Developing and Assessing Long Distance Travel Accessibility Measures to Support Intercity Travel Analyses

by

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Abstract

Long distance and intercity travel continues to grow in importance across the country in terms of its impacts on congestion, economies, and quality of life. Accessibility measures help us quantify access to or from a location, but much of the extensive research into accessibility measures has focused on short-term, daily travel, leaving long distance accessibility measures ripe for study. Research has indicated many factors that influence long distance travel, notably: leisure purposes, long distance commuting, air travel, and a destination's livability. The objective of this thesis was to assess the quality of long distance access for counties across the United States. This was done by calculating thirteen different attribute access measures and four different aggregated access measures, once using straight-line distances between origins and destinations and again using on-road distances. The measures were mapped across the United States to assess any geographic trends and it was found that scores were clustered around the northeast corridor and California. The measures were then grouped into different types of demographics and prominent industries to see if any specific trends could be observed. Additionally, the measures were used in various linear regression models to test their viability. The regression analysis revealed that individual attribute measures performed better than the aggregated measures. Additionally, using measures with straight-line distances had a higher correlation than measures using on-road distances, when looking at things from a macro-level perspective. Furthermore, a key trend observed from these results was that measures that use straight-line distances may not be completely accurate on a micro-level, as many counties that had good access scores with straight-line distances were revealed to have lower scores once driving distances were considered.

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1: INTRODUCTION

Long distance and intercity travel (defined as any trip longer than 50 miles that leaves the county) continues to grow in importance across the country in terms of its impacts on congestion, economies, and quality of life. As demand for long distance and intercity travel grows (1), more external trips travel through large metropolitan areas, most of which already experience high levels of traffic congestion on their highways (2). For this reason, many planners and engineers seek to understand the factors and related choices influencing long distance travel demand, in order to more accurately estimate future demand. With traffic congestion already linked to reductions in economic activity (3) and decreases in quality of life through health conditions such as increased risk of hypertension and obesity (4), it is critically important that future traffic estimates accurately account for long distance and intercity travel.

While research seeking to understand long distance travel behavior and forecasting long distance travel demand has increased in the past decade, the relationships between geography and long distance travel are still ripe for study. For example, many planners and forecasters posit that there are a number of regional factors that influence why individuals are drawn to specific destinations and how far individuals are willing to travel to reach specific destinations, but these regional factors are missing in many forecasting models or analyses.

One approach to describing these regional factors is using accessibility measures, typically defined as the ease with which people can access preferred goods, services, and jobs (7). As such, accessibility measures consider both the distances (or travel times) to reach these goods, services, or jobs, as well as the quality or desirability of these destinations. For example, accessibility measures have been applied extensively in research to quantify local access to preferred job markets, healthy foods, high-performing schools, appropriate medical facilities, efficient transit systems, etc. (with this work predominantly focused on urban areas). Additionally, these measures can be used to describe access *to* a specific location, access *from* a specific location, or *averaged* across locations to describe a larger region. It is also important to recognize that while access is defined separately from the concept of mobility, the two are implicitly intertwined.

Access, as defined by accessibility measures, has been shown to have a profound impact on our daily lives. Citizens from communities with better general access measures tend to have better social well-being and better overall health (5). Additionally, better access is often correlated with more economic activity (6). This can be partially attributed to the observed urban agglomeration effects that continue to cause cities and industries to cluster. As goods, services, and jobs become more accessible, it becomes easier for people to conduct business with each other, thereby generating more economic activity.

This concept of better access being tied to communities with higher quality of life can create a kind of a feedback loop, if left unchecked. Communities with better access have better social well-being and health, which attracts people to move to that community and leaves areas that have worse access less of a community to build around. Communities with better access also generate more economic impact, which can then be used to help improve accessibility for that area. If specific attention is not given to communities suffering from a lack of access, it can help widen the gap between the haves and the have-nots.

