Spatial competition in airport markets: An application of the Huff model

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SPATIAL COMPETITION IN AIRPORT MARKETS:

AN APPLICATION OF THE HUFF MODEL

An Abstract of Thesis

Submitted

In Partial Fulfillment

of the Requirements for the Degree

Master of Arts

Joel Heilman

University of Northern Iowa

December 2017
ABSTRACT

Airports typically attract travelers from the immediate vicinity, but travelers may be willing to travel farther for better fares and more frequent flights. This study attempts to map the spatial variation of airport catchment areas using the Huff model. This model, originally designed to analyze retail store competition, can be applied to many forms of spatial competition, but it is a relatively unexplored approach in the context of airports. Unlike other air transportation travel choice models, it emphasizes spatial variation in market share and provides spatial representation in the form of a map. It is used in this study to analyze spatial variation in behavior choice patterns. County-level data on Iowa license plates were collected in parking lots at nine different airports to calibrate the model and approximate airport catchment areas in Iowa.
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Entitled: Spatial Competition in Airport Markets: An Application of the Huff Model

Has been approved as meeting the thesis requirement for the

Degree of Master of Arts

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Attraction of activity from surrounding areas is important for the health of airports, and the vitality of an airport is important to the economic development of a community. Proximity to airports has been shown to promote growth and development (Chi, 2012). Easy access to quality air service encourages firms to move to those areas, increasing job opportunities and population.

Revenue passenger miles in the US tripled between 1980 and 2010 (Appold & Kasarda, 2013). Many tourist destinations could not exist as we know them without the large airline system we have today, and yet 40 percent of US air travel is business related (Appold & Kasarda, 2013). It is hard to tell if this rapid growth will continue for decades to come. The decline of railways and ports are testament to the ever changing world of technological innovation (Knippenberger, 2010). Such transportation networks bolstered economies and grew metropolises from nothing. Airports can offer similar potential for growth (Florida, Mellander, & Holgersson, 2015; Percoco, 2010).

The growth in the airport system has been uneven. Airports have a complex relationship with each other. They cooperate by offering flights between each other, and generating traffic for connecting flights, creating a network of flight patterns. They also compete with nearby airports for a customer’s airport choice of origin and destination. Customers are willing to drive farther to larger airports than smaller airports. Smaller
airports struggle to offer viable service. In the United States, some small airports receive subsidies through a program called the Essential Air Service. There has been much debate whether this is the best use of federal funds (Grubesic, Murray, & Maticziw, 2013).

Much of the current research on airport choice focuses on non-spatial discrete choice methodologies, typically for large multi-airport metropolitan areas (Cho, Windle, & Dresner, 2015; Hess & Polak, 2006; Fuellhart, O’Connor, & Woltemade, 2013; Marcucci & Gatta, 2011; Pels, Nijkamp, & Rietveld, 2000; Pels, Nijkamp, & Rietveld, 2001). Several of these studies use access time as a factor and look at whether this variable is statistically significant (Cho et al., 2015; Hess & Polak, 2006; Pels et al., 2000; Pels et al., 2001). The studies do not attempt to map this spatial variation. The current study will use a larger study area to look at spatial competition between airports, and how that competition changes across space. The goal is to determine which airports people go to, based on where they live.

As distance increases to an airport, the less willing people are to travel the distance to it. Airports will typically attract customers from the immediate area, but how far this catchment reaches depends on several factors that affect the perceived attractiveness of airports. This study attempts to understand this phenomenon through the creation and calibration of a Huff model to map these patterns. The Huff model is a relatively unexplored approach in the context of airports. Originally designed to model retail store competition, it can be applied to many forms of spatial competition. Unlike other models, it emphasizes spatial variation, and provides a visual in the form of a map.
The versatility allows a calibrated model to theoretically be applied anywhere in the world. It allows us to see how behavior choice patterns change over space and gives new perspective for analyzing traveler patterns to small airports that often rely on public subsidies, such as the Essential Air Service.

This study has three objectives:

- Create a Huff model of airport catchment areas calibrated with observed data.
- Assess the effectiveness of applying the Huff model to the context of airports.
- Assess the effectiveness of Essential Air Service airports.

The following chapters highlight literature related to the commercial airport system, the Huff model, and airport choice methodologies; outline the methods of applying and calibrating the Huff model to airport choice; present the results of the model; and discuss the implications of the results.
CHAPTER 2
LITERATURE REVIEW

2.1 Airports and the Economy

The economic importance of airports has been studied in a variety of ways. Florida et al. (2015) found that population size is the most important factor in determining if a city has an airport. They also found that airports tend to be in cities with higher shares of cultural workers and that experience warmer winters. This is likely due to the fact that these types of cities generate more tourism. High-tech industry, human capital, and unemployment were not shown to be statistically significant when explaining the presence of an airport. Most airports were developed long ago and are not as affected by the modern economy. Having an airport is a result of being in a more developed region with a larger population.

Areas around airports are growing faster than other areas of metropolitans. Appold and Kasarda (2013) found that areas around airports increased in employment at over twice the rate of the cities’ respective central business districts. They also found that as growth in passenger travel decreased, so did employment growth near airports.

Chi (2012) examined how population change is affected by airports and highways in Wisconsin. His results show that airport accessibility and highway improvement are related to population change, but this was not the case for highway accessibility and airport improvement. He also found that rural, suburban, and urban areas are affected
differently. In rural areas, highway investment is important and can improve easy access to airports. This leads to employment and population growth. In suburban areas, proximity to an airport is important to promote growth. People living in suburbs tend to be well educated and have higher incomes. These people tend to travel more for leisure and business, so access to an airport is crucial. Highway accessibility is actually negatively associated with population growth in suburban areas. Highways promote flow, not only in, but also out. In urban areas, highway and airport accessibility are not statistically significant in explaining population growth.

Determining the indicators of economic growth can be difficult, it is particularly problematic to separate how air service promotes economic growth from how, conversely, economic growth increases demand for air service. Even after controlling for factors such as population size, studies show that airports increase economic growth (Florida et al., 2015; Percoco, 2010).

There is often a missing link between airports and city planning. This missing link is due to different planning jurisdictions, whether it be different sectors of planning or different scales of planning: national, regional, or local (Knippenberger, 2010). The potential relationship between airport and region can be seen in Luxembourg. Luxembourg Airport is Europe’s fifth largest cargo airport and has attracted many firms that are involved in global air cargo supply (Knippenberger, 2010). Luxembourg has implemented a clear governmental strategy to encourage investment from the logistics sector through tax incentives. The government has been able to effectively use the airport to promote economic growth in the region.
In areas where demand is high, expansion of airports should increase jobs. The mayor of Chicago and the governor of Illinois called for plans that double the flight capacity of Chicago O’Hare Airport. If capacity remained constrained after expansion of the airport, traffic would double. Brueckner (2003) found that even if the expansion only created a 50 percent increase in traffic, the metro would gain 185,000 service-related jobs, an increase of five percent. The expansion of a capacity constrained airport represents a powerful force in economic development.

If airports promote growth, should every small community build itself a large airport? Without significant demand, the investment is not always worth the price. “Airports are among the largest investments a city and region can make” (Florida et al. 2015). While airports are often under the jurisdiction of a local government, the benefits are felt by the whole region (Green, 2007). Networking between airports and their hinterlands can be powerful in fostering an airport’s success (Knippenberger, 2010). This indicates that it may be better for regional entities to control airport policy; however, the negatives are inherently felt more locally. The loss of land and noise disturbance are key arguments for those opposed to airport expansion, and these are only felt by those in the immediate area (Brueckner, 2003). Green (2007) notes that if the regional benefits are large enough, the costs of fair compensation should not be a problem.

