau defines several groups of land covers to group communities into geographic metropolitan regions. These land covers are naturally suited to be treated as airport catchment areas. Recognizing the fact that passengers will often drive for several hours or more to access an airport with better service or lower fares, we use the largest geographic regions defined by the U.S. Census Bureau: the Primary Statistical Area (PSA). PSAs often incorporate multiple urban subunits (Metropolitan Statistical Areas (MSAs) and Micropolitan Statistical Areas (μSAs)) and often contain within their boundaries several primary commercial service airports, making them an ideal unit of analysis for a macroscopic view of air service accessibility.

In this paper, we propose a new methodology for computing accessibility to commercial airline service for metropolitan regions in the United States. To do so, we first map U.S. commercial service airports into PSA catchment areas and discuss some general characteristics. Then, adapting an airport connectivity model first introduced in Wittman and Swelbar (2014) that takes into account the quality and quantity of available non-stop and connecting service, we compute regional air service accessibility for 323 U.S. PSAs from 2007-2012. Taking a cue from Brueckner et al. (2014), we compute accessibility between regions, not airports, such that flights from Boston to Chicago/O'Hare and from Manchester, N.H. to Chicago/Midway are both treated equally as flights from the "Boston area" to the "Chicago area."

The resulting air service accessibility index provides a way to rank and compare the quality of air service available in regions of various sizes across the United States. We provide a ranking of most-connected regions and investigate changes in air service accessibility as a result of changing airline networks, paying particular attention to how accessibility changed in different ways in regions of various sizes. Finally, we discuss some future extensions to the work that take advantage of the PSA-based catchment area definition introduced for U.S. airports.

The remainder of this paper is structured as follows: Section 2 focuses on defining airport catchment areas. We discuss some recent literature and limitations to current approaches, and introduce the U.S. Census Bureau Primary Statistical Area (PSA) as a proposed airport catchment area. In Section 3, we turn our attention to accessibility modeling; we discuss some recent developments in the literature and introduce our modification to the Wittman and Swelbar (2014) Airport Connectivity Quality Index. In Section 4, we provide some relevant results from the accessibility model calculation, including maps that show which regions gained and lost the most air service accessibility from 2007-2012. Section 5 concludes, discusses some overall implications, and discusses some future extensions.

2. Defining Airport Catchment Areas using Primary Statistical Areas

Building an air service accessibility model requires three components: (1) a model of airport connectivity, (2) a methodology by which to aggregate airports into geographic regions of service (i.e., “catchment areas”), and (3) a methodology by which to compute regional accessibility for regions with more than one airport (“multi-airport regions”).

Before turning our attention to the airport connectivity model, this section examines some of the past literature regarding airport catchment areas and highlights some of the issues with commonly-used approaches. We then propose the use of U.S. Census Bureau Primary Statistical Areas (PSAs) as a reasonable proxy for airport catchment areas. After reviewing the Census Bureau land cover definitions, we discuss our methodology for mapping airports into PSAs and review some summary statistics for 323 U.S. PSAs that contained at least one primary commercial service airport.

2.1 Literature Review: Catchment Areas

Aviation forecasters and airport officials have long struggled to find an adaptable definition of an airport's catchment area. Understanding the catchment area of an airport is critical for marketing and forecasting efforts, as well as identifying which passengers in the catchment areas might be spilling to other airports in the region due to better offerings of frequencies or average fares at those airports. Traditionally, catchment areas are often created by drawing a circle of a fixed radius with a particular airport as the centroid (Wang 2000; McLay and Reynolds-Feighan 2006; Bilotkach et al. 2012). Any center of population or economic activity within the circle would be treated as being within the airport's catchment area. For some analyses, maximum travel times are used instead of distances when drawing the catchment area.

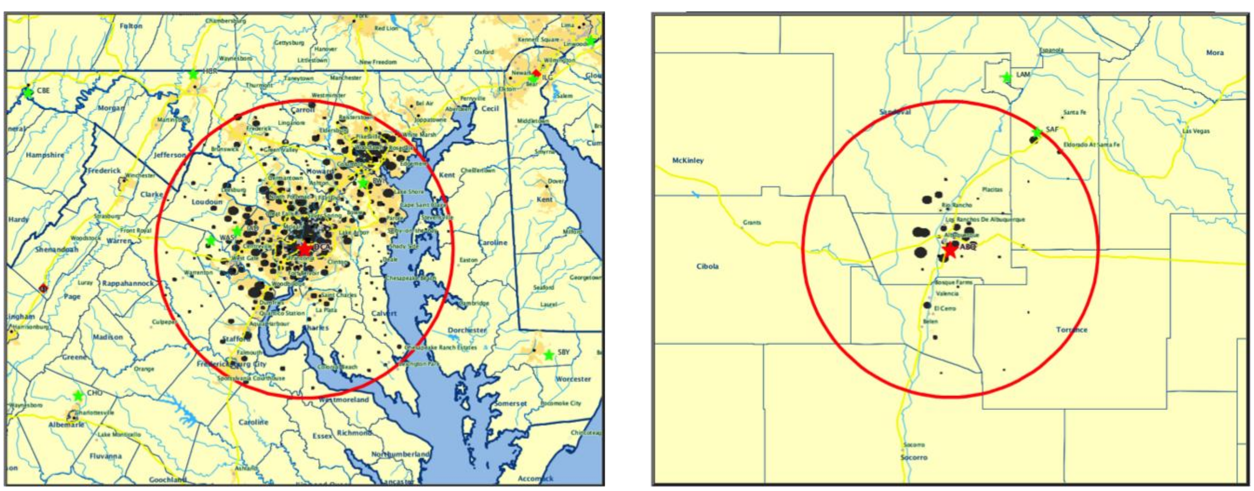

Figure 1: 50-mile radius catchment areas for DCA (left) and ABQ (right). Source: Diio Mi

Yet these traditional circular distance-based catchment areas rely on an arbitrary definition of travel time or distance, and may be too broad to fully explain passenger behavior. For instance, consider the two catchment areas shown in Figure 1. In Figure 1, a catchment area with a 50-mile radius has been drawn around two airports in the United States: Ronald Reagan Washington National Airport (DCA) and Albuquerque International Sunport (ABQ). The black regions on each map represent population centers.

Note that the population centers in the Washington region fill almost the entire catchment area, whereas the Albuquerque population centers are located very close to the airport. The tolerance for driving distance in each of these regions may also vary; traffic in the Washington area may reduce the overall distance a passenger is willing to drive to an airport as compared to the Albuquerque region. Travel time to each airport in the region can also depend on local conditions and the existence of public transportation options to the airport. Therefore, it appears that the optimal catchment area size may vary based on the area of the country in which an airport is located, as well as the commuting patterns of local residents. Selecting a single distance radius is unlikely to capture how these preferences might change across regions.

Additionally, setting a single radius-based catchment area assumes that metro regions take a circular shape. This is not always the case, particularly in coastal regions. For instance, consider Figure 2, which shows a 50-mile catchment area for Boston Logan International Airport (BOS), Note that almost half of the catchment area for BOS is in the Atlantic Ocean; meanwhile some areas of New Hampshire, Rhode Island, and western Massachusetts have been excluded from the catchment area. This may not be a realistic representation of the true airport choice decision faced by residents of the Boston metropolitan region.

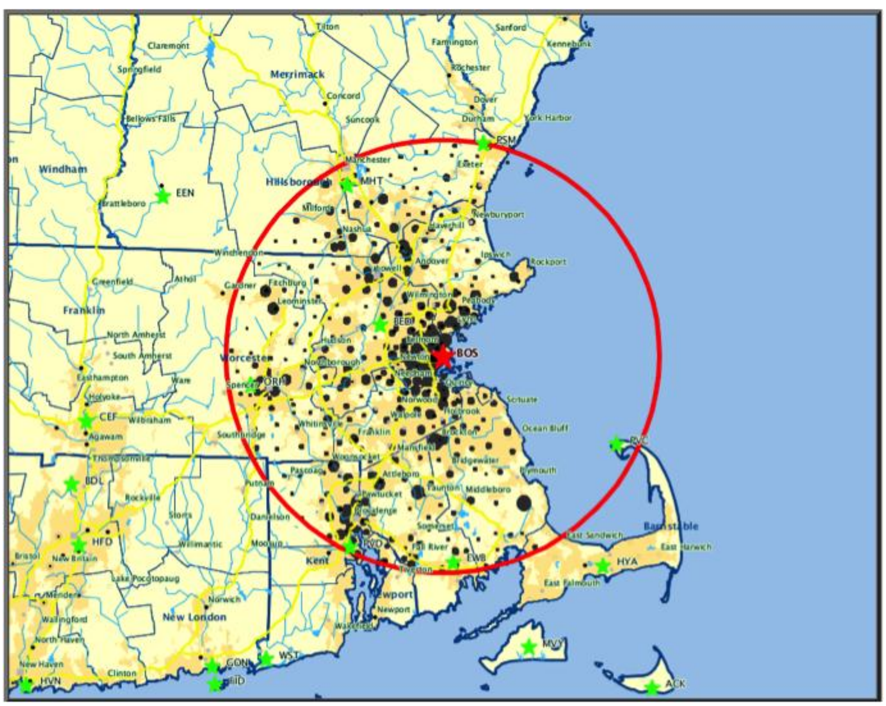

Figure 2: 50-mile radius catchment areas for BOS. Source: Diio Mi

Ultimately, defining catchment areas individually for each region would provide the most robust estimate of airport accessibility. However, doing so requires some degree of local knowledge of the cultural and geographic boundaries of each metropolitan region in the United States. While some authors have provided methodologies to define detailed catchment areas for individual regions (Fuellhart 2007; Lian and Rønnevik 2011; Lieshout 2012; Maertens 2012), this approach is infeasible in a macroscopic analysis of the entire country.

Suau-Sanchez et al. (2014) have suggested using land covers defined by an external agency to sort airports into relevant catchment areas. The authors use the CORINE land cover data set created by the European Environmental Agency. Such an externally-provided data set is useful because it allows for a finer grain of analysis. Since the definition of land cover is made by professionals with specific knowledge about each community, desirable heterogeneity can result from these data sets. Yet while the CORINE land data have a higher degree of specificity than other available data sets in Europe, Suau-Sanchez et al. (2014) still rely on fixed-distance catchment areas of 25-100 km to compute regional population size and demographic characteristics.

Instead of having to select an arbitrary distance-based catchment area, we can instead select a land cover to represent metropolitan areas that can be defined heterogenously across regions (Maertens 2012). That is, the resulting airport catchment areas would have different shapes and sizes based on the individual characteristics of the regions in question.

To this end, the U.S. Census Bureau divides the United States into a series of geographic regions to aid with statistical and geographic analysis. These regions, which are referred to as Statistical Areas, are also associated with a wealth of Census data tailored to each region. Using predefined regional catchment areas like the ones created by the Census Bureau also has several advantages over the conventional distance-based or time-based approach:

- Districts are defined consistently by a central authority, removing the need to make arbitrary judgments about the size and shape of catchment areas;
- Census analysts use local knowledge to define districts/metro regions; they do not just use a single distance-based metric;
- Census areas can cross political boundaries (such as state lines);
- Using a pre-defined land cover helps to avoid the Modifiable Areal Unit Problem—an analytical bias that can exist when choosing an arbitrary unit or distance for analysis of a geographic area (Suau-Sanchez et al. 2014).

There are five levels of Statistical Area aggregation employed by the U.S. Census Bureau, based on the size of the community at the core of the statistical area. Figure 3 provides an overview of these five levels of aggregation.