Surprisingly, this method has not been extended to quantify the ease with which individuals can access preferred long distance destinations or modes. Therefore, the four objectives of this thesis are to (a) develop a comprehensive set of long distance access measures, (b) calculate these long distance access measures for each county within the United States, (c) assess the transferability of these long distance access measures, and (d) demonstrate the relationship between long distance accessibility measures, regional characteristics, and propensity for intercity travel. Specifically, this thesis considers four main accessibility metrics: how connected communities are to (a) hotspots with leisure events, (b) hubs of economic activity, (c) livable communities, and (d) regional airports (which then allow travelers broader travel options). These measures can be used to support many different types of long distance and intercity travel analyses in practice.

The thesis is structured as follows: First, a discussion is provided regarding research into long distance travel and access measures used in planning applications. Next, a description of the geography, sources, and trends in the data that were used in the calculations is provided. The process for quantifying the destination attraction components is described, including discussions about what each component characterizes about long distance travel and the attributes used to characterize each component. Third, a description of how the distance between origins and destinations was quantified is provided. Following this is an explanation of the final steps used to calculate the scores, summary statistics that describe the calculated scores, and maps showing how these scores are distributed across the United States. Next, the scores are assessed when cross-referenced with different demographic factors to better identify trends in access. After this, the results of the regression analysis using the scores are presented and discussed. Finally, conclusions, applications and suggestions for future work are shared.

2: LITERATURE REVIEW

In this section, background is provided on accessibility measure calculation techniques, the geographic factors one might consider in long distance travel, and how accessibility measures should be applied to study long distance travel.

Accessibility Measures

Accessibility measures, defined as the ease with which people can access preferred goods, services, and jobs, are used in transportation research for many applications, with an emphasis on local travel opportunities (7-11). Specifically, accessibility measures quantify spatial relationships of access *to* a specific location, access *from* a specific location, or *averaged* across locations to describe a larger region. These measures are calculated based on (a) travel distance or time between locations, as well as (b) quantifiable characteristics of locations. There are 3 main techniques researchers use to calculate accessibility: cumulative models, gravity models, and utility-based models (12).

Cumulative models that are used to measure accessibility essentially count "the number or proportion of opportunities accessible within a certain travel distance or time from a given location" (13). These models were conceived by several researchers, most notably Wachs (14) and Dalvi (15). The general equation for this concept can be seen below:

$$A_i = \sum_j B_j * a_j \tag{1}$$

Where: A_i = Accessibility measured at point i to potential activity in zone j
a_j = Opportunity in zone j
B_j = A binary value equal to 1 if the zone is within the predetermined threshold and 0 otherwise

These methods are typically used because they require little data, are quick and easy to calculate, and are easy to interpret (12). Describing accessibility in terms of the number of jobs that are within a 20 minute driving distance from a community, for example, can be much easier than describing accessibility using more complex measures. However, the simplicity of these models are also generally their main drawback. Cut-off distances or times are often arbitrarily decided and can sometimes skew results, although a more suitable cut-off can sometimes be found using frequency distributions (13). Additionally, the attractiveness of opportunities is not considered by these models (12). Concepts like the quality of a job opportunity or the quality of a healthcare provider are not considered by these models. These weaknesses tend to make cumulative models less attractive then alternatives.

By far the most commonly used accessibility measures are those that are known as gravity models (16). In these models, accessibility "is calculated based on zones as a function of activity opportunity attractiveness and the travel distance between other zones" (12). The general equation for these models can be seen below:

$$A_{im} = \sum_{j} O_j \, f(C_{ijm}) \tag{2}$$

Where:
A_{im} = Accessibility at point i to potential activity at point j using mode m
O_j = Opportunity at point j
$f(C_{ijm})$ = The impedance or cost function to travel between i and j using mode m

Unlike the cumulative models, this concept "penalizes" an opportunity the further away it is from an origin by using an impedance function to quantify the cost that the target audience tends to associate with distance. The function is typically predetermined and can be tailored to better suit different regions, activity types, or trip types (17). Thus, the model better represents the importance of distance to opportunities. For example, a small town near an origin may provide more accessibility to job opportunities than a larger city that is further away, despite the fact that the larger city clearly has more jobs overall. These models can be useful since they are relatively easy to interpret, do not require overly complex calculations, and can be calculated primarily from publicly available data, among other advantages (16, 18). However, gravity models do still assume that each opportunity is equally attractive (19), fail to consider travel behavior on an individual level (16), and lack the capacity to incorporate known time constraints into initial calculations (18).