Although Brueckner (2003) found a growth in service-related jobs associated with airport expansion, the same was not true for all sectors. He found that airport expansion had no effect on manufacturing and goods-related employment. Sheard (2012) reached a similar conclusion in his paper, finding that an increase in flights actually has a negative
effect on the manufacturing sector, but a positive effect on tradable services (services that can be delivered to remote locations from where they were produced, such as publishing, insurance, and management) and no measurable effect on non-tradable services (services that cannot easily be delivered to remote locations, such as hairdressing, auto repair, and cleaners). Blonigen and Cristea (2012) found that wholesale and retail industries experienced the most significant growth.

These findings suggest that tradable services utilize airlines more than other sectors. People in this sector more commonly travel for business. Venture capitalists prefer investing in places that are a short direct flight away, so they can easily monitor their progress in person (Florida et al., 2015). Increasing face-to-face interaction can greatly improve productivity in the tradable service sector (Percoco, 2010). Moving people rather than goods has a larger effect on economic development (Florida et al. 2015; Green, 2007).

The less obvious negative effect on other industries may be a result of a reduction in availability of factors like land and workers (Sheard, 2012). Lower incomes associated with these sectors may also indicate fewer people traveling for leisure.

2.2 Airport Competition and Leakage

The 1978 Airline Deregulation Act dramatically changed commercial aviation in the United States (Blonigen & Cristea 2012). Prior to deregulation, the airline industry was overseen by the Civil Aeronautics Board (CAB). They controlled everything from flight frequencies to price levels. This made it easy for smaller airports with smaller
markets to be economically viable. After 1978, the free market was allowed to rule. The competition drove down prices and increased efficiency. It also encouraged the introduction of a “hub-and-spoke” system of airports (Phillips, Weatherford, Mason, & Kunce, 2005).

The hub-and-spoke system increases efficiency by increasing the number of passengers per flight, by moving people from a variety of locations to a central hub and then moving them to their destinations. Smaller airports act as spokes that feed into the larger hub airports that then interact with each other. This means that travelers starting at a smaller spoke airport have one more flight than those starting at larger hub airports. This extra flight means higher prices and extra travel time required. Driving to the hub airport is sometimes a more attractive option. This phenomenon of travelers using more distant alternatives to local airports is called airport leakage.

![Figure 1. Point-to-Point and Hub & Spoke architecture (Cook & Goodwin, 2008).](image-url)
Many airports compete to become hubs. These cities get direct flights to a variety of locations. Sometimes it can be advantageous for a medium sized airports to remain “hub-less.” Places like Kansas City are actually benefitting from the fact that no major airline runs a hub there. The airport is less congested and the variety of carriers drives down prices (Hale, 1999). Because there are so many carriers, there are also more direct flight options. Of course, this only works at a larger airport with multiple airlines. Smaller airports often have only one airline and struggle to lower prices.

Small airports have a hard time attracting customers. Passengers tend to favor larger airports over smaller ones, giving larger airports larger catchment areas. Lian and Rønnevik (2011) studied this phenomenon in Norway and found a 50-50 market share split between regional and major airports when the regional airport was four hours closer. This is due to the magnitude of services a larger airport has that a smaller airport cannot afford. Since they generate less traffic, they cannot provide the same level of service as other airports. They generally have higher prices, lower flight frequencies, and fewer destination options. The advantage of small airports to people in the immediate area is their proximity. Customers can choose to use a larger airport with a better level of service, but it may take them longer to reach the airport than it would be for them to use a smaller, local airport. A smaller airport can only be successful in a location that makes them independent from larger airports (Kanafani & Abbas, 1987). It is not surprising that subsidized airports experience more flights per capita as the distance to the nearest hub increases (Grubesic & Wei, 2013).
2.3 Essential Air Service

After the deregulation act of the late 1970s, some smaller airports still received subsidies through a program called the Essential Air Service (EAS). Some community airports manage without subsidies, but airports in smaller communities, especially in areas of lower economic growth, cannot compete with bigger airports without subsidies (Reynolds-Feighan, 2000). EAS was designed to ensure air service to remote and rural communities that would not have viable service on their own. Critics argue that the program is too expensive and the airports are underutilized (Grubesic & Wei, 2013). One subsidized route between Billings and Lewistown, Montana averaged only two passengers per day in 2006 (Grubesic, Matisziw, & Murray, 2012). The implementation of temporary subsidies has had little success to increase demand at regional airports (Phillips et al., 2005).

Grubesic and Wei (2013) pointed at three factors that affect the flight activity at EAS airports: the subsidy levels, the proximity to a hub airport, and the population in the regional area. Remoteness from a larger airport is important for the viability of smaller airports, and many EAS airports are located farther from these hubs, but they are not always placed remotely from each other. Grubesic et al. (2012) argues that the clustering of EAS airports in some areas is leading to inefficiencies. They describe a structured, objective approach to evaluate the spatial configuration of the EAS program, which suggests the removal of some redundant airports in the program.

Airports tend to promote business, especially in the tradable service sector. Özcan (2014) found that a 1% increase in air passenger traffic in an EAS airports leads to a
0.12% increase in per capita income. Others argue this is not always the case. As Grubesic and Wei (2013) point out, these smaller communities are just not large enough to support a significant tradable service sector. These remote areas do not follow typical economic patterns. They are part of an “economic bizarro land” that depends on other economic sectors, with little growth in tradable services (Gandel, 2011). Other times, EAS airports are located in the shadow of a larger metropolitan area, and businesses utilize the services of the larger airports in the area. The main advantage of using a regional airport is decreased travel time, but many other factors impact a customer’s choice of airport, such as the price and frequency of flights (Zhang & Xie, 2005).

2.4 Factors that Affect Airport Choice

A range of factors affect a customer’s choice of airport. Research indicates the three most important factors are price, flight frequency, and access time, although a variety of other factors play an important role, such as the type of traveler and their destination (Cho et al., 2015; Lian & Rønnevik, 2011; Lieshout, 2012; Marcucci & Gatta; 2011; Zhang & Xie, 2005).

Price has been shown to be a very important variable in airport choice. People are often willing to drive significantly farther for a cheaper flight (Fuellhart, 2003). People who travel longer distances for these flights will then become accustomed to driving to that same airport (Kim & Fu, 2016; Pantazis & Liefner, 2006).

In addition, customers are attracted to larger airports based on the frequency of flights (Cho et al., 2015; Lian & Rønnevik, 2011). More flights allow the customer much
more flexibility in trip planning. Indirect flights require more travel time and add the possibility of missing a connecting flight (Lian & Rønnevik, 2011). When a connecting flight is missed, it is easier and more convenient to catch a different flight when a route is more frequent.

Travelers make decisions based on their priorities, often balancing time and cost. Higher income and business travelers are typically more concerned with time than price. They are more concerned with variables like flight time, access time, and flight frequency (Cho et al., 2015). People traveling for leisure are more concerned about price and are likely to drive farther (Suzuki, Crum, & Audino, 2003).

People who plan their trips in advance typically are most concerned with price. These people tend to drive farther to get a cheaper flight (Phillips et al., 2005). These reasons are likely related, that is, people tend to plan leisure trips more in advance than business trips.

Destination will also affect the airport choice of customers. Airport catchment areas were found to be smaller when airports in the region offered the same destination (Lieshout, 2012). The airport’s catchment area was much larger when the destination was not offered by nearby competing airports. For example, large airports typically have larger catchment areas for international routes than domestic.

Phillips et al. (2005) proposed that the type of aircraft alone may discourage people from using smaller airports. Lian and Rønnevik (2011) conducted a study in Norway in which regional airports typically have turboprop planes and main airports
have jet planes. These small aircraft offer only a limited capacity, which could be problematic for last-minute fliers. However, since turboprop service is only offered at the smallest airports, Lian and Rønnevik (2011) suggest that the aircraft type in itself is only significant to a very limited extent.