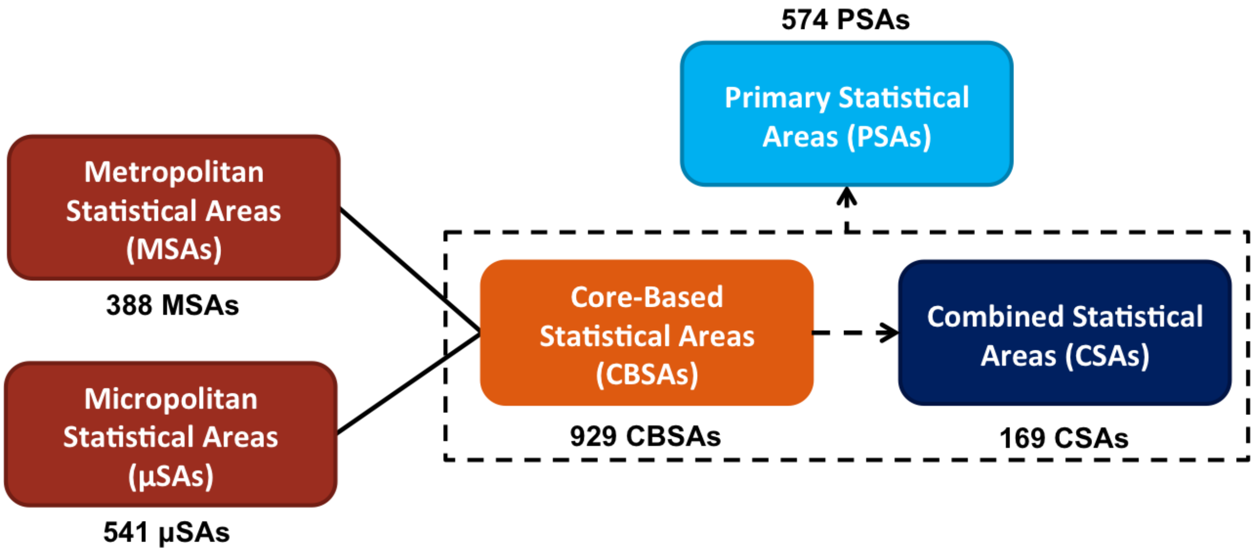

Figure 3: Schematic of U.S. Census Bureau Statistical Area Definitions

The primary units of division used by the Census Bureau are the Metropolitan Statistical Area (MSA), which contain urban cores of more than 50,000 people, and the Micropolitan Statistical Area (µSAs), which contain urban cores of 10,000-50,000 people. As of 2014, there were 388 MSAs and 541 µSAs in the United States. Together, MSAs and µSAs are called Core-Based Statistical Areas (CBSAs)—therefore, there were 929 CBSAs in the United States as of 2014.

On a larger scale, Combined Statistical Areas (CSAs) are made up of two or more CBSAs. For instance, the New York-Newark, NY-NJ-CT-PA Combined Statistical Area is made up of 7 MSAs and 1 µSA. In total, there were 169 CSAs in the United States in 2014.

Since past research shows that passengers are willing to commute long distances by car to access an airport with a low fare or an attractive schedule (Fuellhart 2007; Fournier et al. 2007), these large Combined Statistical Areas are an attractive level of aggregation since they encompass large commuting regions that can often cross state boundaries. Figure 4 shows two representative CSAs in the New York and Boston metropolitan areas. Note that each of these two CSAs encompasses multiple counties in several states.

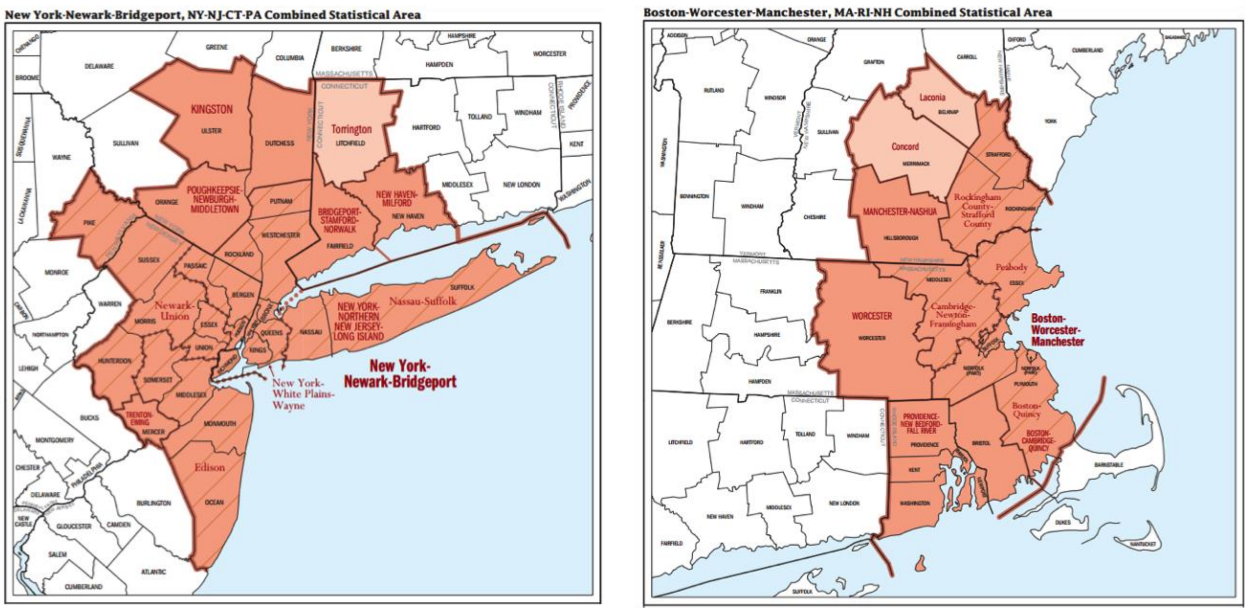

Figure 4: Combined Statistical Areas (CSAs) for New York and Boston. Source: U.S. Census Bureau

Some large cities, like Phoenix, AZ, are not included in a Combined Statistical Area because their individual MSAs already contain all of the population centers in their region. Therefore, the Census Bureau has defined a fifth category of aggregation: Primary Statistical Areas (PSAs). Primary Statistical Areas cover all areas in the United States with urban cores of at least 10,000 residents. They are composed of all 169 CSAs, as well as any MSAs and μSAs (such as Phoenix, AZ) that are not a component of a CSA. There were 574 PSAs in the United States as of 2014.

Since the Primary Statistical Area is the largest unit of analysis that covers all areas of the United States with populations of over 10,000 people, it was selected as the level of aggregation for this study. That is, each airport's catchment area was defined as the entire PSA to which that airport belongs. In other words, a resident of the Boston-Worcester-Manchester PSA would have access to BOS, MHT, and PVD airports (and some other smaller airports within the region). This helps us capture the types of multi-airport choice decisions that passengers in these large multi-airport regions face when deciding which airport to use to travel. Furthermore, this definition of catchment areas will allow us to compute air service accessibility for each PSA in the United States.

2.2 Dividing U.S. Airports into PSAs

There are nearly 500 primary commercial service airports in the United States. To complete the accessibility analysis, each of these airports needed to be assigned to its correct Primary Statistical Area. Airports were mapped into PSAs using the following procedure:

1. First, latitude and longitude coordinates for each airport were obtained from the OpenFlights data project. OpenFlights is an open source website that contains geographic locational data for nearly 7,000 airports worldwide.
2. Then, an application programming interface (API) from the Federal Communications Commission (FCC)[1] was used to convert each airport's lat-long coordinates into a 15-character US Census Bureau Census Block number, also known as a Federal Information Processing Standard (FIPS) code. These FIPS codes provide information about the state and region in which each airport is located. A Python script was used to repeatedly query the FCC API to obtain the necessary FIPS codes for each airport.
3. A FIPS code to CBSA "crosswalk" created by the National Bureau of Economic Research[2] was then used to convert each airport's FIPS code to the relevant Primary Statistical Area.
4. Finally, airport mappings were spot-checked to ensure accuracy of the mapping process.

In all, 462 primary commercial service airports in the United States were mapped into 323 of the country's 574 Primary Statistical Areas. 58 airports were located in regions that were too small to be mapped to a PSA; that is, areas with metropolitan urban cores of less than 10,000 people. In our analysis, we will focus on the airports in regions large enough to be mapped into PSAs. This leaves 404 airports in 323 PSAs as the sample size for this analysis.

In the United States, 39 Primary Statistical Areas contained two or more airports. Table 1 shows some of these PSAs that could be classified as "multi-airport regions."

Primary Statistical Area	# of Airports
Boston-Worcester-Providence, MA-RI-NH-CT	8
New York-Newark, NY-NJ-CT-PA	8
Los Angeles-Long Beach, CA	6
Las Vegas-Henderson, NV-AZ	6
San Jose-San Francisco-Oakland, CA	5
Kahului-Wailuku-Lahaina, HI	4
Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	4
Orlando-Deltona-Daytona Beach, FL	3
Miami-Fort Lauderdale-Port St. Lucie, FL	3
Flagstaff, AZ	3
29 other PSAs	2

Table 1: PSAs Classified as Multi-Airport Regions

[1] More details about this API are available at http://www.fcc.gov/developers/census-block-conversions-api.
[2] The crosswalk is available at http://www.nber.org/data/cbsa-msa-fips-ssa-county-crosswalk.html.

To summarize, we defined heterogeneously-shaped catchment areas for each U.S. airport based on the U.S. Census Bureau Primary Statistical Area in which the airport is located. We assume that any resident living in a PSA in which an airport is located can reasonably be expected to access that airport. This approach provides an advantage over simply constructing catchment areas based on a fixed distance-based radius, since PSAs are defined in a more nuanced, individualized manner that can better capture the commuting patterns and transportation options available to residents in each region. After mapping airports into PSAs, we found that 39 of these regions contained more than one airport—these "multi-airport regions" will be analyzed in more detail in subsequent sections.

3. Measuring Air Service Accessibility in Geographic Regions

After assigning airports into metropolitan regions (PSAs) and establishing airport catchment areas based on the geographies of those regions, we can turn our attention to defining air service accessibility based on the available scheduled service at each airport in the region. In this section, we review some recent work on creating accessibility indices and define our Air Service Accessibility Index, which modifies the Airport Connectivity Quality Index (ACQI) introduced in Wittman and Swelbar (2014) by computing the quality and quantity of service available between different *regions* as opposed to different *airports*.

3. 1 Recent Advances in Connectivity and Accessibility Modeling

In the past ten years, researchers from a variety of disciplines have given considerable attention to the properties and characteristics of the global air transportation network. These papers often examine the air transportation network in terms of its connectivity. Some papers, such as Guimerà et al. (2005) use network and graph theory concepts to measure the centrality and connectedness of the air transportation network. Others, like Goedeking (2010) and Malighetti et al. (2008), use time-of-day schedule data for a "representative day" to generate possible passenger itineraries, from which connectivity scores are then computed. In most of these analyses, connectivity is computed at an airport level of detail. As such, in regions with multiple airports, each airport's connectivity is treated separately.

Accessibility models which define access to well-connected air service at a geographic or regional level appear less frequently in the literature, and the analyses in these papers are generally limited to only the largest cities. Derudder et al. (2007) is one such example of a paper that examines the geographic air service connectivity of various cities using global distribution system (GDS) passenger booking data; in a more thorough US-centric analysis, Grubesic and Zook (2007) also use GDS data to measure air service accessibility in various U.S. metro regions.

Following on this work, Matisziw and Grubesic (2010) create perhaps the most robust recent example of an air service accessibility index for U.S. metro regions. Matisziw and Grubesic

(2010) evaluate accessibility independently for 64,855 U.S. census tracts and 431 commercial service airports. While this paper provides a detailed overview of accessibility at a very fine level of detail, the airport catchment area issue still exists. Since the Matisziw and Grubesic (2010) analysis does not use a higher level of geographic regional aggregation to define catchment areas, such as the Primary Statistical Area, the authors introduce several arbitrary distance-based metrics to which census tracts have access to each airport. As discussed earlier, defining such a metric uniformly across the entire country can lead to inconsistent estimate of catchment area sizes. With reference to air passenger flows at airports, O'Kelly (2012) has noted the need to perform sensitivity analyses on these distance-based measures of spatial interaction.