The third way to calculate accessibility measures are through utility-based models, the general equation for which can be seen below. They are different from the other two techniques because they include the attractiveness of an opportunity in the calculation of accessibility.

$$A_n^i = ln\left[\sum_{C_n} exp\left(V_{n(c)}\right)\right] \quad (3)$$

Where: A_n^i = Accessibility measured for individual n at location i
$V_{n(c)}$ = Observable temporal and spatial component of indirect utility of choice c for person n
C_n = Choice set of person n

Accessibility is calculated through the utility, or satisfaction level, that individuals have for their preferred activity opportunity or the average of all opportunities, something that is typically found through travel surveys (12). This allows these types of models to take into account the possibility of factors other than distance alone affecting an individual's perception of the opportunities that are available. For instance, someone may see a steakhouse in a downtown location 30 minutes away to be a better opportunity for a dinner date than a deli on the corner of their own street. These models take the attractiveness level of the restaurant into account when calculating accessibility. This is one of the main benefits of using utility-based models, as they avoid the assumption that each individual has similar preferences and behaves identically, allowing for more robust representations of human behavior (16, 20). However, these models tend to be avoided due to the complexity in developing them. They require extensive data collection, which tends to be difficult and very expensive (16).

Geographic Factors Influencing Travel

The majority of long distance travel research has focused on trip generation, or developing models that predict the number of tours (typically 50-miles or more away from home) from a household or from a community. There are a number of factors that have been shown to influence long distance tripmaking. Households with higher incomes tend to take more long distance trips (21). Household structure, gender, and the presence of children all tend to affect the amount of overnight work travel an individual takes (22-24). Race and age have been shown to affect tourism and leisure travel patterns (25).

However, one set of factors not often considered in long distance trip generation models are geographic characteristics (e.g. how close a household is to other destinations, what activities are available locally, etc.). For example, the Netherlands found "that the overall structure of the urban system" and the local population density have an effect on long distance travel volumes and distances (26). The combination of the lifestyles and economic advantages of mobile urban populations (27) and access to better long distance infrastructure has been linked to a higher volume of long distance travel among urban residents, as opposed to rural residents (28, 29). This would suggest that megaregions are more likely to experience higher volumes of long distance travel, since their residents have personal advantages and infrastructure advantages that make long distance travel more attractive.

While research specific to how geography affects long distance travel can be scarce, geography has been widely studied in the context of daily travel (30-34). The geographic organization of land uses, in particular, has been extensively studied. Boarnet and Crane found high correlations between land use, travel speed, and distance in San Diego, but did not find such results in Los Angeles (33). Further research has found that built environments have significant effects on travel demand measured through Vehicle Miles Traveled (VMT) per household (31, 32, 35, 36). Additionally, Ewing and Cervero found that Vehicle Hours Traveled (VHT), along with VMT, can be primarily explained through regional accessibility (37).

The amount of research regarding the factors associated with long distance destintation choices is also scarce. Early studies by Fesenmair, and Eymann and Ronning (38, 39) both established that distance from home was a significant factor in tourist destination choice. This was later strengthened by other studies that also found tourists prefer destinations closer to home (40-42). Additionally, a 1990 study by Johnson and Ashworth found the climate of a destination to be significant in attracting tourism (43). The findings of distance and climate being significant were later supported by other studies (39, 44). Furthermore, LaMondia and Bhat found that destinations that provide a wide variety of activities to participate in tend to perform better in attracting tourists (45). Many of these assertions are confirmed in a study of travel motivations from the UK that found that “cleanliness & safety”, “easy-to-access & economical deal”, and “sunny & exotic atmosphere” were all considered to be important characteristics of destinations when determining destination choice (46). While this research is important in understanding the factors that affect long distance travel in tourism, it does not discuss the factors attracting other types of long distance travel.