Some customers chose an airport based on the airline (Marcucci & Gatta, 2011). Low-cost carriers bring in more traffic to an airport by offering low fares. They also bring in more traffic beyond adjusting for fare (Cho et al., 2015); that is the reputation that low-cost carriers are cheap attracts customers, even when other airlines offer the same flight for less. Many customers will not bother comparing prices. The presence of a low-cost carrier also attracts more customers to the airport, even to competing airlines. One study created a variable known as the “Southwest Effect,” which measured the percentage of destinations in which Southwest Airlines offers the lowest fare or is the largest airline (Fuellhart et al., 2013). It was shown to be one of the most influential variables affecting airport choice.

Other factors can have a significant factor on airport choice. Marcucci and Gatta (2011) included factors such as waiting time and parking in their model. Past experiences at an airport may also have an impact on airport choice. Travelers are more likely to use airports where they have had good experiences as opposed to airports where they have had bad experiences or airports they have never been too (Suzuki et al., 2003). Suzuki (2004) looked at the effect of service failures on airline choice, including seat denials, flight delays and baggage mishandling. However, the study concluded that service failures had little impact on airline choice.
There is an important distinction between drive time and distance. The presence of excellent highway systems makes it easier for travelers to drive farther to reach an airport. Fuellhart (2003) found this was an important influence on market leakage from the Harrisburg airport to other airports. Travel time was shorter to these airports due to the interstate highway system.

Access cost is more than just time; it also costs the customer money to drive farther. This variable includes fuel, as well as the maintenance, insurance, and depreciation on the vehicle (Lieshout, 2012). This variable can easily be lumped together with access time, but can vary depending on how many people use the same vehicle.

Most models assume travelers arrive at the airport by their personal vehicle. This assumption is generally true for the United States, but in places like Europe, public transportation is a more viable option. This could have a significant impact on airport selection (Lieshout, 2012). High-speed rail service could also compete directly with airports, so that people living in areas with good rail service are less likely to fly (Lieshout, 2012).

Paliska, Drobne, Borruso, Gardina, and Fabjan (2016) found that national boundaries may have an influence on airport choice decision; passengers tend to favor airports in their own country. This was even true in their study area, the upper Adriatic within the European Union’s Schengen Area, where there are no border checks between countries. Perhaps this phenomenon is partially present across state borders as well; however, Poulaki, Papatheodorou, and Stergiou (2013) found that the Greek-Turkish
border was not a deterrent and that even an intermodal, cross-border route was the most preferable. Intermodal routes are viable options and are necessary to consider in archipelagos like on the islands of the Aegean Sea.

2.5 Development of the Huff Model

The Huff model is a well-established framework used to analyze spatial competition in retail market areas. The foundational concept for the Huff model comes from Reilly’s “Law of Retail Gravitation,” which examines how business areas of cities are affected by both distance and population (Reilly, 1929). Huff took this fundamental concept and revised it into a very simple and versatile formula (Huff & Haggerty, 1962). Huff’s model predicts the probability of a customer’s retail choice based on only two variables: travel time and square footage of selling space. Square footage is simply a measure of the attractiveness of a store and travel time can be approximated with distance (Dramowicz, 2005).

One of the problems that Huff points out with Reilly’s original model is that it is only concerned with the breaking points of market areas (Huff, 1964). Instead, Huff formed a model that maps the spatial gradient between market areas, which creates a more realistic picture.

Estimating the parameters for the model is the hardest part of applying the Huff model (Huff, 2003). These parameters can only be calibrated using actual choice behavior data, which can sometimes be time consuming to collect. Without these data, the model cannot be empirically calibrated.
A distance decay parameter of about 2 or between 1 and 2 for retail models is agreed upon in literature (Dolega, Pavlis, & Singleton, 2016; Dramowicz, 2005; Lin et al., 2016). Other studies suggest an S-shaped distance decay curve (Bauer & Groneberg, 2016; Lian & Rønnevik, 2011).

2.6 Modeling Airport Catchment Areas

Multinomial Logit (MNL) models have been used to calculate the customer’s maximum utility. A variety of variables can be used to calculate a customer’s best utility. Lieshout (2012) considered access costs, airfares, access time costs, and airside time costs.

Marcucci and Gatta (2011) created an MNL model for estimating utility maximization for airports. It considers type of airline, connection capability, waiting time, type of parking, and flight frequency. Their model does not consider access time; however, the four airports considered in the study are relatively close to each other.

Rusu, Bănică, Buraga, and Roșu (2014) modeled airport catchment areas in Eastern Europe. They determined the catchment areas of airports by mapping the cumulative population by distances to airports in 2010, using the 50% isoline was used to define the catchment areas. They considered the population and travel times to airports, but did not consider the attractiveness of airports.

Brueckner, Lee, and Singer (2014) conducted a study to determine which airports in multi-airport regions should be grouped together for market area definitions. For
example, in Chicago, the catchment areas for O’Hare International Airport and Midway International Airport should be treated as the same market area.

2.7 Data Collection Techniques for Huff Model Calibration

Several methods have been used to collect data to calibrate the Huff model.

Traditional surveys have been used to calculate market shares (Dolega et al., 2016; Lian & Rønnevik, 2011; Lin et al., 2016; Paliska et al., 2016; Poulaki et al., 2013). These have been effective, but they require a good deal of time and effort, and it is difficult to get a truly random sample. Lin et al. (2016) also used license plate survey data obtained from state government agencies. They used the license plate numbers and registration to determine the individual’s home location.

A license plate survey was conducted by the Iowa Department of Transportation (2008) for the Iowa Air Service Study. They were able to determine what county travelers were coming from based on the county printed on the license plate. In 2006, data was collected from 19 different airports in and around Iowa. They grouped Rochester and Minneapolis-Saint Paul airports into one category and La Crosse and Madison airports into one category.

Lu, Shaw, Fang, Zhang, and Yin (2017) tracked people in Shenzhen, China using their mobile phones. A location record was generated every time a person received or sent a phone call or text message. The data was received from a telecommunications company. The study did not obtain any personal information because of privacy concerns.
Social media can be used to track an individual’s location. Feng (2015) used data from twitter to determine airport choice. The data was consolidated by county and catchment areas were determined, although a gravity model was not configured. Wang, Jiang, Liu, Ye, and Wang, (2016) obtained data from Sina Weibo, a Chinese social media site, similar to Twitter in the United States. The location of millions of geo-tagged messages in Beijing could be used to determine approximately where users were from and which activity centers they were frequenting.

One of the weaknesses of using social media is it is mostly used by specific user groups, mostly young people (Feng, 2015). These users cannot be considered a random sample of the population. Feng also noted that there are blind spots in mountainous regions where there is no mobile service. This may also be related to the low population densities in these regions.

Yue et al. (2012) used GPS data from around 12,000 taxis in Wuhan, China to extract trip trajectories. They were able to use this data to calibrate a traditional Huff model, as well as a few variants.

This thesis used license plate data to develop and calibrate a Huff model in the region of eastern Iowa, and then developed airport catchment areas using the procedures outlined in the next chapter.
CHAPTER 3

METHODOLOGY

3.1 Overview of the Iowa Region

There are eight commercial airports in Iowa, as described in Table 1. Many Iowa residents also travel to commercial airports in other states, notably the airports listed in Table 2. It is important to understand the contrast in magnitude between the smaller airports and the medium-sized airports, and the contrast in magnitude between the medium-sized airports and the larger airports. The number of enplanements, or the number of people who board a commercial aircraft during a year, at Chicago O’Hare is more than 5000 times larger than at Fort Dodge and Burlington.

Figure 2. Airports in the Iowa region.
Table 1

Airports in Iowa.