Finally, in a series of papers, Grubesic and Matisziw (2011), Matisziw et al. (2012), Grubesic et al. (2012), and Grubesic and Wei (2012) have considered the geographic characteristics and accessibility of the Essential Air Service program—a federal subsidy program intended to increase the amount of air service provided to small communities in the United States. These papers rightly identify that some airports that receive Essential Air Service subsidies may be in the catchment areas of larger regional airports. Since the EAS subsidies are only intended to be provided to communities in which residents would otherwise have no access to air transportation, those communities within the catchment areas of larger airports may be good targets for reductions in subsidies.

3. 2 The Air Service Accessibility Index Model

In this paper, we will use the PSA catchment areas defined in the previous section to avoid having to create arbitrary distance-based radii for our accessibility analysis. However, we still need to define a connectivity model that will be used to aggregate access to air service for airports within each region. To do so, we will modify an airport connectivity model introduced in Wittman and Swelbar (2014). The Airport Connectivity Quality Index measures connectivity at an airport based on the quantity and quality of available nonstop and connecting service. That is, an additional flight to a large airport will be given a higher weight in the model than an additional flight to a smaller airport.

While the ACQI model can be used to compute connectivity for individual airports, the method of aggregating these scores across regions with multiple airports remains unclear. Additionally, when measuring accessibility, Brueckner et al. (2014) have recently argued that in multi-airport regions, the amount of service from one airport to another does not matter as much as the level of service from the entire *region* to other regions. That is, we should not compute accessibility separately for each of the airports in the Washington-Baltimore-Arlington, DC-MD-VA-WV-PA Primary Statistical Area, but instead consider how well connected the entire PSA is to other PSAs in the country. This approach takes a "city-pair" definition of air service accessibility, as opposed to an "airport-pair" definition as in past work such as Grubesic and Zook (2007) and Matisziw and Grubesic (2010).

Following Wittman and Swelbar (2014), the Air Service Accessibility Index (ASAI) score for a Primary Statistical Area is defined as follows: let P be a set of all PSAs in which there is at least one airport, and T be a set of region types to which each region $p \in P$ is mapped.[3] Then, the ASAI score for a region $p \in P$ is:

$$\boldsymbol{ASAI_p = \sum_{t \in T} f_{p,t} d_{p,t} w_t + \alpha \sum_{t \in T} d'_{p,t} w_t}$$

where:

- $\boldsymbol{f_{p,t}}$ is the average number of daily scheduled flights per destination from region p to region type t
- $\boldsymbol{d_{p,t}}$ is the number of nonstop destination regions of type t served from region p.
- $\boldsymbol{d'_{p,t}}$ is the number of online or codeshare connecting regions of type t served from region p.
- $\boldsymbol{w_t}$ is a weighting factor based on the size of the region type t.
- $\boldsymbol{\alpha}$ is a scaling factor that weights the importance of nonstop service vs. one-stop service.

The ASAI computes regional accessibility based on the quality and quantity of available service from a region to other regions in the U.S., as well as international destinations. Destination quality is differentiated by the weighting term w_t, which varies based on the region type of each destination. In other words, an additional flight to a large, economically important region would be given a higher weight than service to a smaller, less economically important region.

While regions could be assigned into categories using a variety of different factors, in this analysis, region types are defined based on 2012 U.S. Census Bureau estimates of population within each region. For each region type t, the weighting term w_t was computed by dividing that region type's average population by the average population of the largest region type. This ratio ensures that flights to the largest regions are given the highest weight. Table 2 lists the region types used in this analysis, as well as the w_t weighting terms used for each region.

Region Type	# of PSAs	Avg. Population (2012)	w_t
5+ million	12	9,630,884	1.0
1 – 5 million	47	2,025,759	0.21
250,000 – 1 million	91	518,668	0.05
10,000 – 250,000	168	114,117	0.01
International	343	N/A	1.0

Table 2: PSA Region Types and Accessibility Model Weighting Terms

[3] Region types could be defined based on population size, economic characteristics, or other factors

Note that international destinations were assigned a w_t weighting term of 1.0, such that an international flight is valued equally highly as an additional flight to one of the 12 largest regions in the United States. While this represents the importance that international service plays in many U.S. regions, this weight is subject to sensitivity analysis. The ASAI model was tested using international airport weighting values that varied between 0.75 and 1.25. In each case, small changes to the international weighting term w_t result in only limited changes in the rank order of regions within the ASAI model. Therefore, a simple weight of 1.0 was chosen for international destinations to reduce complexity.

Additionally, the ASAI score for each region is also a function of the weighting term α, which measures the relative value of non-stop versus connecting service. That is, if α were set equal to 1, an additional non-stop flight would be equally valuable as an additional connecting flight. In reality, however, passengers prefer non-stop service to connecting service. This relationship is often modeled using the Quality of Service Index (QSI), a heuristic used by airline and airport planners to assess the change in market share that results from additional non-stop or connecting frequencies.

In the QSI model, weights are applied to non-stop, one-stop, and connecting itineraries to express customer preferences for each of these itineraries. While academic literature surrounding the QSI model is very limited, some practical applications (e.g. Kayloe 2010, Welch 2012) suggest "one-stop" weighting terms of between 0.25 and 0.4. Additionally, Emrich and Harris (2008) have suggested that connecting itineraries are "up to eight times as valuable" as connecting itineraries for passengers. Following this work, the weighting term α was set to 0.125. A sensitivity analysis was also performed on this parameter on values from 0.03 to 0.3; again, small changes in $\boldsymbol{\alpha}$ resulted in only minimal changes to the rank order of regions in the ASAI model.

4. Results of the Air Service Accessibility Index Model for U.S. Primary Statistical Areas

4.1 Computing ASAI scores for U.S. PSAs

Based on the Air Service Accessibility Index model, accessibility scores for the years 2007-2012 were computed for each of the 323 Primary Statistical Areas with at least one airport. Index scores were computed using schedule data from Diio Mi, which accesses the Innovata Schedule Reference Service (SRS) database. This schedule data includes information on airline schedules for over 800 airlines worldwide, including full schedule coverage of airlines that operate in the United States. The number of regions served from each PSA, as well as the levels of service to each region, were extracted from the schedule data for each year.

It is useful to examine the geographic picture of air service accessibility in the United States to see how accessibility is distributed throughout the country. Figure 5 shows the ASAI scores of each U.S. Primary Statistical Area in 2007, whereas Figure 6 shows the ASAI scores of each PSA in 2012.

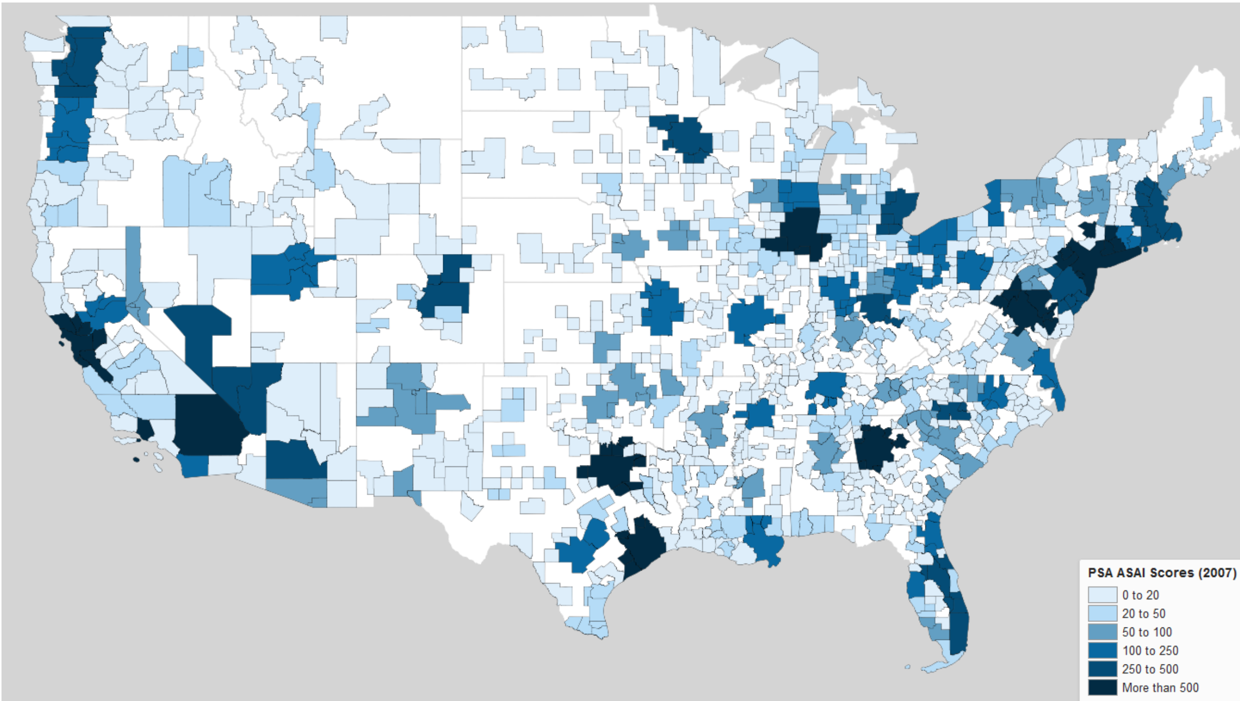

Figure 5: Air Service Accessibility Index scores for U.S. Primary Statistical Areas (2007)

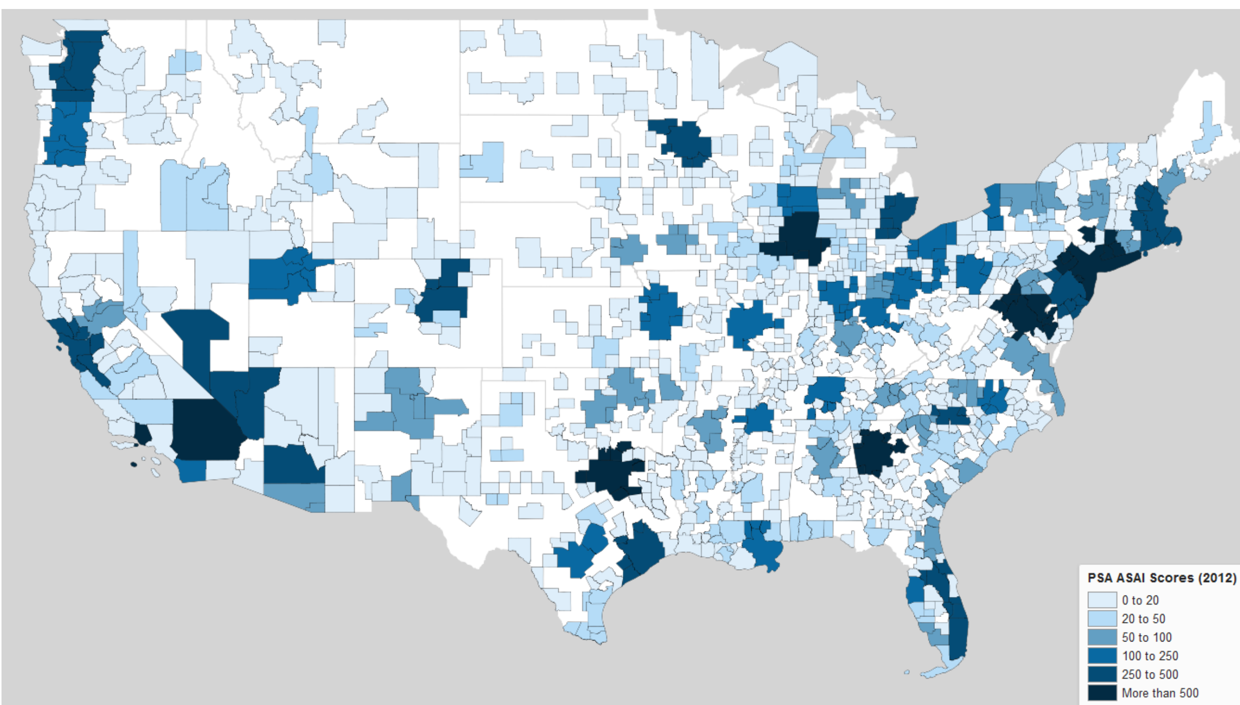

Figure 6: Air Service Accessibility Index scores for U.S. Primary Statistical Areas (2012)

As the figures show, air service accessibility is generally clustered around large metropolitan regions, and then falls off quickly in hinterland regions. Reduced accessibility in some peripheral PSAs may cause residents of those cities to leave their PSAs to commute to a nearby region with better accessibility. While this behavior is not directly modeled in this analysis, the movement of passengers across PSA regions is an important factor to consider, particularly at the borders of PSAs with one another. Clusters of accessibility exist in the "Northeast Corridor" from Boston to Washington, DC, in the Los Angeles and San Francisco metro regions, in Southern Florida, and in the Seattle-Portland area.