In addition to trip generation and trip attraction, certain geographic factors have also been shown to influence mode choice. A 2002 study from Cervero concluded that built-environment factors, along with attitudinal and lifestyle preference variables, influenced mode choice (47). These conclusions were further solidified by a 2004 study that went further in their conclusions, specifically listing the presence of sloping terrain and percentage of non-motorized infrastructure available as two important factors in determining mode choice (48). In 2007, Wardman found that a combination of an increase in on-route bicycle facilities, a small daily payment to cycle to work, and comprehensive trip end facilities would have a significant impact on the percentage of commuters biking to work in the UK (49). In more recent times, new modes of transportation such as electric bikes and electric scooters have prompted many questions. Research in Beijing from 2016 found that the presence of an e-bikeshare system in a city draws users from "sheltered" modes more than traditional bikeshare systems, mainly because e-bikeshare use is less sensitive to longer distances, worse air quality, and bad weather (50).

Introducing Accessibility Measures to Long Distance Travel

Based on these accessibility measure calculation options and the known geographic factors influencing travel behavior, this thesis calculates accessibility measures for each county in the United States using a gravity model to describe connectivity in four comprehensive ways. Past long distance travel research emphasizes that individuals pursue long distance trips for both recreational and business purposes, so when applying access measures to this field it is important to consider both leisure and economic attractiveness of destinations. Additionally, long distance travel is influenced by transportation opportunities to reach further destinations, as well as at the destination itself. Therefore, this paper calculates accessibility measures for each county based on four attraction components: leisure activity, economic activity, airport activity, and livable activity. This final section of the literature review summarizes our current knowledge related to these four topic areas.

First, long distance commuting is a source of long distance travel that is of particular importance, considering that travelers who make long distance trips for commuting purposes often arrive at and leave large urban areas during times of peak travel in cities, when congestion is likely at its highest. Recent research by Sandow indicates "a growing number of people are long distance commuters” (56). This is partly due to the general trend that as cities get larger, and more businesses of different types agglomerate, workers are typically left with longer commutes (57). Rather than migrating closer to these agglomerations, where living costs may be higher and commute times lower, workers are beginning to explore alternatives such as long distance daily and weekly commuting (58, 59, 60). As more workers resort to long distance commuting, it will be increasingly important for cities to account for these long distance trips.

Second, one of the factors that often contributes to long distance travel demand are trips made for leisure purposes. Various studies have found that large urban areas offer a repertoire of consumer services and goods that cannot be found in most mid-size, suburban, and rural communities, such as live arts performances, museums, and professional sports teams (51, 52, 53) Additionally, research from the 1990s came to the conclusion that “individuals are willing to spend more time traveling to destinations where they plan to spend a longer period of time” (54, 55). These findings show that large metropolitan areas attract many more trips of longer distances than smaller communities do, and that these trips may make up a significant portion of long distance trips being made into urban areas.

Third, many long distance travel trips use more than a single mode, and a large portion of these multi-modal long distance travel trips involve driving to an airport before taking a flight to the traveler’s eventual destination. Previous research has found that “access distance to an airport affects both airport attractiveness and the demand for air travel in short-haul markets” (61), but also that “high flight concentrations at an airport are often attractive enough to outweigh a substantial access disadvantage” (62). In addition, later studies have found that “business travelers are more similar to leisure travelers, who are willing to travel to more distant airports to reduce airfare costs” (63, 64). These findings indicate that travelers likely have a threshold for how far they are willing to drive when choosing an airport, but that they will often drive much longer distances to larger metropolitan areas if an airport offers more flights that may be more direct or have cheaper fares. This was further confirmed by a 2011 study that found regional airports to be losing ground to hub airports, mainly due to the previously mentioned reasons (65). Therefore, the airports themselves can serve as an attracting force for long distance car trips from surrounding counties.

Fourth, many metropolitan areas across the United States are dealing with the problems that are presented with growing populations, chief among them being traffic congestion. This congestion can be a detriment to tourists' experiences within a city and, as a result, a 2015 study found public transportation "plays an important role in tourism development at a destination, especially in urban areas" (66). This is supported from findings that tourists' experiences with public transportation service while on vacation may have an effect on their satisfaction levels with a destination (67). Additionally, cities that have extensive and effective public transportation networks have been shown to be potentially more attractive to tourists (68, 69). This would indicate that the quality and flexibility of a city's public transportation system can be an important factor in determining how many tourists the city will attract.