<table>
<thead>
<tr>
<th>IATA</th>
<th>Airport</th>
<th>City</th>
<th>2016 Enplanements</th>
</tr>
</thead>
<tbody>
<tr>
<td>DSM*</td>
<td>Des Moines International Airport</td>
<td>Des Moines</td>
<td>1,214,307</td>
</tr>
<tr>
<td>CID*</td>
<td>The Eastern Iowa Airport</td>
<td>Cedar Rapids</td>
<td>546,316</td>
</tr>
<tr>
<td>DBQ*</td>
<td>Dubuque Regional Airport</td>
<td>Dubuque</td>
<td>37,954</td>
</tr>
<tr>
<td>SUX</td>
<td>Sioux Gateway Airport</td>
<td>Sioux City</td>
<td>36,268</td>
</tr>
<tr>
<td>ALO*</td>
<td>Waterloo Regional Airport</td>
<td>Waterloo</td>
<td>27,069</td>
</tr>
<tr>
<td>MCW*</td>
<td>Mason City Municipal Airport</td>
<td>Mason City</td>
<td>7734</td>
</tr>
<tr>
<td>FOD*</td>
<td>Fort Dodge Regional Airport</td>
<td>Fort Dodge</td>
<td>7271</td>
</tr>
<tr>
<td>BRL*</td>
<td>Southeast Iowa Regional Airport</td>
<td>Burlington</td>
<td>7086</td>
</tr>
</tbody>
</table>

*Denotes Surveyed Airport.

Table 2

Notable airports outside of Iowa.

<table>
<thead>
<tr>
<th>IATA</th>
<th>Airport</th>
<th>City</th>
<th>2016 Enplanements</th>
</tr>
</thead>
<tbody>
<tr>
<td>ORD</td>
<td>O’Hare International Airport</td>
<td>Chicago, IL</td>
<td>37,499,201</td>
</tr>
<tr>
<td>MSP*</td>
<td>Minneapolis-Saint Paul International Airport</td>
<td>Minneapolis/Saint Paul, MN</td>
<td>18,109,982</td>
</tr>
<tr>
<td>STL</td>
<td>St Louis Lambert International Airport</td>
<td>St Louis, MO</td>
<td>6,782,911</td>
</tr>
<tr>
<td>MCI</td>
<td>Kansas City International Airport</td>
<td>Kansas City, MO</td>
<td>5,370,028</td>
</tr>
<tr>
<td>OMA</td>
<td>Eppley Airfield</td>
<td>Omaha, NE</td>
<td>2,125,319</td>
</tr>
<tr>
<td>MSN</td>
<td>Dane County Regional Airport</td>
<td>Madison, WI</td>
<td>903,006</td>
</tr>
<tr>
<td>FSD</td>
<td>Sioux Falls Regional Airport</td>
<td>Sioux Falls, SD</td>
<td>510,001</td>
</tr>
<tr>
<td>MLI*</td>
<td>Quad City International Airport</td>
<td>Moline, IL</td>
<td>364,328</td>
</tr>
<tr>
<td>PIA</td>
<td>General Wayne A. Downing Peoria International Airport</td>
<td>Peoria, IL</td>
<td>307,189</td>
</tr>
<tr>
<td>RST</td>
<td>Rochester International Airport</td>
<td>Rochester, MN</td>
<td>112,861</td>
</tr>
<tr>
<td>LSE</td>
<td>La Crosse Regional Airport</td>
<td>La Crosse, WI</td>
<td>93,895</td>
</tr>
</tbody>
</table>

*Denotes Surveyed Airport.
There seems to be viable alternatives to the airports in eastern Iowa. I attempted to survey airports that were logical alternatives to the residents of eastern Iowa.

### 3.2 Data Collection

License plate surveys were conducted at nine airports in and around Iowa: DSM, CID, DBQ, ALO, MCW, FOD, BRL, MSP and MLI. Permission was granted by the airports to conduct the surveys. In Iowa, the county is displayed on most license plates. The number of plates from each county was tallied, and other state plates were tallied by state. The actual license plate numbers were not recorded at all, only the county or state of the license plate. Iowa plates that did not display the county (e.g., University plates) were tallied in the ‘Other Iowa’ category. All other plates (e.g., US Government plates, dealership plates) were put in the ‘Other’ category, as well as cars without visible plates. Since these cars had no geographic reference they had to be excluded from calculations. These categories were usually small and accounted for less than five percent of all the cars surveyed, which should not create any bias as long as the geographic distribution of these cars is similar to the geographic distribution of the rest of the surveyed cars.

Surveys were conducted at least twice at each airport. The times and dates of each survey are recorded below. Cars in the rental car lots were not recorded. Some airports were small enough that the entire lot could be surveyed in less than five minutes. Other lots were so big that only a sample of the lots could be taken during each visit. These larger airports also had several different lots. A sample was taken from each of the different lots. I attempted to spread out collection dates, especially for lots that were only sampled twice, so that cars that were parked long term at the airport were less likely to be
counted twice. When Des Moines and Minneapolis-Saint Paul were sampled within a short time period, samples were taken from separate lots on the two days. Due to time constraints, a few were likely counted twice, since some sample dates were only a week apart. Although airports experience more traffic on some days than others, it was assumed that the geographic distribution did not change significantly over time.

Table 3

*See text.*

<table>
<thead>
<tr>
<th>Airport</th>
<th>Date surveyed</th>
<th>Approximate time of survey</th>
<th>Number of cars surveyed</th>
</tr>
</thead>
<tbody>
<tr>
<td>BRL</td>
<td>7/17</td>
<td>5:00 PM</td>
<td>49</td>
</tr>
<tr>
<td>BRL</td>
<td>7/24</td>
<td>4:10 PM</td>
<td>74</td>
</tr>
<tr>
<td>BRL</td>
<td>7/31</td>
<td>4:10 PM</td>
<td>60</td>
</tr>
<tr>
<td>BRL</td>
<td>8/6</td>
<td>4:45 PM</td>
<td>53</td>
</tr>
<tr>
<td>MCW</td>
<td>8/15</td>
<td>10:40 AM</td>
<td>35</td>
</tr>
<tr>
<td>FOD</td>
<td>8/15</td>
<td>12:00 PM</td>
<td>28</td>
</tr>
<tr>
<td>DSM</td>
<td>8/15</td>
<td>2:10 PM – 4:30 PM</td>
<td>1327</td>
</tr>
<tr>
<td>DSM</td>
<td>8/17</td>
<td>1:55 PM – 4:30 PM</td>
<td>1320</td>
</tr>
<tr>
<td>MLI</td>
<td>8/18</td>
<td>11:15 AM – 12:40 PM</td>
<td>938</td>
</tr>
<tr>
<td>FOD</td>
<td>8/28</td>
<td>11:30 AM</td>
<td>22</td>
</tr>
<tr>
<td>MCW</td>
<td>8/28</td>
<td>12:55 PM</td>
<td>35</td>
</tr>
<tr>
<td>MLI</td>
<td>8/30</td>
<td>11:20 AM – 12:40 PM</td>
<td>920</td>
</tr>
<tr>
<td>DSM</td>
<td>9/4</td>
<td>10:00 AM – 11:50 AM</td>
<td>2220</td>
</tr>
<tr>
<td>MCW</td>
<td>9/8</td>
<td>8:35 AM</td>
<td>24</td>
</tr>
<tr>
<td>MSP</td>
<td>9/8</td>
<td>10:45 AM – 4:15 PM</td>
<td>4350</td>
</tr>
<tr>
<td>DBQ</td>
<td>9/11</td>
<td>2:00 PM</td>
<td>228</td>
</tr>
<tr>
<td>MCW</td>
<td>9/16</td>
<td>8:50 AM</td>
<td>36</td>
</tr>
<tr>
<td>MSP</td>
<td>9/16</td>
<td>11:00 AM – 2:00 PM</td>
<td>3025</td>
</tr>
<tr>
<td>DBQ</td>
<td>9/22</td>
<td>10:15 AM</td>
<td>248</td>
</tr>
<tr>
<td>CID*</td>
<td>Various</td>
<td>Various</td>
<td>45,464</td>
</tr>
<tr>
<td>ALO*</td>
<td>Various</td>
<td>Various</td>
<td>2657</td>
</tr>
</tbody>
</table>

*See text.*
The Waterloo and Cedar Rapids airports offered the data they collected themselves. Waterloo collected data on 38 different days from April to July, and Cedar Rapids collected data for every day in June.