4. 2 Regional Analysis of Air Service Accessibility

We can also examine in detail some regions with particularly high accessibility. While a full ranking of all 323 PSAs by accessibility score is available in the appendix, Table 3 shows the 12 PSAs with the highest ASAI scores in 2012. The table also shows how many airports were located within each PSA, as well as the percent change in score from 2007-2012.

Rank (2007)	Rank (2012)	Name of PSA	# of Airports	ASAI (2007)	ASAI (2012)	% Change
1	**1**	New York-Newark, NY-NJ-CT-PA	8	954.38	841.42	**-11.8%**
2	**2**	Chicago-Naperville, IL-IN-WI	2	874.13	790.28	**-9.6%**
3	**3**	Atlanta--Athens-Clarke County--Sandy Springs, GA	2	792.74	745.65	**-5.9%**
4	**4**	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	4	687.20	633.95	**-7.7%**
6	**5**	Dallas-Fort Worth, TX-OK	2	679.01	583.57	**-8.5%**
5	**6**	Los Angeles-Long Beach, CA	6	638.03	576.01	**-15.2%**
8	**7**	San Jose-San Francisco-Oakland, CA	5	542.66	485.03	**-8.1%**
10	**8**	Charlotte-Concord, NC-SC	1	527.69	459.14	**8.5%**
7	**9**	Houston-The Woodlands, TX	2	454.44	450.46	**-17.0%**
11	**10**	Denver-Aurora, CO	1	423.01	415.68	**0.7%**
13	**11**	Miami-Fort Lauderdale-Port St. Lucie, FL	3	412.75	377.67	**-5.5%**
9	**12**	Boston-Worcester-Providence, MA-RI-NH-CT	8	401.02	372.92	**-17.9%**

Table 3: Top 12 Primary Statistical Areas by 2012 ASAI Scores

As Table 3 shows, the rankings of the top 7 PSAs by accessibility remained relatively unchanged from 2007-2012. However, some single-airport PSAs moved up in the rankings over those years; Charlotte-Concord, NC-SC increased its ranking from 10th to 8th from 2007-2012, and Denver-Aurora, CO increased its ranking from 11th to 10th over the same time period. These two regions were the only two PSAs in the top 30 to show an increase in ASAI from 2007-2012, as they benefited from bolstered hub service. Charlotte-Douglas International Airport (CLT) saw increased service from US Airways, and Southwest Airlines, Frontier Airlines, and United Airlines built up additional service at Denver International Airport (DEN) in the Denver-Aurora, CO PSA.

However, most regions saw a decrease in air service accessibility from 2007-2012 as airlines cut available service and limited the amount of connecting service at secondary hubs. This can be seen broadly in Figure 7, which shows the percent change in ASAI score for each PSA from 2007 to 2012.

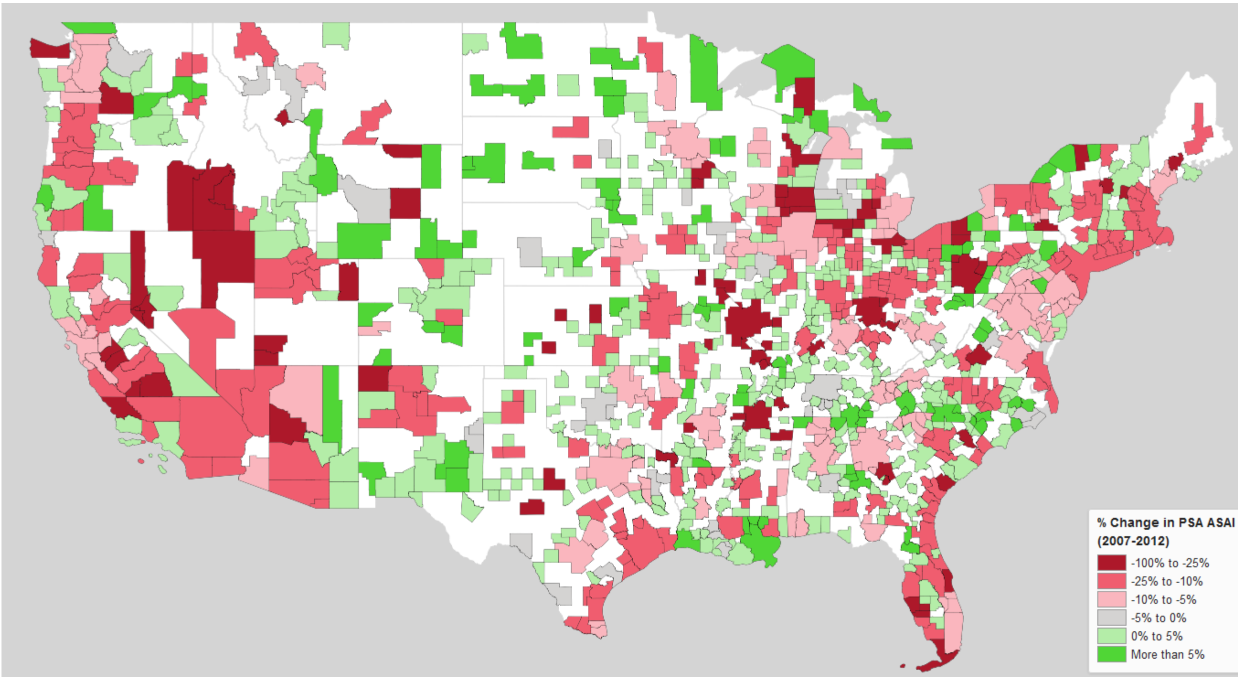

Figure 7: Changes in Air Service Accessibility Index scores for U.S. Primary Statistical Areas, 2007-2012

There are several reasons why most U.S. metropolitan regions saw a decline in average air service accessibility from 2007-2012. Most significantly, the number of flights at most U.S. airports decreased from 2007-2012 as airlines reconfigured their networks and practiced "capacity discipline" in the face of high fuel prices and a recessed economy (Wittman and Swelbar 2013). Even after the economy started to recover in 2011, airlines continued to keep capacity growth low in an effort to raise yields and increase load factors. As such, many U.S. airports saw the cuts in service they received in the midst of the economic downturn persist as a result of capacity discipline. As a result, the number of destinations accessible from many regions, as well as the number of flights to those destinations, decreased during the time period, leading to a decrease in air service accessibility.

These cuts were felt most heavily by mid-sized airports like Cincinnati/Northern Kentucky International Airport (CVG) and Memphis International Airport (MEM). These airports had served as secondary connecting hubs for major network carrier Delta Air Lines. After Delta merged with Northwest Airlines, it began rationalizing its network, which included cutting service to these secondary hubs. Although passengers throughout the Delta system could still reach approximately the same number of destinations connecting through Atlanta Hartsfield-Jackson International Airport (ATL), the severe cuts in service at CVG and MEM meant that the

Cincinnati and Memphis Primary Statistical Areas saw a tremendous decline in air service accessibility from 2007-2012.

The same pattern of network rationalization also negatively affected secondary airports in multi-airport regions—for instance, in the San Francisco primary statistical area, flights at Oakland International Airport (OAK) and Mineta San Jose International Airport (SJC) both decreased by over 35% from 2007-2012 (Wittman and Swelbar 2013). Even though flights and connectivity at San Francisco International Airport (SFO) increased by over 20% during the same time period, the magnitude of the reduction in service at OAK and SJC meant the San Jose-San Francisco-Oakland, CA PSA lost 8.1% of its air service accessibility from 2007-2012. In other words, the service cuts at secondary airports outweighed any gain in service at primary airports in multi-airport regions, leaving these Primary Statistical Areas with less access to air transportation than before the recession.

Since medium-sized airports were most affected by airline cuts during the capacity discipline period, we would also expect medium-sized geographic regions to have seen the largest decrease in air service accessibility over the same time period. Table 4 shows the average Air Service Accessibility Index scores for 2007 and 2012, as well as the percent change in accessibility, for primary statistical regions of various population sizes. The population estimates for each Primary Statistical Region were obtained from U.S. Census Bureau Population Estimation Program (PEP) for the year 2012.

PSA Population (2012)	# of PSAs	Average ASAI (2007)	Average ASAI (2012)	% Change in Avg. ASAI
5+ million	12	608.56	546.51	-10.2%
1 – 5 million	47	160.78	137.66	-14.4%
0.5 – 1 million	43	41.93	35.95	-14.3%
250,000 – 500,000	48	27.03	23.73	-12.2%
100,000 – 250,000	90	14.68	13.37	-8.9%
< 100,000	79	5.76	6.62	14.9%
Total[4]	319	62.07	54.84	-11.6%

Table 4: Average ASAI scores for PSAs of various population sizes, 2007-2012

As could be expected, Table 4 shows that there is a general positive correlation between population size and air service accessibility. That is, regions with larger populations can be expected to have better access to well-connected air service. There are several reasons for this relationship; larger regions may have more demand for air transportation, leading to better service or more destinations. Higher populations may also signal a larger base of economic

[4] Population estimates were not available for four PSAs in Puerto Rico.

activity in that region; this could also cause better connected air service to be scheduled to that region to take advantage of the strong local economy.

Note also from Table 4 that geographic regions of different sizes felt the effects of airline capacity discipline in diverse ways. Very large regions of over 5 million residents saw their average Air Service Accessibility Index score decrease by 10.2% from 2007-2012. While this is a significant decline, it is less than the average decline of 11.6% for all regions smover the same period. Medium-sized regions with populations of 0.5 million - 5 million felt the biggest brunt of the decline in service at medium-sized U.S. airports. These regions lost about 14.3% of their air service accessibility, on average, from 2007-2012.

It may be surprising that the very smallest regions, particularly those of less than 100,000 people, were the only regions to see a net increase in their air service accessibility over this period. Note that these regions started with a baseline of very little service, and have been the target of several government subsidy programs (the Essential Air Service program and the Small Community Air Service Development Grant program) which were intended to increase the amount of air service to small communities by subsidizing the carriers that provided this service. These programs seem to have worked effectively; many small regions saw a dramatic increase in their air service accessibility form 2007-2012. However, the large increase in accessibility in some small regions can all mask other regions of this size that lost significant amounts of accessibility over the same period as carriers discontinued some or all commercial air service.

5. Conclusions and Future Work

This paper introduced two main contributions to the air service accessibility literature: a definition of airport catchment areas based on U.S. Census Bureau Primary Statistical Areas (PSAs), and an accessibility model that aims to measure the level of accessibility to commercial air transportation in each of these geographic regions. The PSA-based catchment area definition offers an improvement over traditional distance-based catchment area definitions because it does not rely on an arbitrary assignment of a distance-based radius. The heterogeneously defined PSAs reflect local knowledge about the commuting patterns of area residents and can cross political borders.