3: DEFINING LONG DISTANCE ACCESS MEASURES

In this section, details are provided for how long distance access measures in this thesis are defined. This thesis calculates long distance access measures for each county using the standard gravity model accessibility measure equation, adapted from the National Cooperative Highway Research Program (NCHRP) Report 735 Long Distance and Rural Travel Transferable Parameters for Statewide Travel Forecasting Models (2012):

$$Access\ Score_i = \sum \left[\beta * d^b * \ e^{(c*d)}\right] \tag{4}$$

where i is the ID of each county in the US, β is the opportunity factor attribute value for each geographic area being studied, and d is the travel distance from the county to the geographic area being characterized. This equation sums up all the attribute-distance calculations from a single county to every geographic area in the United States (e.g. MSAs or airports). Constants b and c are also defined from NCHRP Report 735, outlined in Table 1. The access score for a county is increased by being (a) *closely* connected to geographic areas with (b) *high* opportunity factor attribute values. For example, if a county is close to a Metropolitan Statistical Area (MSA) with a high attribute value, this would increase the county access score. Alternatively, if the county is also connected to an MSA with a high attribute value, but it is very far away, it does not increase the access score greatly. Finally, if the county is close to an MSA with a low attribute value, this would also not increase the access score greatly.

Table 1: Coefficients by Trip Purpose

	LD BUSINESS		**LD PLEASURE**		**LD PERSONAL BUSINESS**	
	"b"	**"c"**	**"b"**	**"c"**	**"b"**	**"c"**
LONG DISTANCE TRIPS	-0.421	-0.0022	-0.578	-0.0023	-0.567	-0.0024

There are four different types of opportunity factors considered in this thesis, and the coefficients were selected to mimic the type of travel described in the aforementioned NCHRP report. The business coefficients were used in the *Economic Activity* accessibility calculations, the pleasure coefficients were used in the *Leisure Activity* accessibility calculations, and the personal business coefficients were used in the *Airport Activity* and *Livable Activity* accessibility calculations.

Two important pieces of data are needed to complete these calculations. The first is data that quantifies the opportunities available at a destination, entered as the β values in the calculations, and the other is data containing the travel distances from every county to every geographic area, entered as the *d* values in the calculations.

4: GENERATING OPPORTUNITY FACTOR DATA

In this section, the opportunity factor attribute data used to characterize destinations is defined, as the first step of developing an accessibility measure is defining the attractiveness of different opportunities. Four different opportunity factors are identified that drive long distance travel: economic activity, leisure activity, airport activity, and livable activity. Each factor is nuanced and complex, with multiple distinct ways to describe a factor. To capture this, multiple attributes were used to characterize the attractiveness of each factor. This section outlines what each factor characterizes about long distance travel, the attributes used to characterize the attractiveness of this opportunity factor, the geography of these attributes, the sources of the attribute data, how the attributes were calculated, and the trends that can be seen in these attributes.

Factor 1: Economic Activity

Commuting for business activities is one of the main long distance trip purposes (either daily, intermittently, or sporadically) (70). In fact, much of the interstate traffic in the United States is attributed to people commuting long distances to work each day (71). The *Economic Activity* factor characterizes how each potential opportunity destination might attract long distance commute trips. Each of the attributes was calculated for every one of the 389 US Metropolitan Statistical Areas (MSAs) in the continental United States (72). These attributes were calculated using data from the 2016 County Business Patterns dataset, which was extracted from the Business Register (BR), a database maintained by the U.S. Census Bureau which contains data on all known employer companies in the United States (72). Most useful for this analysis was the fact that the dataset identified aggregate employment statistics for each MSA, as well as statistics that were disaggregated by each of the North American Industry Classification System (NAICS) groups. Economic Activity in each MSA was characterized through five specific attributes:

- *Total Number of Employers:* This attribute defines the number of employment centers, for all industries, located within each MSA. As can be seen in Table 2, the values for this attribute range from 112 to 60,669. The mean is a little less than 3 times as large as the median for this value, indicating the attribute is skewed with more MSAs having a higher number of establishments. Larger values are hypothesized to be associated with more long distance trip attractiveness.