From these raw counts, the total number of cars from each county (and state) was divided by the total number of cars surveyed at that airport (excluding the ‘other’ categories) to give a percentage for each county (and state). These percentages were multiplied by the total number of annual enplanements for the airport (based on 2016 data) to give an approximation of how many people from each county were driving to each airport. From the values for each airport by county, the percentage of people going from each county to each airport was estimated. These percentages became the observed values to calibrate the models.

3.3 Applying the Huff Model

Huff designed his model to calculate the catchment areas of retail stores (Huff, 1963). This model can be applied to many things other than retail, including the catchment areas of airports. The original model states:

$$P(C_{ij}) = \frac{S_j}{T_{ij}^a} \sum_{j=1}^{a} \left( \frac{S_j}{T_{ij}^a} \right)$$

where \(P(C_{ij})\) is the probability of a consumer at a given point of origin \(i\) traveling to a given shopping center \(j\); \(S_j\) is the square footage of selling space devoted to the sale of a particular class of goods by shopping center \(j\); \(T_{ij}\) is the travel time involved in getting
from a consumer’s travel base i to shopping center j; and λ is a parameter to be estimated empirically to reflect the effect of travel time on various kinds of shopping trips.

The square footage variable is a measure of the non-spatial attractiveness of a retail store. An analogous measure of attractiveness for airports in the context of the Huff model is, in this study, the total number of enplanements. These numbers are easy to find and are a good size indicator. It is thus assumed that larger airports are more attractive, since larger airports tend to have lower prices and higher flight frequencies. The literature points to prices and flight frequencies as the strongest non-spatial indicators of airport attractiveness.

The key challenge concerns calibrating the model. Real data need to be applied to estimate the parameter values. Once these values are determined, the model should be able to be applied anywhere, assuming there is enough homogeneity in what people consider to be an attractive airport.

The model uses only two inputs to predict market areas: travel times to the airports and the total number of enplanements for each airport. For the purposes of this study, it is assumed that most people drive their personal vehicle to the airport, and travel time can be calculated based on the road systems.

3.4 Calculating Travel Times

Instead of simply using Euclidean distances as travel times, approximate travel times were calculated. ArcGIS Online was used to calculate drive times to the airports at different intervals: 10, 20, 30, 45, 60, 90, 120, 180, 240, and 300 minute drive times.
These polygons were exported to shapefiles and brought into ArcGIS Desktop. The polygons were simplified and the vertices converted to points. I added a new field called “time” to each set of points and used field calculator to fill in the time for each interval. The points were merged into one file and each airport was selected out to get a set of points for each airport. A few points were added here. I added a zero point at the airport itself and a few points beyond 5 hours (5 hours, or 300 minutes, was the limit for ArcGIS Online). Google maps was used to manually calculate these values. There were considerably less values beyond 5 hours, but accuracy was less important at this range since most people do not drive more than 5 hours to the airport. Enough points were added so that all of Iowa could be included. I then used the Natural Neighbor tool to interpolate the values between points. The result was a travel time raster for each airport. Although they may not be completely accurate, they are much better than using Euclidean distances.

From these travel time rasters, I calculated the drive time between each county and each airport. Each county was represented by a population weighted centroid as shown in Figure 3. This weighted centroid was calculated using the total 2010 populations of block groups. Most centroids did not move significantly from the geographic centroid, but some moved quite a bit (e.g. Story, Dallas, Clinton, Des Moines, and Dubuque counties). This gives us the approximate drive time for the average citizen of each county to each airport.
Designating a Study Area for Calibration

A study area for this research was defined explicitly considering the calibration of the Huff model based on sample data from airports in eastern Iowa. Counties in western Iowa were not represented well at the surveyed airports. Not a single Monona county plate was seen during the study. A few western counties were only seen at Cedar Rapids, not because more people were driving to Cedar Rapids from these counties, but simply because more cars were counted at this airport. Most of these people are going to other

Figure 3. Weighted mean centers of counties.
airports (like Omaha, Sioux Falls, and Kansas City). There are also a lot of people in northeast Iowa that go to La Crosse or Madison. Including these counties in calibration does not make sense. Since these airports are un-surveyed, I need a way of estimating how many people are going to those airports.

The Iowa Air Service Study may be able to shed some light (Iowa Department of Transportation, 2008). Boundaries have changed, but hopefully not too much. I can map out the percentage of people going to a surveyed airport. Another complication is the study does not differentiate between Rochester and Minneapolis-Saint Paul. I assumed Rochester does not have a high market share in Iowa.

Counties with over 50% of people going to one of the surveyed airports based on the Iowa Air Service Study would be an adequate definition for the study area. Even if many of the people are going to a different airport, we would expect the proportions to the surveyed airports would remain the same. We should still regard the counties in the middle of the study area to be more reliable than counties at the fringe of the study area. The resulting study area consists of the 69 counties in central and eastern Iowa shown in Figure 4.

3.6 Calibrating the Huff Model

After the data was collected, the next step was to calibrate the model based on the 69 counties in the study area. As outlined in section 3.24, the percentages of counties per airport were multiplied by the total enplanements of the airports to approximate the total number of people going from each county to each airport. These were totaled for each
county and percentages calculated for each airport for each county yielding a matrix containing the estimated percentages of travelers for each county to each airport. This matrix of percentages are the values I want to predict with my model.

The utility was calculated based on these drive times and the 2016 total enplanements using the following equation:

$$U_{ij} = \frac{A_{ij}^x}{T_{ij}}$$
where $U_{ij}$ is the utility of going from origin $i$ to airport $j$; $A_j$ is the attractiveness of airport $j$ (number of enplanements); $T_{ij}$ is the travel time to airport $j$ from origin $i$; $X$ is the attractiveness parameter to be calibrated; and $Y$ is the distance decay parameter to be calibrated.

To estimate the probability of selecting a particular airport, the total utility for each county was found, and each utility value was divided by the total utility per county:

$$P_{ij} = \frac{U_{ij}}{\sum_{j=1}^{n} U_{ij}}$$

Or

$$P_{ij} = \frac{A_j^X}{T_{ij}^Y} \left( \sum_{j=1}^{n} \frac{A_j^X}{T_{ij}^Y} \right)$$

where $P_{ij}$ is the probability of selecting airport $j$ from origin $i$; and $n$ is the number of airports. This predicted percentage for each county to each airport can then be compared to the observed values found by the license plate survey. The r-squared can be calculated and the parameter constants adjusted to maximize this r-squared value.

3.7 S-Curve Model

Some studies suggest an S-shaped distance decay curve (Bauer & Groneberg, 2016; Lian & Rønnevik, 2011) and the results of the traditional Huff model suggest the presence of an S-shaped attractiveness curve. So an S-Curve was applied to both the
number of enplanements and the travel time. This resulted in a new S-Curve model that is based on a new equation for utility:

\[ U_{ij} = \frac{1 + e^{-\left(\frac{T_{ij} - Y_1}{Y_2}\right)}}{1 + e^{-\left(\frac{A_j - X_1}{X_2}\right)}} \]

where \( U_{ij} \) is the utility of going from origin \( i \) to airport \( j \); \( A_j \) is the attractiveness of airport \( j \) (number of enplanements); \( T_{ij} \) is the travel time to airport \( j \) from origin \( i \); \( X_1 \) and \( X_2 \) are the attractiveness parameters to be calibrated; and \( Y_1 \) and \( Y_2 \) are the distance decay parameters to be calibrated.