However, it is worthwhile to identify some caveats with this approach, such as the performance of the catchment area definition on the borders of the Primary Statistical Areas. This definition may exclude residents in a nearby community from having “access” to an airport, solely due to the definition of the PSA. Additionally, residents in all areas of the PSA are assumed to have equal access to all airports within the PSA. This assumption could be further refined by a decaying “travel function” for computing accessibility *within* each PSA. Finally, it may be the case that the PSA definition is still not large enough to model the draw of extremely well-connected airports to regions that are two or three hours away. Residents in regions with poor accessibility may drive to a nearby PSA with better air service accessibility, which would increase the size of the catchment area of these larger airports (Fournier et al. 2007).

After 462 primary commercial service airports were mapped into 323 U.S. PSAs, an accessibility index model based on the quantity and quality of available service from a region was used to compute a measure of air service accessibility for each PSA. As opposed to other connectivity and accessibility models that compare service on an airport-to-airport basis, our model considers service on a region-to-region basis, such that flights from BOS-ORD and MHT-MDW would both be considered as service from the "Boston area" to the "Chicago area."

We computed air service accessibility for each of the 323 PSAs with at least one airport on a yearly basis from 2007-2012. We found that, on average, U.S. regions lost about 11.6% of their accessibility to air service during the study period as airlines consolidated service and restricted the sizes of their networks. In multi-airport regions, losses in service at secondary airports outpaced potential gains at primary airports; many of these regions lost significant amounts of accessibility over the study period. On the other hand, some regions with only one airport, such as Charlotte, NC and Denver, CO, saw gains in accessibility as their region's airports added flights and destinations. In general, mid-sized regions with populations of 0.5 million to 5 million people lost the most accessibility from 2007-2012—an average decline of about 14.3%.

Airport planners, particularly those in multi-airport regions, could use the accessibility model developed in this paper to understand how their region gained or lost access to air transportation during six of the most turbulent years in the domestic airline industry in recent memory. Planners will also want to monitor how future changes to the U.S. domestic airline industry, such as the merger of American Airlines and US Airways, will continue to affect air service accessibility as the combined carrier consolidates its network. Administrators of small community airport subsidy programs may also be interested in examining the general success of smaller regions in gaining accessibility to well-connected air service in our model.

There are many possible extensions to this approach of catchment area definition and accessibility modeling. One attractive area of future research is an examination of the demographic determinants of regional air traffic accessibility. One of the benefits of using U.S. Census areas as the definition of airport catchment areas is that there is a wealth of detailed demographic data that is already aggregated on the PSA level. Future researchers may wish to use these data to explore which characteristics of a region are correlated with better air service accessibility. Additionally, as in Lieshout (2012), future work could consider dynamic changes in catchment areas over time, or the market shares of individual airports *within* each catchment area. In any event, a better understanding of airport catchment areas will help airport officials better measure potential demand within airport regions, and can lead to more accurate fleet and network planning on the behalf of airlines in the future.

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Appendix A – References

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Appendix B – Air Service Accessibility Scores for U.S. Metropolitan Regions

Rank (2012)	Region	Population (2012)	# of Airports	ASAI (2007)	ASAI (2008)	ASAI (2009)	ASAI (2010)	ASAI (2011)	ASAI (2012)	% Change (07-12)
1	New York-Newark, NY-NJ-CT-PA	23,362,099	8	954.38	916.95	861.34	857.01	863.02	841.42	-11.8%
2	Chicago-Naperville, IL-IN-WI	9,899,902	2	874.13	818.41	761.76	794.33	806.33	790.28	-9.6%
3	Atlanta--Athens-Clarke County--Sandy Springs, GA	6,092,295	2	792.74	781.81	782.98	764.01	742.51	745.65	-5.9%
4	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	9,331,587	4	687.20	664.21	651.91	661.06	658.30	633.95	-7.7%
5	Dallas-Fort Worth, TX-OK	7,095,411	2	638.03	611.60	597.72	592.62	582.47	583.57	-8.5%
6	Los Angeles-Long Beach, CA	18,238,998	6	679.01	628.02	560.49	567.83	573.78	576.01	-15.2%
7	San Jose-San Francisco-Oakland, CA	8,370,967	5	527.69	503.50	462.41	455.84	460.32	485.03	-8.1%
8	Charlotte-Concord, NC-SC	2,454,619	1	423.01	430.92	417.87	435.46	447.05	459.14	8.5%
9	Houston-The Woodlands, TX	6,371,677	2	542.66	521.97	482.10	467.46	450.88	450.46	-17.0%
10	Denver-Aurora, CO	3,214,218	1	412.75	410.25	402.30	423.01	423.68	415.68	0.7%
11	Miami-Fort Lauderdale-Port St. Lucie, FL	6,375,434	3	399.60	388.96	360.70	379.87	387.93	377.67	-5.5%
12	Boston-Worcester-Providence, MA-RI-NH-CT	7,991,371	8	454.44	430.85	403.34	409.53	412.15	372.92	-17.9%
13	Detroit-Warren-Ann Arbor, MI	5,311,449	2	401.02	401.22	386.88	398.43	388.18	367.18	-8.4%
14	Philadelphia-Reading-Camden, PA-NJ-DE-MD	7,129,428	2	351.85	346.08	343.94	349.38	345.74	334.00	-5.1%
15	Phoenix-Mesa-Scottsdale, AZ	4,329,534	2	369.41	352.50	327.63	319.67	330.96	329.89	-10.7%
16	Las Vegas-Henderson, NV-AZ	2,247,056	6	378.26	355.37	320.66	305.76	314.19	307.99	-18.6%
17	Minneapolis-St. Paul, MN-WI	3,759,978	1	316.35	309.55	304.41	301.96	298.67	299.99	-5.2%
18	Orlando-Deltona-Daytona Beach, FL	2,920,603	3	336.88	319.24	287.66	289.08	287.98	275.57	-18.2%
19	Seattle-Tacoma, WA	4,399,332	2	276.00	280.76	261.09	257.40	257.21	250.64	-9.2%
20	Cleveland-Akron-Canton, OH	3,497,711	2	246.25	237.94	208.59	204.29	198.51	194.85	-20.9%
21	Salt Lake City-Provo-Orem, UT	2,350,274	2	215.54	206.61	206.07	204.42	195.27	183.30	-15.0%
22	Tampa-St. Petersburg-Clearwater, FL	2,842,878	2	227.83	214.24	184.41	183.15	178.10	174.82	-23.3%
23	San Diego-Carlsbad, CA	3,177,063	2	212.16	207.21	184.61	178.16	172.70	174.67	-17.7%
24	St. Louis-St. Charles-Farmington, MO-IL	2,900,605	1	220.40	213.99	185.30	164.73	164.05	162.83	-26.1%
25	Raleigh-Durham-Chapel Hill, NC	1,998,808	1	188.35	177.13	168.63	163.22	159.09	159.53	-15.3%
26	Portland-Vancouver-Salem, OR-WA	2,992,924	1	179.17	175.77	154.50	153.22	148.02	152.60	-14.8%
27	Nashville-Davidson--Murfreesboro, TN	1,845,235	1	148.94	144.56	140.03	140.11	138.68	142.13	-4.6%
28	Pittsburgh-New Castle-Weirton, PA-OH-WV	2,661,369	2	182.87	157.37	141.34	138.25	141.81	135.73	-25.8%
29	Kansas City-Overland Park-Kansas City, MO-KS	2,376,631	1	156.56	146.65	133.17	133.34	133.75	129.42	-17.3%
30	Cincinnati-Wilmington-Maysville, OH-KY-IN	2,188,001	1	295.51	263.03	203.75	155.24	142.63	128.27	-56.6%
31	Columbus-Marion-Zanesville, OH	2,348,495	1	144.36	135.95	131.48	128.69	130.41	126.12	-12.6%
32	Indianapolis-Carmel-Muncie, IN	2,310,360	1	144.90	146.48	134.20	129.10	123.06	123.87	-14.5%
33	Austin-Round Rock, TX	1,834,303	1	127.55	129.16	114.87	114.91	116.16	120.81	-5.3%
34	Memphis-Forrest City, TN-MS-AR	1,369,548	2	195.59	199.57	186.99	183.08	156.67	118.20	-39.6%
35	New Orleans-Metairie-Hammond, LA-MS	1,452,502	1	109.02	116.54	113.01	115.15	117.04	117.47	7.8%
36	Milwaukee-Racine-Waukesha, WI	2,037,542	1	149.36	143.39	138.84	155.37	137.64	107.41	-28.1%
37	San Antonio-New Braunfels, TX	2,234,003	1	113.59	115.54	108.74	111.00	109.00	106.79	-6.0%

Appendix B (continued) – Air Service Accessibility Scores for U.S. Metropolitan Regions

Rank (2012)	Region	Population (2012)	# of Airports	ASAI (2007)	ASAI (2008)	ASAI (2009)	ASAI (2010)	ASAI (2011)	ASAI (2012)	% Change (07-12)
39	Virginia Beach-Norfolk, VA-NC	1,803,080	2	117.93	114.43	109.92	110.44	106.95	99.46	-15.7%
40	Sacramento-Roseville, CA	2,462,722	1	122.47	114.66	97.09	95.40	96.96	95.66	-21.9%
41	Hartford-West Hartford, CT	1,488,570	1	104.27	98.55	87.91	89.30	95.12	90.26	-13.4%
42	Jacksonville-St. Marys-Palatka, FL-GA	1,502,515	1	107.99	102.22	95.28	97.59	98.38	89.83	-16.8%
43	Richmond, VA	1,231,980	1	96.58	98.31	93.72	90.74	90.52	87.68	-9.2%
44	Kahului-Wailuku-Lahaina, HI	158,316	4	110.32	95.92	93.26	90.81	87.91	86.07	-22.0%
45	Cape Coral-Fort Myers-Naples, FL	977,720	1	96.99	94.44	88.60	90.11	87.73	84.61	-12.8%
46	Louisville/Jefferson County--Elizabethtown--Madison, KY-IN	1,478,637	1	85.77	84.79	81.22	81.58	79.76	79.34	-7.5%
47	San Juan-Carolina, PR	#N/A	2	78.21	76.50	76.87	77.70	73.57	76.96	-1.6%
48	Albuquerque-Santa Fe-Las Vegas, NM	1,162,777	2	90.01	88.30	79.86	81.06	79.47	76.10	-15.5%
49	Rochester-Batavia-Seneca Falls, NY	1,177,566	1	86.65	85.20	81.35	80.06	75.88	75.67	-12.7%
50	Oklahoma City-Shawnee, OK	1,367,325	1	75.73	75.09	69.72	70.92	69.51	72.60	-4.1%
51	Charleston-North Charleston, SC	697,439	1	69.95	72.35	70.35	69.48	73.66	72.20	3.2%
52	Omaha-Council Bluffs-Fremont, NE-IA	922,051	1	75.68	73.49	71.41	72.00	69.42	68.47	-9.5%
53	Syracuse-Auburn, NY	740,486	1	79.17	76.40	72.50	73.15	70.16	68.30	-13.7%
54	Dayton-Springfield-Sidney, OH	1,079,417	1	78.70	77.59	72.07	72.11	69.04	67.48	-14.3%
55	Tulsa-Muskogee-Bartlesville, OK	1,122,259	1	72.70	72.70	66.94	68.83	68.15	66.78	-8.1%
56	Greensboro--Winston-Salem--High Point, NC	1,611,243	1	79.16	76.56	70.86	68.05	65.40	65.98	-16.7%
57	Birmingham-Hoover-Talladega, AL	1,309,818	1	69.37	70.30	68.34	68.70	64.45	64.73	-6.7%
58	Albany-Schenectady, NY	1,170,483	1	78.51	74.13	69.49	67.07	69.94	64.29	-18.1%
59	Hilo, HI	189,191	2	81.20	71.17	73.75	62.31	61.84	63.00	-22.4%
60	Knoxville-Morristown-Sevierville, TN	1,091,370	1	65.94	65.46	66.78	68.06	65.94	62.35	-5.4%
61	Grand Rapids-Wyoming-Muskegon, MI	1,395,128	2	63.24	62.79	60.53	62.31	63.45	61.93	-2.1%
62	Greenville-Spartanburg-Anderson, SC	1,384,996	1	64.63	62.79	57.78	58.04	61.33	60.21	-6.8%
63	Little Rock-North Little Rock, AR	893,610	1	66.23	64.42	66.26	66.68	62.40	60.04	-9.3%
64	Urban Honolulu, HI	976,372	1	64.84	62.56	56.65	59.25	56.69	57.30	-11.6%
65	Portland-Lewiston-South Portland, ME	625,726	1	62.33	62.92	61.05	59.13	59.71	56.56	-9.3%
66	El Paso-Las Cruces, TX-NM	1,045,180	1	54.10	55.61	55.86	58.03	55.95	55.17	2.0%
67	Harrisburg-York-Lebanon, PA	1,228,559	1	56.04	54.06	51.11	54.95	56.71	53.01	-5.4%
68	Fayetteville-Springdale-Rogers, AR-MO	482,200	1	57.21	58.51	54.94	54.75	53.50	52.96	-7.4%
69	Savannah-Hinesville-Statesboro, GA	516,154	1	59.83	59.74	57.39	58.89	56.13	52.75	-11.8%
70	Des Moines-Ames-West Des Moines, IA	742,936	1	58.97	60.16	55.75	52.30	52.78	52.36	-11.2%
71	Tucson-Nogales, AZ	1,039,697	1	67.93	66.32	53.91	54.05	52.18	51.98	-23.5%
72	Madison-Janesville-Beloit, WI	843,793	1	52.78	53.28	48.87	47.57	49.77	49.89	-5.5%
73	Columbia-Orangeburg-Newberry, SC	913,797	1	56.81	58.94	55.98	54.48	51.39	48.80	-14.1%
74	Burlington-South Burlington, VT	213,701	1	59.96	60.67	57.15	52.86	52.38	47.94	-20.0%
75	Pensacola-Ferry Pass-Brent, FL	461,227	1	47.44	45.46	42.41	48.09	47.18	47.70	0.5%
76	Kapaa, HI	68,434	1	15.95	17.79	48.15	42.79	41.79	44.67	180.0%