- *Total Employment:* This attribute defines the total number of employees in each MSA. MSA employment ranges from 12,478 to 8.2 million, as seen in Table 2. This attribute tracks similarly to the previous attribute, but with an even stronger skew towards MSAs with more employees. Larger values are hypothesized to be associated with more long distance trip attractiveness.

- *Total Annual Payroll:* This attribute defines the total annual payroll (in thousands of dollars) for an MSA. As can be seen in Table 2, this attribute varies from $13 million to $15.6 billion. The mean is also 3.92 times larger than the median which indicates skewness towards higher values. Larger values are hypothesized to be associated with more long distance trip attractiveness.

- *Breadth of Specialized Industries:* This attribute defines the number of industries that are specialized in that MSA, as defined by location quotients (LQs) (73). LQs measure the local employment ratios against national employment ratios for a specific industry. For example, if 20% of a MSA's jobs come from the finance industry, and the national average shows 10% of all jobs in the United States come from the finance industry, then that MSA has an LQ of 2 for the finance industry. National employment statistics on the 19 major industry sectors provided by the Bureau of Labor Statistics (BLS) were used (74). Any industry with an LQ equal to or over 1 is considered to be a specialized industry, and the higher the LQ, the more specialized the industry is in that MSA (73). LQs are calculated as follows:

$$LQ_i = \left(\frac{e_i}{e}\right) \Big/ \left(\frac{E_i}{E}\right) \quad (5)$$

Where: e_i = Local employment in industry i
e = Total local employment
E_i= National employment in industry i
E = Total national employment

The maximum number of specialized industries was found to be 19, indicating that the MSA employs more workers in every NAICS field compared to the employment rates of the entire country, but the median number of specializations was 7. Larger values are hypothesized to be associated with more long distance trip attractiveness.

- *Intensity of Specialized Industries:* This attribute defines the level of industry specialization for each MSA, again using LQs. Specifically, this attribute is recorded as the highest LQ calculated (from the 19 categories) for each MSA. With a maximum value of 41.67, it is clear that there are some MSAs that command large specializations of certain industries. This could be a contributing factor into whether someone decides to commute long distance to a specific metropolitan area to work. Larger values are hypothesized to be associated with more long distance trip attractiveness.

Factor 2: Leisure Activity

Leisure travel is another significant long distance trip purpose, and this factor describes how enticing each potential opportunity destination in the country is to visit for leisure opportunities (e.g. a specific event or general vacationing). Again, each of the attributes was calculated for every United States MSA using data from the 2016 Business Patterns dataset. In fact, the four attributes calculated for this factor mimic those presented in the previous section, but only focused on the Arts, Entertainment, and Recreation NAICS category. Out of about 7.7 million establishments in the United States, 137,210 fall into this category. *Leisure Opportunities* in each MSA was characterized through four specific attributes:

- *Total Number of Leisure Center Employers:* This attribute defines the number of leisure or recreational employment centers that are located within each MSA. As can be seen in Table 2, the values for this attribute range from 10 to 16,557 employers. Larger values are hypothesized to be associated with more long distance trip attractiveness.

- *Total Leisure Center Employment:* This attribute defines the total number of employees working in recreational industry jobs in each MSA. MSA employment ranges from 39 to 191,112 employees, as seen in Table 2. The data suggests larger MSAs are able to support recreational establishments with higher employment levels. Larger values are hypothesized to be associated with more long distance trip attractiveness.

- *Total Leisure Center Annual Payroll:* This attribute defines the total annual payroll (in thousands of dollars) for an MSA associated specifically with leisure activity centers. As can be seen in Table 2, this attribute varies from $657,000 to $10.7 billion. The mean is 6.75 times larger than the median which indicates significant skewness towards higher values. Larger values are hypothesized to be associated with more long distance trip attractiveness.