To estimate the probability of selecting a particular airport, the total utility for each county was found, and each utility value was divided by the total utility per county:

\[ P_{ij} = \frac{U_{ij}}{\sum_{j=1}^{n} U_{ij}} \]

Or

\[ P_{ij} = \frac{\left(1 + e^{-\left(\frac{T_{ij} - Y_1}{Y_2}\right)}\right)}{\left(1 + e^{-\left(\frac{A_j - X_1}{X_2}\right)}\right)} \]

where \( P_{ij} \) is the probability of selecting airport \( j \) from origin \( i \); and \( n \) is the number of airports. This predicted percentage for each county to each airport can then be compared.
to the observed values found by the license plate survey. The r-squared can be calculated and the parameter constants adjusted to maximize this r-squared value.
CHAPTER 4

RESULTS

4.1 Survey Results

The survey results can be seen in Figure 5. The pie charts for each county show us the proportion of people from each county that go to each airport. Note that counties on the fringe of the study area are more likely to have residents travel to airports that were not surveyed. For example, counties to the west have people going to airports in Omaha, Kansas City, and Sioux Falls. Market shares are only based on the airports surveyed.

Figure 5. License plate survey results.
The raw results are largely intuitive, as expected, except for some noticeable anomalies. Not a single car was seen from Pocahontas, Humboldt, or Wright counties at the Minneapolis-Saint Paul airport. Based on the counties around them, it seems logical to assume that at least some significant percentage of these counties travel to the Minneapolis-Saint Paul airport. These counties have small populations so it is rare to see these plates at any airport. A larger sample from the Minneapolis-Saint Paul airport would be useful for understanding its true catchment area in Iowa.

An unexpectedly high number of cars were seen at the Des Moines airport from places in eastern Iowa such as Buchanan, Delaware, and Louisa counties. It is possible that such a high number of people are travelling from these counties to Des Moines, but it could be due to random error. It could also be an indicator of urbanization in Iowa; it is possible that people from these rural areas in eastern Iowa could be moving to the rapidly growing Des Moines Metropolitan Area and have not changed their license plates yet. This is one of the drawbacks of the license plate survey method.

4.2 The Calibrated Huff Model

This predicted percentage for each county to each airport can then be compared to the observed values found by the license plate survey. The r-squared can be calculated and the parameters adjusted to maximize this r-squared value. The r-squared was maximized at .861 when the attractiveness parameter was .6 and the distance decay parameter was 2.
Figure 6. The calibrated Huff model.

The raster in Figure 6 represents the airport with the highest market share (not to be confused with the majority market share) over space. This does not provide the whole picture. The percentage of the market share is also needed. The pie charts in Figure 6 show the percentages predicted by the model. These percentages can also be mapped for individual airports, such as Waterloo Regional Airport (ALO) in Figure 7. Other market share maps for the Huff model can be found in Appendix A.
Figure 7. The predicted market share of the Waterloo Regional Airport (ALO).

Comparing the predicted and observed percentages (Figure 8) brings up some interesting patterns. The model overestimates smaller airports; it erroneously predicts that Waterloo, Fort Dodge, Mason City, and Burlington should have the largest market shares in Black Hawk, Webster, Cerro Gordo, and Des Moines counties respectively. These four airports were not observed to have the largest market share in any counties. Minneapolis-Saint Paul is overpowered at far distances. The model predicts that almost a quarter of the market share for Van Buren County in southern Iowa belongs to Minneapolis-Saint Paul.
Figure 8. The predicted vs. observed market shares of each airport per county.

The cutoffs are more pronounced in observed values. The Huff model emphasizes gradual changes, which is accurate in some ways, but not to the extent the model shows. There are counties on the border of catchment areas, but counties on either side of the border counties have particularly high market shares to their respective airports. For example, Jefferson County is split almost equally between Cedar Rapids and Des Moines, but Wapello County has a high market share to Des Moines. The catchment area for Minneapolis-Saint Paul stops abruptly around US 20, while the model predicts a smooth transition.
The residuals show that overall the model over predicts every airport except Des Moines, which is very under predicted. This over predicting of smaller and larger airports suggests that an S-Curve for attractiveness would be a better predictor.

The residuals farthest from zero (more than .5), show where the model performs the worst. The model over predicts Black Hawk going to Waterloo. It also over predicts Pocahontas and Wright going to Minneapolis-Saint Paul instead of Des Moines. No plates were observed from these low population counties at Minneapolis-St Paul. A larger sample from this airport is required to accurately describe the presence of these counties.

The last of these residuals were the model under predicting Poweshiek and Van Buren counties going to Des Moines. Part of this is due to an over prediction of Cedar Rapids. Both are on the border of the catchment areas, but the model also over predicts these counties going to Minneapolis-Saint Paul. This is a weakness of the model. It seems unlikely that so many people would drive over five hours from Van Buren County. The county is on the fringe of the study area, and it would seem logical for people there to drive to another airport like St. Louis. This does not explain Poweshiek County, which is in the middle of the study area. Poweshiek and Van Buren are both relatively far from Cedar Rapids and Des Moines and show a low utility to each, allowing the low Minneapolis-Saint Paul utility to be more significant. This can be seen in Tama County. Only one plate was observed at Minneapolis-Saint Paul from Tama County. A larger sample from the airport is required to understand how many people are driving to Minneapolis-Saint Paul from Poweshiek and Tama counties.
4.3 The Iowa Air Service Study Huff Model

I compared data from the Iowa Air Service Study collected in 2006 with the data I collected (Iowa Department of Transportation, 2008). This comparison can be seen in Figure 9. There seems to be a decline in Cedar Rapids and Moline and a rise in Des Moines and Minneapolis-Saint Paul. Some of this could be due to random error, but the trend is also present when looking at the total enplanements (see Table 4). Although Cedar Rapids did not decline in the number of enplanements, it did not grow as fast as Des Moines.

Figure 9. The observed market share in 2006 vs. 2017.
### Table 4

*Enplanement change from 2006 to 2016.*

<table>
<thead>
<tr>
<th>Airport</th>
<th>2016 Enplanements</th>
<th>2006 Enplanements</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLI</td>
<td>364,328</td>
<td>453,554</td>
<td>-89,226</td>
</tr>
<tr>
<td>DBQ</td>
<td>37,954</td>
<td>46,973</td>
<td>-9019</td>
</tr>
<tr>
<td>ALO</td>
<td>27,069</td>
<td>33,211</td>
<td>-6142</td>
</tr>
<tr>
<td>MCW</td>
<td>7734</td>
<td>12,142</td>
<td>-4408</td>
</tr>
<tr>
<td>BRL</td>
<td>7086</td>
<td>7967</td>
<td>-881</td>
</tr>
<tr>
<td>FOD</td>
<td>7271</td>
<td>6911</td>
<td>360</td>
</tr>
<tr>
<td>CID</td>
<td>546,316</td>
<td>516,095</td>
<td>30,221</td>
</tr>
<tr>
<td>DSM</td>
<td>1,214,307</td>
<td>947,393</td>
<td>266,914</td>
</tr>
<tr>
<td>MSP</td>
<td>18,109,982</td>
<td>17,192,410</td>
<td>917,572</td>
</tr>
</tbody>
</table>

I also calibrated a new model based on the Iowa Air Service Study using enplanements from 2006 as the attractiveness and assuming travel times were about the same. The 2006 Iowa highway network was different than it is today. In particular, a number of new 4-lane highways. These include: US 63 between New Hampton and Denver, US 34 between Ottumwa and Mount Pleasant, US 30 near State Center, US 30 near Tama and Toledo, and US 20 between Fort Dodge and Early. There are also other variations in the network including differences in traffic densities. Overall, there should not be any significant differences.

The 2006 model optimized r-squared to .833 with an attractiveness parameter of .53 and a distance decay parameter of 2. The model was pretty similar to the other Huff model. The large residuals seem to be mostly the same. The model under predicts Des Moines and Cedar Rapids and over predicts small airports in their own counties (e.g., Black Hawk to Waterloo).
Both traditional Huff models over predict larger and smaller airports, while under predicting medium-sized airports. This is evidence that the relationship between the number of enplanements and the attractiveness of an airport is best described by an S-Curve.