Appendix B (continued) – Air Service Accessibility Scores for U.S. Metropolitan Regions

Rank (2012)	Region	Population (2012)	# of Airports	ASAI (2007)	ASAI (2008)	ASAI (2009)	ASAI (2010)	ASAI (2011)	ASAI (2012)	% Change (07-12)
77	Lexington-Fayette--Richmond--Frankfort, KY	703,271	1	49.75	49.95	46.75	49.63	49.90	44.62	-10.3%
78	Huntsville-Decatur-Albertville, AL	679,743	1	48.23	49.39	47.64	50.24	48.85	44.54	-7.6%
79	Reno-Carson City-Fernley, NV	587,004	1	63.86	60.51	47.67	50.16	47.35	43.86	-31.3%
80	Jackson-Vicksburg-Brookhaven, MS	669,133	1	54.32	53.20	49.78	48.13	44.89	43.80	-19.4%
81	Wichita-Arkansas City-Winfield, KS	672,393	1	52.35	52.69	48.10	46.35	43.87	42.63	-18.6%
82	Cedar Rapids-Iowa City, IA	419,992	1	43.67	43.76	43.63	34.06	41.28	42.16	-3.5%
83	Colorado Springs, CO	668,353	1	47.56	47.78	44.18	44.43	39.93	40.42	-15.0%
84	Baton Rouge, LA	815,298	1	45.89	45.01	41.16	40.76	40.30	39.47	-14.0%
85	Charleston-Huntington-Ashland, WV-OH-KY	705,264	2	40.67	40.13	38.78	40.21	42.16	38.14	-6.2%
86	Myrtle Beach-Conway, SC-NC	454,731	1	43.12	42.49	41.46	43.49	37.03	37.01	-14.2%
87	Davenport-Moline, IA-IL	474,226	1	40.21	41.31	40.57	38.70	36.74	36.47	-9.3%
88	Asheville-Brevard, NC	465,255	1	33.79	35.24	37.14	41.16	40.26	36.13	6.9%
89	Roanoke, VA	310,118	1	41.61	40.87	37.99	37.56	35.93	36.03	-13.4%
90	Santa Maria-Santa Barbara, CA	431,249	2	47.40	45.01	40.19	37.80	35.48	35.82	-24.4%
91	Crestview-Fort Walton Beach-Destin, FL	247,665	1	35.15	36.90	36.10	36.02	35.32	35.58	1.2%
92	Tallahassee-Bainbridge, FL-GA	402,880	1	38.45	39.45	38.33	37.03	33.55	35.22	-8.4%
93	Shreveport-Bossier City, LA	447,193	1	42.35	42.81	39.27	37.48	35.28	34.62	-18.2%
94	Springfield-Branson, MO	529,141	1	39.96	41.19	38.49	37.79	34.36	33.94	-15.1%
95	Edwards-Glenwood Springs, CO	126,090	2	33.02	34.80	33.01	33.37	32.84	33.68	2.0%
96	Charlottesville, VA	222,860	1	33.97	34.14	32.61	31.63	31.92	32.96	-3.0%
97	Scranton--Wilkes-Barre--Hazleton, PA	563,629	1	29.24	32.51	33.61	31.71	34.37	32.72	11.9%
98	Fort Wayne-Huntington-Auburn, IN	616,785	1	36.99	37.57	33.59	31.67	32.33	32.26	-12.8%
99	Wilmington, NC	263,429	1	30.95	32.29	30.31	31.31	31.91	32.15	3.9%
100	Lafayette-Opelousas-Morgan City, LA	611,774	1	33.16	33.54	32.85	31.09	31.47	32.14	-3.1%
101	Peoria-Canton, IL	417,098	1	32.33	33.53	31.48	24.55	25.87	32.06	-0.9%
102	Fresno-Madera, CA	1,100,113	1	40.84	38.61	35.23	34.60	31.84	31.89	-21.9%
103	Chattanooga-Cleveland-Dalton, TN-GA-AL	936,142	1	30.35	32.38	29.90	30.80	32.09	31.89	5.1%
104	North Port-Sarasota, FL	917,203	2	42.59	43.45	32.54	30.09	29.96	31.74	-25.5%
105	Corpus Christi-Kingsville-Alice, TX	511,319	1	40.56	39.85	33.10	32.95	32.32	31.29	-22.8%
106	Midland-Odessa, TX	295,987	1	30.75	30.70	30.81	31.24	30.34	31.26	1.7%
107	Mobile-Daphne-Fairhope, AL	604,726	1	33.73	35.12	33.92	33.57	32.58	31.14	-7.7%
108	Killeen-Temple, TX	420,375	1	34.84	35.27	34.19	33.99	32.17	30.47	-12.5%
109	Boise City-Mountain Home-Ontario, ID-OR	717,388	1	46.87	46.02	39.09	31.58	31.49	29.60	-36.9%
110	Key West, FL	74,809	1	39.54	36.61	30.10	30.56	28.43	29.50	-25.4%
111	Gulfport-Biloxi-Pascagoula, MS	379,582	1	36.05	38.23	32.66	33.06	31.17	29.49	-18.2%
112	Lubbock-Levelland, TX	320,741	1	33.30	33.11	32.02	30.49	30.13	29.02	-12.9%
113	South Bend-Elkhart-Mishawaka, IN-MI	721,296	1	34.86	35.98	31.89	30.73	29.37	28.44	-18.4%
114	Amarillo-Borger, TX	279,500	1	32.04	31.46	30.11	29.52	28.48	28.39	-11.4%

Appendix B (continued) – Air Service Accessibility Scores for U.S. Metropolitan Regions

Rank (2012)	Region	Population (2012)	# of Airports	ASAI (2007)	ASAI (2008)	ASAI (2009)	ASAI (2010)	ASAI (2011)	ASAI (2012)	% Change (07-12)
115	Vineyard Haven, MA	17,041	1	31.32	31.33	30.75	30.69	33.55	28.30	-9.7%
116	Sioux Falls, SD	237,251	1	25.12	25.08	24.98	28.09	29.43	27.99	11.4%
117	Brownsville-Harlingen-Raymondville, TX	437,615	2	30.98	30.96	30.69	30.24	29.89	27.98	-9.7%
118	Bangor, ME	153,746	1	35.69	32.77	30.93	28.13	29.03	27.75	-22.2%
119	Evansville, IN-KY	313,433	1	30.71	31.42	28.24	26.53	28.61	27.62	-10.1%
120	Alexandria, LA	154,441	1	28.85	29.12	28.27	27.41	27.73	26.78	-7.2%
121	McAllen-Edinburg, TX	868,167	1	32.75	29.47	22.33	21.64	27.08	26.49	-19.1%
122	Traverse City, MI	145,283	1	28.81	25.43	28.36	28.01	26.13	26.20	-9.1%
123	Bloomington-Pontiac, IL	227,362	1	32.28	32.77	30.30	29.75	29.11	26.09	-19.2%
124	Augusta-Richmond County, GA-SC	575,898	1	24.89	26.00	27.17	29.41	30.12	25.65	3.1%
125	Fayetteville-Lumberton-Laurinburg, NC	546,175	1	21.45	22.31	23.39	25.42	26.43	25.62	19.5%
126	Gainesville-Lake City, FL	336,198	1	23.77	23.25	21.37	23.11	23.90	25.62	7.8%
127	Montgomery, AL	377,149	1	26.32	26.94	24.57	25.23	26.12	25.59	-2.8%
128	Appleton-Oshkosh-Neenah, WI	397,244	1	32.93	31.67	28.95	28.58	26.99	25.57	-22.4%
129	Anchorage, AK	392,535	1	31.39	32.53	28.26	30.64	27.53	25.03	-20.2%
130	Green Bay-Shawano, WI	357,045	1	35.28	34.96	26.39	26.72	28.81	24.52	-30.5%
131	Monroe-Ruston-Bastrop, LA	252,294	1	28.21	27.70	26.16	25.77	25.70	24.49	-13.2%
132	Ithaca-Cortland, NY	152,028	1	26.27	26.60	27.21	26.60	25.88	24.32	-7.4%
133	Jackson, WY-ID	31,727	1	21.24	23.10	22.23	21.23	20.55	24.18	13.9%
134	Bozeman, MT	92,614	2	22.21	24.13	22.38	22.88	21.59	23.92	7.7%
135	State College-DuBois, PA	236,355	1	27.27	27.66	23.61	23.35	27.28	23.28	-14.7%
136	Spokane-Spokane Valley-Coeur d'Alene, WA-ID	674,610	1	29.79	29.62	23.49	26.99	23.26	23.08	-22.5%
137	Montrose, CO	40,725	1	24.44	25.36	24.57	24.40	24.22	22.29	-8.8%
138	Johnson City-Kingsport-Bristol, TN-VA	509,690	1	23.86	25.05	25.07	24.72	25.10	21.89	-8.3%
139	Elmira-Corning, NY	187,974	1	19.64	18.79	18.04	17.08	18.58	21.80	11.0%
140	Salinas, CA	426,762	1	28.62	26.88	23.46	22.07	21.33	21.68	-24.3%
141	Steamboat Springs-Craig, CO	36,534	1	25.10	26.11	25.16	25.17	22.35	21.64	-13.8%
142	Rapid City-Spearfish, SD	163,135	1	14.23	13.93	13.63	18.15	18.09	21.05	47.9%
143	Binghamton, NY	248,538	1	28.98	22.26	22.25	21.69	21.73	20.39	-29.6%
144	Bakersfield, CA	856,158	1	22.69	15.95	14.57	14.52	13.65	20.19	-11.0%
145	Jacksonville, NC	183,263	1	18.73	19.56	19.69	18.90	18.81	20.13	7.5%
146	Columbus-Auburn-Opelika, GA-AL	491,852	1	17.34	18.78	18.16	18.94	20.44	19.46	12.2%
147	College Station-Bryan, TX	234,501	1	22.19	21.40	20.10	20.38	20.44	19.20	-13.5%
148	Fargo-Wahpeton, ND-MN	239,114	1	16.58	16.56	16.46	19.42	19.00	19.12	15.4%
149	Tyler-Jacksonville, TX	266,027	1	20.73	20.86	19.83	19.65	19.53	19.07	-8.0%
150	Fort Smith, AR-OK	280,521	1	21.35	22.88	20.90	13.25	12.90	19.04	-10.8%
151	Lansing-East Lansing-Owosso, MI	534,964	1	28.29	20.60	19.69	20.30	19.54	18.50	-34.6%
152	Laredo, TX	259,172	1	19.20	18.80	18.19	18.63	18.74	18.28	-4.8%