- *Intensity of Leisure Industry Specialization*: This attribute defines the intensity of the specialization found in the arts, recreation, and entertainment industry in each MSA, as defined by LQ calculations. As can be seen in Table 2, this number ranges between 0.18 to 3.73, which makes sense, as many MSAs do not have a large portion of their workforce made up of arts, recreation, and entertainment jobs. One example on the high end of the spectrum is Las Vegas, whose MSA has a LQ greater than 3 and where the percentage of the workforce is noticeably made up of more arts, recreation, and entertainment jobs. Larger values are hypothesized to be associated with more long distance trip attractiveness.

Factor 3: Airport Activity

Airlines remain one of the dominant modes for long distance travel, so it is hypothesized that locations near highly active airports are more likely to make long distance trips. The relationship of whether individuals choose to fly or fly more often *because* they are in proximity to an active airport or if they chose to live in proximity to an active airport to *support* their desire to fly or fly more often is still unclear. Specifically, the attribute was calculated for each of the 61 airports designated as medium- or large-sized by the U.S. Bureau of Transportation Statistics (75). The attribute was calculated using data from the DB1B Airline Origin and Destination Survey, which provides a 10% sample of all passenger enplanements each year. The raw dataset was broken down into four quarters, which were summed to calculate data for the year. One attribute value is used to describe the activity or attractiveness of airports in the US:

- *Relative Number of Annual Enplanements:* This attribute defines the 10% sample of the number of passengers that boarded a plane at each of the 61 medium- or large-sized airports in the U.S. in 2016, in thousands of passengers. The median value of this attribute is 9,723 and the minimum is 2,372 (as seen in Table 2), indicating that there is a high number of people coming through these airports that should attract much more long distance trips than smaller airports would. Larger values are hypothesized to be associated with more long distance trip attractiveness.

Factor 4: Livable Activity

The final factor often associated with long distance travel destination choices is how generally appealing or livable a destination is, including ease of getting around and enjoyment of being there. The livability of a destination is generally defined as a community's quality of life. With quality of life being a somewhat abstract concept, this factor is difficult to quantify. Therefore, this thesis uses transit service and use as proxies for livability. Research often links strong transit use with general community quality of life and local mobility (76). Therefore, the *Livable Activity* factor characterizes how well each potential opportunity destination provides local mobility, and by proxy, livability, through transit-themed attributes. Each of the attributes was calculated for every one of the 3,569 US Census-defined urban areas (77), which includes many areas not characterized as MSAs. These attributes were calculated using data from AllTransit, which is a website hosting United States transit data that is maintained by the non-profit organization Center for Neighborhood Technology (CNT). This data is built from various sources, including the 2015 ACS, U.S. Census TIGER Files, and 2016 General Transit Feed Specification (GTFS) data, among other sources. *Livable Activity* in each urban area was characterized through three specific attributes:

- *Total Number of Trips per Week:* This attribute defines the total number of trips each week taken by all public transportation modes in the urban area. Specifically, the attribute looks at all fixed route transit services provided in an urban area and sums the total number of trips that are taken on fixed route transit in the urban area. Larger values are hypothesized to be associated with more long distance trip attractiveness, since studies have shown that an urban area's quality of public transportation can play a role in attracting tourism (66-69). Table 2 demonstrates that few of the urban areas have significant tripmaking by transit with minimum and median values both zero for this attribute.

- *Percentage of Weekly Travel by Transit:* This attribute defines the percentage of all the trips made weekly within the urban area that are done by public transportation. The mode split data that was specifically used in calculating this attribute came from the 2017 ACS 5-year estimates. Larger values are hypothesized to be associated with more long distance trip attractiveness. Again, Table 2 highlights that fewer residents in urban areas rely on transit (median of 0.3%), but that the top 10% of the urban areas include significantly more transit use (average of 5.3% of trips being made by transit).

- *Area Served by Transit:* This attribute defines the total square miles served by transit in each urban area. This is defined by AllTransit's variable known as Transit Access Shed (TAS). This varaible uses GIS software to measure all areas within ¼ mile of a fixed route transit stop within an urban area. These areas are summed to obtain the total area served by transit. Larger values are hypothesized to be associated with more long distance trip attractiveness. Consistent with the trends seen in the previous two attributes, many of the urban areas do not include transit service and have a median score of zero square miles.