4.4 The S-Curve Model

The percentage for each county to each airport predicted by the S-Curve model can be compared to the observed values found by the license plate survey. The r-squared can be calculated and the parameters adjusted to maximize this r-squared value. The r-
squared was maximized at .950 when the attractiveness parameters were 1,719,391.91 and 279,410.55 and the distance decay parameters were 537.74 and 31.43.

The raster in Figure 11 represents the airport with the highest market share (not to be confused with the majority market share) over space. The pie charts in Figure 11 show the percentages predicted by the model. These percentages can also be mapped for individual airports, such as Waterloo Regional Airport (ALO) in Figure 12. Other market share maps for the S-Curve model can be found in Appendix B.

Figure 11. The calibrated S-Curve model.
Comparing the predicted and observed percentages brings up some interesting patterns (see Figure 13). The residuals follow a much different pattern, but are smaller on average compared to the standard Huff model. The S-Curve model underestimates Moline, and slightly underestimates Cedar Rapids. It also overestimates Des Moines and Burlington.
There were no residuals farther than .5 from zero and only two that were farther than .4. The first was the model over predicts Wright going to Minneapolis-Saint Paul. Again, no plates were observed from this county at this airport. The second was the model underestimates Muscatine to Moline. This seems to be a result of the model under predicting Moline in general.

*Figure 13.* The predicted vs. observed market shares of each airport per county.
4.5 The Iowa Air Service Study S-Curve Model

I was also able to calibrate a new S-Curve model based on the Iowa Air Service Study (Iowa Department of Transportation, 2008). Since this data was collected in 2006, I used enplanements from 2006 as the attractiveness and assumed travel times were about the same. I also used all 17 airports (excluding Rochester and Madison) from the Iowa Air Service Study.

The 2006 model optimized r-squared at .903 with attractiveness parameters of 548,535.77 and 135,193.24 and distance decay parameters of 316.1 and 33.94. The distance decay parameters were similar, but the attractiveness parameters were quite different. Perhaps this is due to the addition of many other airports.

Overall, the model under predicts Minneapolis-Saint Paul and slightly under predicts Kansas City and La Crosse. It over predicts Des Moines and slightly over predicts Cedar Rapids and Fort Dodge. The model has four residuals greater than .5. The model under predicts Howard and Chickasaw to Minneapolis-Saint Paul and Clayton to La Crosse. The model also over predicts Clayton to Cedar Rapids. These residuals are partially because the study did not distinguish between La Crosse and Madison and between Minneapolis-Saint Paul and Rochester. I assumed people in these categories were going to La Crosse and Minneapolis-Saint Paul instead of Madison and Rochester respectively. People in Clayton County, for example, likely travel to Madison more than La Crosse. This is why the survey showed so many people going to Wisconsin from Clayton County, despite being somewhat far from La Crosse. In a similar way, Chickasaw and Howard are likely to travel to Rochester, so the survey shows high levels
from these counties going to Minnesota. Many of the other poor residuals are counties in northeast Iowa, so this assumption is likely the problem.

*Figure 14.* The predicted vs. observed market shares of each airport per county in 2006.
5.1 Underserved Areas

Based on the interpolated travel times for each airport, travel time to the nearest commercial airport was calculated across Iowa (see Figure 15). Rural areas in southern, northeastern, and western Iowa have the longest to drive to a commercial airport.

Figure 15. Travel time in Iowa to the nearest airport.
The situation changes without EAS airports (see Figure 16). Areas in northwestern Iowa would be more than two and a half hours from the nearest commercial airport. Mason City and Fort Dodge would be almost two hours from the nearest commercial airport. Burlington and Sioux City would be about 90 minutes, and Waterloo would be about an hour.

Figure 16. Travel time in Iowa to the nearest non-EAS airport.

The total utility index of areas in Iowa in Figure 17 is based on the S-Curve model, the utility again being a function of both the size of the airport (total number of enplanements in 2016) and the travel time. Rural areas in southern, northeastern, and
northwestern Iowa have the lowest utility. The pattern is similar to the raw travel time; however, a difference can be seen in western Iowa. Taylor County, for example, has a somewhat high utility despite being almost two hours to the nearest airport. This is because the nearest airports are the somewhat larger airports of Omaha, Kansas City, and Des Moines. This is in contrast with Palo Alto County, which is just over an hour to the airport, but has a low utility because the nearest airports are the smaller Fort Dodge and Mason City airports. Northeast Iowa, like Allamakee County is similar, with the closet airports being the smaller Waterloo, Dubuque, and La Crosse Airports.

*Figure 17. Total utility index in Iowa.*
Figure 18 shows the utility with the removal of EAS airports. Utility decreases only slightly, suggesting that the utility offered by nearby EAS airports is small compared to the utility offered by larger airports a few hours away.

![Utility Index without EAS Airports](image)

Figure 18. Total utility index in Iowa without EAS airports.

There has been discussion recently about removing subsidy to EAS airports, but it is interesting to see which areas are most underserved in terms of commercial air service, and which cities would be good candidates for new EAS airports (Grubesic et al., 2013).
Southern Iowa had commercial air service in Ottumwa from 1947 to 1983 and again from 1985 to 2001. This seems the most viable option for a new commercial airport in southern Iowa, since it is the largest city in the area; however, the city is not quite remote enough from Des Moines. The airport in Kirksville, MO offers flights to St Louis 3 times a day. The service is growing and may help the region of southern Iowa (Garlock, 2015).

The underserved areas in northwest Iowa are centered on Clay and Palo Alto counties. Spencer and Storm Lake are the biggest cities in this region. This part of Iowa is not very densely populated and although a town like Spencer is remote enough, it is unlikely any airport in this region would do well due to the lack of population.

The area in northeast Iowa is also sparsely populated. It is important to note that this model does not include Rochester and Madison. These two airports likely serve the area slightly. Otherwise, Decorah is the biggest city in the area, although it is small, and with the proximity of other airports, not likely to have a sizeable market.

5.2 The Viability of EAS Airports

Despite the many considerations to the methods of the surveys, it is still reasonable to say that none of the four surveyed airports collect even half of the market share in their home counties. In fact, the survey reports none of the airports take even 20% of the market share. The Iowa Air Service Study shows a similar result (Iowa Department of Transportation, 2008). The study indicates no EAS airport collects more than 25% from its home county.
What does this say about the viability of EAS airports? If these airports are not able to supply a sufficient level of service to their local communities, should subsidies be stopped or increased?

The Dubuque Airport (DBQ) is an interesting case, especially compared to the Waterloo Airport (ALO). Black Hawk County has a population of over 130,000, while Dubuque County has a population just under 100,000. Waterloo Airport has a larger population within in 30 minutes than the Dubuque Airport. While Waterloo receives subsidy, Dubuque does not.

Table 5
Comparison of small airports in Iowa.

<table>
<thead>
<tr>
<th>Airport</th>
<th>EAS Subsidy</th>
<th>2016 Enplanements</th>
<th>Approximate Travel time to Nearest Large Airport*</th>
<th>Approximate Population within 30 minutes</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALO</td>
<td>$945,546</td>
<td>27,069</td>
<td>74 minutes</td>
<td>157,516</td>
</tr>
<tr>
<td>BRL</td>
<td>$1,917,566</td>
<td>7086</td>
<td>92 minutes</td>
<td>52,826</td>
</tr>
<tr>
<td>FOD</td>
<td>$3,715,952</td>
<td>7271</td>
<td>108 minutes</td>
<td>50,083</td>
</tr>
<tr>
<td>MCW</td>
<td>$3,715,952</td>
<td>7734</td>
<td>119 minutes</td>
<td>61,528</td>
</tr>
<tr>
<td>SUX</td>
<td>$611,434</td>
<td>36,268</td>
<td>88 minutes</td>
<td>127,090</td>
</tr>
<tr>
<td>DBQ</td>
<td>None</td>
<td>37,954</td>
<td>83 minutes</td>
<td>100,283</td>
</tr>
</tbody>
</table>

*Large Airport defined as having more than 200,000 Enplanements

Yet, Dubuque Airport has more annual enplanements and a higher market share of the home county. About 15% of Black Hawk County residents use the Waterloo Airport over the other surveyed airports while about 49% of Dubuque County residents
use the Dubuque Airport over the other surveyed airports. Both offer service to Chicago, Waterloo offers two flights a day, while Dubuque offers three.