Appendix B (continued) – Air Service Accessibility Scores for U.S. Metropolitan Regions

Rank (2012)	Region	Population (2012)	# of Airports	ASAI (2007)	ASAI (2008)	ASAI (2009)	ASAI (2010)	ASAI (2011)	ASAI (2012)	% Change (07-12)
153	Fairbanks, AK	100,272	1	20.70	23.59	18.09	17.99	18.48	18.17	-12.2%
154	Kalamazoo-Battle Creek-Portage, MI	525,929	1	31.57	24.42	19.28	20.33	19.56	18.00	-43.0%
155	Saginaw-Midland-Bay City, MI	389,110	1	20.48	20.16	24.72	19.97	18.64	17.99	-12.1%
156	San Luis Obispo-Paso Robles-Arroyo Grande, CA	274,804	1	25.26	22.34	16.97	18.51	18.39	17.97	-28.8%
157	Lake Charles, LA	201,195	1	16.24	16.76	18.08	18.91	19.55	17.97	10.7%
158	Grand Junction, CO	147,848	1	8.79	13.68	14.05	13.82	18.45	17.95	104.3%
159	Aguadilla-Isabela, PR	#N/A	1	21.42	19.29	19.31	19.31	18.21	17.83	-16.7%
160	Waco, TX	256,317	1	21.02	20.33	18.47	18.53	18.47	17.56	-16.5%
161	Wausau-Stevens Point-Wisconsin Rapids, WI	307,984	1	19.27	21.30	21.52	21.23	18.14	17.39	-9.8%
162	Springfield-Jacksonville-Lincoln, IL	317,206	1	16.28	16.10	15.15	15.49	17.29	16.80	3.2%
163	Palm Bay-Melbourne-Titusville, FL	547,307	1	22.53	22.91	19.31	19.13	17.72	16.66	-26.0%
164	Kalispell, MT	91,633	1	18.74	20.20	18.84	18.52	17.17	16.40	-12.5%
165	Medford-Grants Pass, OR	289,342	1	21.75	20.45	17.14	17.14	16.20	16.32	-25.0%
166	New Bern-Morehead City, NC	195,751	1	17.10	18.81	18.00	17.53	16.78	16.30	-4.7%
167	Eugene, OR	354,542	1	20.85	19.48	16.10	16.14	15.84	16.17	-22.5%
168	Champaign-Urbana, IL	233,788	1	19.49	19.50	17.87	17.08	15.99	15.83	-18.8%
169	Dothan-Enterprise-Ozark, AL	249,316	1	18.00	18.56	17.77	17.12	16.51	15.63	-13.1%
170	Erie-Meadville, PA	368,244	1	24.56	17.77	17.45	16.50	16.11	15.61	-36.5%
171	Duluth, MN-WI	279,452	2	11.52	11.42	13.94	15.82	15.18	14.90	29.4%
172	Abilene, TX	166,963	1	21.15	20.09	14.03	14.43	15.02	14.88	-29.6%
173	Valdosta, GA	144,343	1	16.41	17.30	16.84	16.16	15.78	14.76	-10.1%
174	Columbus, MS	59,670	1	16.28	17.38	16.35	15.63	15.27	14.69	-9.8%
175	Albany, GA	157,399	1	17.11	17.73	16.71	16.12	15.68	14.66	-14.3%
176	Brunswick, GA	113,448	1	16.24	17.27	16.60	16.05	15.62	14.54	-10.4%
177	Manhattan-Junction City, KS	135,823	1	1.43	1.48	8.53	11.72	13.69	14.42	911.4%
178	Meridian, MS	107,111	1	15.38	16.58	15.81	15.16	14.82	13.84	-10.0%
179	Lincoln-Beatrice, NE	332,148	1	17.26	16.97	22.44	14.78	13.68	13.69	-20.7%
180	La Crosse-Onalaska, WI-MN	135,298	1	13.06	13.37	14.71	15.45	14.88	13.64	4.4%
181	Lawton, OK	132,545	1	13.61	23.08	20.34	13.37	12.98	13.34	-2.0%
182	Missoula, MT	110,977	1	13.86	14.51	13.17	14.11	12.73	13.32	-4.0%
183	Billings, MT	162,848	1	15.21	14.81	20.91	14.23	12.93	13.26	-12.8%
184	Columbia-Moberly-Mexico, MO	219,486	1	1.62	3.89	3.82	3.60	3.40	13.13	709.6%
185	Salisbury, MD-DE	381,868	1	14.20	15.83	15.87	12.99	13.07	12.83	-9.7%
186	Florence-Muscle Shoals, AL	146,988	1	3.32	3.50	15.05	15.30	14.40	12.77	285.0%
187	Del Rio, TX	48,705	1	13.31	13.50	12.53	12.65	12.79	12.72	-4.4%
188	Beaumont-Port Arthur, TX	404,180	1	15.26	15.60	15.05	15.03	15.14	12.66	-17.0%
189	Rochester-Austin, MN	248,979	1	17.65	17.93	16.61	16.25	15.16	12.52	-29.1%
190	Durango, CO	52,401	1	7.49	8.34	8.27	8.30	11.93	12.32	64.4%

Appendix B (continued) – Air Service Accessibility Scores for U.S. Metropolitan Regions

Rank (2012)	Region	Population (2012)	# of Airports	ASAI (2007)	ASAI (2008)	ASAI (2009)	ASAI (2010)	ASAI (2011)	ASAI (2012)	% Change (07-12)
191	Kennewick-Richland, WA	268,243	1	8.37	8.71	12.20	13.22	12.34	12.24	46.1%
192	San Angelo, TX	114,854	1	18.26	17.29	11.84	12.54	11.86	12.10	-33.7%
193	Eureka-Arcata-Fortuna, CA	134,827	1	14.73	15.03	13.26	12.98	12.22	12.02	-18.4%
194	Victoria-Port Lavaca, TX	118,229	1	12.62	12.99	12.47	12.53	12.67	12.00	-4.9%
195	Bismarck, ND	120,060	1	8.39	8.59	12.38	13.14	11.97	11.85	41.2%
196	Wichita Falls, TX	150,829	1	13.56	13.27	11.09	12.18	11.62	11.75	-13.3%
197	Bend-Redmond-Prineville, OR	183,006	1	15.30	14.97	13.12	12.66	11.68	11.57	-24.4%
198	Hilton Head Island-Bluffton-Beaufort, SC	193,882	1	17.92	18.48	18.56	18.64	11.44	11.29	-37.0%
199	Yuma, AZ	200,022	1	12.50	12.93	11.63	12.49	12.39	11.27	-9.9%
200	Texarkana, TX-AR	149,701	1	16.29	16.23	10.91	11.54	11.19	11.10	-31.8%
201	Roswell, NM	65,784	1	8.18	10.13	11.13	11.55	11.69	11.07	35.2%
202	Harrisonburg-Staunton-Waynesboro, VA	247,058	1	9.36	9.64	9.71	10.04	10.24	10.51	12.3%
203	Houghton, MI	38,735	1	6.46	6.72	6.50	11.39	10.07	10.34	60.1%
204	Paducah-Mayfield, KY-IL	136,083	1	3.77	3.96	3.76	10.85	10.07	10.33	173.8%
205	Eau Claire-Menomonie, WI	207,671	1	6.80	6.92	6.51	11.39	10.07	10.33	51.8%
206	Grand Island, NE	83,472	1	1.15	1.03	0.89	1.16	9.67	10.24	787.6%
207	Joplin-Miami, MO-OK	206,563	1	2.07	1.42	0.60	0.58	10.05	10.21	392.9%
208	Longview-Marshall, TX	284,129	1	10.21	10.17	9.18	9.59	10.15	10.07	-1.4%
209	Garden City, KS	41,168	1	1.65	0.78	0.68	0.83	0.96	9.94	503.8%
210	Marquette, MI	67,906	1	14.51	14.22	13.68	11.91	11.66	9.80	-32.5%
211	Williamsport-Lock Haven, PA	156,685	1	11.78	11.34	10.22	9.53	9.64	9.69	-17.7%
212	Johnstown-Somerset, PA	218,541	1	2.73	7.98	8.11	9.10	9.50	9.68	254.2%
213	Toledo-Port Clinton, OH	650,050	1	26.55	25.18	14.91	14.71	10.40	9.57	-63.9%
214	Cheyenne, WY	94,483	1	1.46	1.28	0.97	9.39	10.30	9.49	549.5%
215	Clarksburg, WV	94,310	1	3.54	7.83	7.99	8.47	8.85	9.34	163.6%
216	Morgantown-Fairmont, WV	190,842	1	3.69	8.71	8.80	9.05	9.08	9.08	145.9%
217	Plattsburgh, NY	81,654	1	5.32	4.78	3.98	7.35	9.58	9.02	69.4%
218	Redding-Red Bluff, CA	241,992	1	11.65	11.61	10.86	11.24	10.19	8.90	-23.6%
219	Idaho Falls-Rexburg-Blackfoot, ID	231,995	1	8.76	9.31	8.76	6.70	8.52	8.85	1.0%
220	Modesto-Merced, CA	784,031	2	16.98	14.52	10.56	10.33	8.99	8.82	-48.1%
221	Alpena, MI	29,234	1	8.12	8.26	8.26	8.29	8.49	8.81	8.4%
222	Altoona, PA	127,121	1	9.22	9.15	8.67	8.41	8.42	8.75	-5.0%
223	Sioux City-Vermillion, IA-SD-NE	183,052	1	7.17	7.58	6.79	6.40	6.08	8.64	20.4%
224	Waterloo-Cedar Falls, IA	168,747	1	6.61	6.88	6.55	6.39	6.07	8.64	30.7%
225	Beckley, WV	124,890	1	8.50	8.00	7.27	8.18	8.38	8.46	-0.5%
226	Dubuque, IA	95,097	1	9.74	11.80	10.45	8.44	9.00	8.36	-14.3%
227	Minot, ND	73,146	1	6.46	6.72	6.58	7.68	7.47	8.34	29.1%
228	Chico, CA	221,539	1	8.79	9.10	8.67	8.84	8.51	8.23	-6.4%

Appendix B (continued) – Air Service Accessibility Scores for U.S. Metropolitan Regions