What makes the Dubuque Airport more viable than the Waterloo Airport? One answer may be its remoteness. Waterloo is about 75 minutes from Cedar Rapids while Dubuque is nearly 90 minutes from both Cedar Rapids and Moline. Although Dubuque is closer to Chicago, Waterloo is closer to both Des Moines and Minneapolis-Saint Paul.

This pattern can be seen with the La Crosse Airport. Only about 127,000 residents live within 30 minutes of the airport, yet the airport is able to host 2 airlines offering 7 flights a day, all without subsidies. This high level of service is likely due to a lack of airport leakage because the area is so remote from larger airports. The closest commercial airport is the only slightly larger Rochester airport 70 minutes away. Larger airports are over two hours away. This remoteness means people’s options are La Crosse, Rochester, or a drive that is over two hours. This means there is little airport leakage from the area and the La Crosse airport gets plenty of business, which means they can offer a higher level of service. This higher level of service attracts more customers, and so on.

The statement by Grubesic and Wei (2013) is confirmed by this study. A viable small airport needs a significant population in the area, as well as remoteness from larger airports. Towns like Spencer or Decorah are remote enough, but cannot host a viable airport because there is not enough population in the area. Waterloo has a large enough population, but struggles because due to its proximity to bigger airports. A balance of population and remoteness is required, as shown by the success of the La Crosse Airport.
5.3 Assessing the Models

This study shows that the Huff model can successfully be applied to the context of airports. Once real data is acquired, the model can be easily calibrated using only the number of enplanements and the travel times to the airports.

The study also shows that the traditional power equation is not adequate, at least in the context of airports; however, the two S-Curve models were very different, as shown in Figure 19, suggesting that data from more airports is required to properly fit the curve. The geographic pull of an airport is most flexible for airports that have approximately somewhere between 100,000 to 3,000,000 enplanements. Outside of the range, a change in the volume of traffic does not significantly change the catchment area of an airport; however, it is unclear from this study where exactly this range lies. Investment in airports within this range may yield the best rate of return.

Initially, I wanted to use a smaller spatial unit than counties, but I found they worked well. Iowa’s small counties are small enough to show variation, but large enough to be comprehensive. The model was able to include a large number of counties. This provided a large number of data points to accurately calibrate the distance decay. As a result, distance decays of the two S-Curve models were very similar, as shown in Figure 20.

Figure 20 also shows that a power equation for distance decay is inadequate for short distances. It over favors low travel times. As travel times approach zero, the distance decay weight approaches infinity. This means the utility of an airport zero
Figure 19. The attractiveness curves of the models.

Figure 20. The distance decays of the models.
minutes away is infinitely higher than an airport even one minute away. The S-Curve shows a less dramatic change over the low travel times. This better represents reality.

If we assume distance decay follows an S-Curve, we can estimate the attractiveness weight of each airport. These can plotted and compared to the attractiveness S-Curves. Plotting this logarithmically makes it easier to see the smaller airports, as in Figure 21. The 2017 S-Curve fits the data well; however the 2006 does not. This may suggest a different form of the equation would fit the data better.

![Graph of attractiveness S-Curves](image)

*Figure 21. The attractiveness S-Curves plotted logarithmically.*
It is interesting that Chicago O’Hare appears less attractive than Minneapolis-Saint Paul, despite being much bigger. This may suggest that at some point a bigger airport is less attractive because of congestion or some other reason. O’Hare has only a small presence in Iowa, so it is difficult to estimate the attractiveness of the airport using only data from Iowa.

There are some exceptions, like O’Hare, but the study shows that generally an increase in enplanements results in an increase in attractiveness. It is unclear which equation best represents this relationship and it could be better understood with more data from more airports.

5.4 Limitations of the Survey Method

The license plate survey method makes several assumptions and this leads to many considerations regarding whether license plates present in airport parking lots truly reflect the geographic distribution of airport customers, how many people actually drive and leave their car in the airport parking lot, and whether the license plates actually show where people are coming from.

In the United States, most people drive to the airport, especially in Iowa. Public transportation is not widely used, or available in this country. The license plate survey method assumes everyone drives to the airport, which is mostly true in this country, especially in low density areas like Iowa; however, Minneapolis-Saint Paul does have a light rail system that can transport travelers directly to the airport.
In addition, the survey method counts all cars equally, and assumes the same amount of people ride in each one. So a mini-van carrying a family of seven is counted the same as a single occupancy vehicle. Some cars are parked longer than others, and therefore have a higher probability of being counted. With a large enough sample, these considerations should even out, assuming the geographic distribution of these different cars are constant.

Another issue is that the survey method assumes everyone parks in the airport parking lot; however, many people are dropped off at the airport by friends, family, or a taxi. Typically, these people live closer to the airport, rather than farther away. People are more willing to ask a friend or family member for a ride to avoid paying parking for a short ride as opposed to a long ride. Thus, it could be assumed the survey method underestimates counties closer to the airport.

The survey method also assumes that the license plate accurately represents the home county of the traveler. The large number of out of state plates seen throughout the study suggest this is not always the case. Often times, plates are not changed immediately after migration. So the license plate will show where the traveler used to live, not where they live now. Although cars in the rental car lots were not counted, some rental cars were parked in the general lots, which have license plates from just about any state. A good example was the U-Haul with the Arizona license plate in the Des Moines Airport parking lot with the local Des Moines address painted on the side.
5.5 Future Directions

To better understand catchment areas, more data are required. It was expected that there would not be enough data from smaller airports due to small sample sizes. Although it was true that only a small number of cars were observed at these airports, each car did not carry much weight. Since these airports had so few enplanements, a small change in the percentages of counties observed did not significantly affect the approximate number of trips from that county. A small change in the percentage of counties observed at a bigger airport had a much larger influence on the approximate number of trips from that county. If only a sample of the cars are counted on visits to larger airports, more visits are required. This was readily apparent in my data as many of the poor residuals encountered were a result of insufficient data from larger airports. Perhaps other, less time consuming data collection techniques should be explored.

Not only more data from the surveyed airports, but data from more airports. A larger number of airports should be sampled to truly understand the relationship between attractiveness and the size of airports. The model does not prove necessarily that the number of enplanements is a poor measure of attractiveness, but there need to be more than a few airports to properly fit an S-Curve to the data. Perhaps another equation form would better represent the relationship.

It would also be good to look at the effects of different variables that effect airport choice, like those discussed in the literature review, not just the distance and size of the airports. Although many factors may show a strong correlation to size, some of these
factors may be significant even when accounting for size, for example, the type of aircraft, different airlines, or crossing national or state boundaries.

It has been noted that leisure travelers are more willing to drive farther to reach lower prices than business travelers (Suzuki et al., 2003). This suggests that an airport’s catchment area is different for these two groups of people. The time of year could influence the catchment area of airports, for example, people may avoid long drive times through during poor weather conditions. Catchment areas may vary depending on the day of the week. Lieshout (2012) also found that catchment areas are different for people traveling to different destinations. Mapping these out separately could provide a better understanding of airport catchment areas; however, there is no way to distinguish these travelers with the license plate survey method.
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APPENDIX A

MARKET SHARES PREDICTED BY HUFF MODEL
APPENDIX B

MARKET SHARES PREDICTED BY S-CURVE MODEL