Rank (2012)	Region	Population (2012)	# of Airports	ASAI (2007)	ASAI (2008)	ASAI (2009)	ASAI (2010)	ASAI (2011)	ASAI (2012)	% Change (07-12)
229	Great Falls, MT	81,723	1	8.66	12.37	8.56	8.33	7.87	8.16	-5.8%
230	Sault Ste. Marie, MI	38,917	1	6.80	7.27	7.27	8.02	8.51	7.90	16.2%
231	Escanaba, MI	36,884	1	2.35	6.91	7.28	7.68	8.54	7.85	234.3%
232	Lynchburg, VA	255,342	1	16.86	17.23	17.28	16.92	14.24	7.81	-53.7%
233	Florence, SC	206,087	1	16.37	17.40	17.28	17.18	14.32	7.81	-52.3%
234	St. George, UT	144,809	1	11.63	11.18	9.58	4.99	7.64	7.80	-32.9%
235	Bellingham, WA	205,262	1	6.38	6.62	5.44	5.93	6.21	7.70	20.8%
236	Greenville-Washington, NC	220,061	1	6.63	6.83	6.95	7.46	7.70	7.62	15.0%
237	Helena, MT	76,277	1	7.85	8.77	8.39	8.08	7.50	7.53	-4.0%
238	Grand Forks, ND-MN	98,888	1	6.80	7.11	7.01	7.18	7.18	7.49	10.1%
239	El Centro, CA	176,948	1	8.69	8.53	7.53	6.72	7.21	7.35	-15.4%
240	Coos Bay, OR	62,534	1	1.80	6.89	7.19	7.59	7.18	7.30	305.4%
241	Watertown-Fort Drum, NY	120,262	1	5.87	2.65	0.63	0.63	6.49	7.29	24.2%
242	Crescent City, CA	28,290	1	6.94	7.22	6.76	6.94	6.58	6.62	-4.5%
243	Claremont-Lebanon, NH-VT	217,390	1	17.43	17.49	5.83	6.16	6.12	6.29	-63.9%
244	Mason City, IA	51,307	1	6.40	6.66	6.44	6.35	6.02	6.21	-3.0%
245	Klamath Falls, OR	65,912	1	1.68	6.80	7.23	7.34	6.86	6.14	266.5%
246	Flagstaff, AZ	136,011	3	6.53	6.93	6.77	6.11	6.31	6.10	-6.5%
247	Watertown, SD	27,606	1	6.27	6.53	6.32	6.22	5.98	6.09	-3.0%
248	Pierre, SD	21,846	1	0.48	6.50	6.17	6.34	6.25	6.08	1161.8%
249	Aberdeen, SD	41,357	1	6.69	6.94	6.61	6.32	6.09	5.95	-11.1%
250	Bemidji, MN	45,375	1	6.64	6.88	6.63	6.50	6.02	5.94	-10.5%
251	Brainerd, MN	91,239	1	6.55	6.74	6.48	6.30	6.01	5.92	-9.7%
252	Casper, WY	78,621	1	8.81	12.08	8.01	6.30	5.87	5.85	-33.6%
253	Hailey, ID	27,500	1	7.37	7.37	6.23	6.25	6.04	5.67	-23.1%
254	Iron Mountain, MI-WI	30,702	1	2.39	6.34	6.11	6.03	5.79	5.61	134.8%
255	Rock Springs, WY	45,267	1	0.99	6.12	6.13	6.03	5.64	5.55	460.3%
256	Gillette, WY	47,874	1	1.02	6.30	6.35	6.24	5.81	5.47	438.5%
257	Ponce-Coamo-Santa Isabel, PR	#N/A	1	20.49	17.13	4.65	4.84	5.34	5.30	-74.1%
258	Laramie, WY	37,276	1	0.65	0.64	0.61	0.61	0.62	4.85	649.0%
259	Lancaster, PA	526,823	1	2.41	0.00	3.88	5.01	5.00	4.51	86.7%
260	Lewiston, ID-WA	61,419	1	5.34	5.25	4.76	4.73	4.47	4.35	-18.5%
261	Twin Falls, ID	101,094	1	5.10	4.86	4.57	4.62	4.17	3.87	-24.1%
262	Juneau, AK	32,556	1	3.78	3.98	3.78	3.78	3.67	3.85	1.9%
263	Ketchikan, AK	13,779	1	3.54	3.77	3.82	3.80	3.69	3.83	8.2%
264	Rockford-Freeport-Rochelle, IL	445,816	1	4.94	5.01	1.11	1.26	3.81	3.80	-22.9%
265	Yakima, WA	246,977	1	5.68	5.52	3.55	3.44	3.25	3.75	-34.0%
266	Macon-Warner Robins, GA	418,201	1	16.24	18.69	5.03	3.74	3.74	3.71	-77.1%

Appendix B (continued) – Air Service Accessibility Scores for U.S. Metropolitan Regions

Rank (2012)	Region	Population (2012)	# of Airports	ASAI (2007)	ASAI (2008)	ASAI (2009)	ASAI (2010)	ASAI (2011)	ASAI (2012)	% Change (07-12)
267	Elko, NV	53,217	1	5.00	4.85	4.55	4.45	3.98	3.67	-26.7%
268	Malone, NY	51,795	1	5.38	4.35	2.92	3.16	3.30	3.56	-34.0%
269	Butte-Silver Bow, MT	34,403	1	4.68	4.36	4.13	4.11	3.59	3.50	-25.2%
270	Cedar City, UT	46,750	1	5.71	5.52	4.09	4.00	3.58	3.47	-39.3%
271	Tupelo, MS	138,976	1	15.79	15.38	14.88	14.32	3.28	3.44	-78.2%
272	Wenatchee, WA	113,037	1	3.50	3.59	3.43	3.37	3.24	3.43	-1.9%
273	Parkersburg-Marietta-Vienna, WV-OH	154,023	1	3.85	9.17	8.81	9.00	3.71	3.41	-11.5%
274	Pullman-Moscow, WA-ID	84,790	1	2.94	3.12	3.11	3.14	3.12	3.37	14.6%
275	Rutland, VT	60,869	1	4.73	2.94	2.92	3.01	3.30	3.32	-30.0%
276	Walla Walla, WA	63,399	1	3.17	3.34	3.18	3.16	3.04	3.20	1.0%
277	Laurel, MS	85,164	1	3.57	3.76	3.64	3.42	3.25	3.14	-11.9%
278	Decatur, IL	110,122	1	3.65	0.55	0.55	2.87	3.22	3.11	-14.7%
279	Jamestown-Dunkirk-Fredonia, NY	133,539	1	2.22	8.15	3.50	3.37	3.40	3.09	39.0%
280	Oil City, PA	54,272	1	2.38	3.91	3.46	3.34	3.37	3.06	28.8%
281	Augusta-Waterville, ME	121,853	1	5.78	4.67	5.65	5.77	3.44	2.92	-49.5%
282	Greenville, MS	49,750	1	3.57	3.75	3.64	3.42	3.25	2.90	-18.7%
283	Bradford, PA	43,127	1	2.42	8.83	3.26	3.13	3.16	2.87	18.2%
284	Burlington, IA-IL	47,383	1	2.33	0.54	0.51	1.89	2.14	2.17	-7.0%
285	Visalia-Porterville-Hanford, CA	603,341	1	4.33	4.12	2.62	1.84	1.97	2.10	-51.4%
286	Prescott, AZ	212,637	1	6.14	6.24	4.67	3.44	1.71	1.95	-68.2%
287	El Dorado, AR	40,867	1	1.73	0.86	0.10	0.53	0.91	1.91	10.3%
288	Owensboro, KY	116,030	1	4.60	3.97	0.84	1.23	1.57	1.54	-66.5%
289	Farmington, NM	128,529	1	5.74	5.22	0.94	1.25	1.39	1.15	-80.0%
290	Quincy-Hannibal, IL-MO	116,393	1	3.54	0.58	0.65	1.09	1.09	1.09	-69.0%
291	Carbondale-Marion, IL	126,745	1	2.32	0.58	0.67	1.09	1.09	1.08	-53.2%
292	Hot Springs-Malvern, AR	130,297	1	1.84	0.88	0.10	0.53	1.14	1.08	-41.4%
293	Pueblo-Cañon City, CO	207,640	1	0.42	0.44	0.54	1.08	1.26	1.07	156.0%
294	Dickinson, ND	26,771	1	0.61	0.64	0.66	0.66	0.76	0.93	52.0%
295	Fort Leonard Wood, MO	53,259	1	2.28	0.69	0.81	0.57	0.85	0.87	-61.6%
296	Harrison, AR	45,413	1	0.36	0.31	0.10	0.60	0.85	0.86	134.8%
297	Hays, KS	29,053	1	1.49	0.76	0.82	0.82	0.82	0.85	-42.8%
298	Jackson, TN	130,450	1	4.60	3.97	0.35	0.70	0.70	0.82	-82.2%
299	Ogdensburg-Massena, NY	112,232	2	0.24	0.45	0.63	0.63	0.76	0.75	215.8%
300	Youngstown-Warren, OH-PA	664,713	1	0.37	0.49	0.52	0.55	0.55	0.73	95.1%
301	Cape Girardeau-Sikeston, MO-IL	136,219	1	4.68	4.22	0.45	0.73	0.73	0.73	-84.5%
302	Scottsbluff, NE	39,039	1	0.65	0.67	0.65	0.69	0.66	0.70	8.7%
303	Sheridan, WY	29,596	1	1.15	0.77	0.67	0.78	0.76	0.69	-40.2%
304	Hermiston-Pendleton, OR	88,064	1	1.30	1.26	0.56	0.64	0.69	0.69	-47.4%

Appendix B (continued) – Air Service Accessibility Scores for U.S. Metropolitan Regions

Rank (2012)	Region	Population (2012)	# of Airports	ASAI (2007)	ASAI (2008)	ASAI (2009)	ASAI (2010)	ASAI (2011)	ASAI (2012)	% Change (07-12)
305	Riverton, WY	41,110	1	0.70	0.79	0.64	0.67	0.72	0.68	-3.8%
306	Kearney, NE	53,948	1	0.63	0.63	0.61	0.60	0.60	0.64	2.3%
307	Kirksville, MO	29,951	1	1.42	1.05	0.07	0.40	0.64	0.63	-55.3%
308	Port Angeles, WA	71,863	1	1.96	1.86	1.46	0.79	0.96	0.63	-67.9%
309	North Platte, NE	37,373	1	0.65	0.65	0.61	0.60	0.60	0.62	-4.3%
310	Show Low, AZ	107,094	1	0.54	0.49	0.48	0.42	0.62	0.59	9.2%
311	Dodge City, KS	34,752	1	1.47	0.48	0.43	0.57	0.43	0.57	-61.1%
312	Jonesboro-Paragould, AR	167,205	1	0.14	0.13	0.10	0.53	0.54	0.55	285.6%
313	Salina, KS	62,060	1	1.10	1.43	0.52	0.51	0.54	0.54	-50.5%
314	Fort Collins, CO	310,487	1	0.63	0.45	0.46	0.60	0.67	0.51	-18.4%
315	Vernal, UT	34,524	1	1.06	1.13	0.40	0.39	0.41	0.47	-56.3%
316	Silver City, NM	29,388	1	0.39	0.39	0.36	0.36	0.36	0.44	14.5%
317	Liberal, KS	23,547	1	0.35	0.47	0.44	0.60	0.55	0.43	23.0%
318	Mayagüez-San Germán, PR	#N/A	1	0.30	0.18	0.17	0.30	0.42	0.42	40.7%
319	Clovis-Portales, NM	70,357	1	0.40	0.39	0.36	0.36	0.36	0.39	-2.4%
320	Carlsbad-Artesia, NM	54,419	1	0.25	0.45	0.69	0.41	0.39	0.37	48.4%
321	Huron, SD	17,753	1	0.38	0.04	0.05	0.05	0.05	0.31	-19.3%
322	Great Bend, KS	27,557	1	1.11	0.44	0.29	0.07	0.07	0.05	-96.0%
323	Topeka, KS	234,566	1	0.54	0.00	0.00	0.00	0.00	0.00	-100.0%