Table 2: Opportunity Factors & Attributes Summary Statistics

	Minimum	Maximum	Mean	Median	Std. Dev.
Economic Activity					
Total Number of Employers	112	60,669	1,671	569	4,203
Total Employment	12,478	8,286,695	284,726	83,654	683,839
Total Annual Payroll ($1000)	13,140	15,644,416	423,380	107,953	1,260,995
Breadth of Specialized Industries	1.00	19.00	7.94	7.00	3.02
Intensity of Specialized Industries	1.24	41.67	2.76	2.11	2.80
Leisure Activity					
Total Number of Leisure Center Employers	10	16,557	312	93	1,125
Total Leisure Center Employment	39	191,112	5,534	1,386	15,476
Total Leisure Center Annual Payroll ($1000)	657	10,777,836	201,277	29,759	811,121
Intensity of Leisure Industry Specialization	0.18	3.73	1.01	0.91	0.53
Airport Activity					
Relative Number of Annual Enplanements	2,372	40,258	11,936	9,723	8,242
Livable Activity					
Total Number of Trips Per Week	0	6,352	90	0	309
Percentage of Weekly Travel by Transit	0.00	0.3410	0.0096	0.0030	0.0201
Area Served by Transit	0	105	2,028	0	5.77

5: GENERATING TRAVEL DISTANCE DATA

In this section, the travel distances from each county to each geographic area is defined and the methods used in calculating these distances are demonstrated. This involves calculating the travel distances from every one of the 3,141 counties in the US to every geographic area being characterized by the factors/attributes described in the previous section. In this thesis, three different geographic areas were used: (a) 389 metropolitan statistical areas (MSAs), (b) 3,569 urban areas (UAs), and (c) 61 medium/large airports. This means that three different travel distance matrices were calculated:

- 3,141 counties to 389 MSAs, resulting in a matrix with 1,221,849 travel distances
- 3,141 counties to 3,569 UAs, resulting in a matrix with 11,210,229 travel distances
- 3,141 counties to 61 airports, resulting in a matrix with 191,601 travel distances

Additionally, long distance travel research often debates the importance of considering straight-line or on-road travel distances. Straight-line distances are calculated by drawing a straight line between each origin and destination, without any consideration for topography or actual travel paths. In contrast, on-road distances are calculated using a road network and calculate the distance on the network that it takes to get from an origin to a destination. Therefore, this thesis calculates each matrix twice, with straight-line and on-road travel distances. This section outlines the steps used to generate the 6 different matrices used for accessibility measure calculations.

Straight-Line Distances

Straight-line distances were calculated using a series of steps, outlined here and repeated 3 times to provide data on the three different geographic areas being reached. First, shapefiles for the counties, MSAs, UAs and airports were downloaded from the Census TIGERfiles website (78) and a workspace was created in ESRI ArcMap that displayed each layer. Second, each county, MSA and UA polygon was converted into its geographic centroid point (i.e. the locational center of each area) using ArcMap's built-in conversion tools, creating three new point layers. Third, the latitude and longitude of each centroid was defined based on the given coordinate system using ArcMap's geography calculator functions. Fourth, the attribute tables were exported from ArcMap and reconfigured into the three large matrices defined above (e.g. rows listing counties, with latitudes and longitudes, and columns listing each geographic area, with latitudes and longitudes).

Fifth, the straight-line distance for each cell was calculated with Excel VBA using the latitude and longitude values of the row and column in the following haversine formula:

$$d = R \cdot 2 \cdot \operatorname{atan2}\left[\sqrt{(\sin^2(\Delta\varphi/2) + \cos\varphi_1 \cdot \cos\varphi_2 \cdot \sin^2(\Delta\lambda/2))}\right], \left[\sqrt{1 - \sin^2(\Delta\varphi/2) + \cos\varphi_1 \cdot \cos\varphi_2 \cdot \sin^2(\Delta\lambda/2))}\right] \quad (6)$$

Where: d is the Haversine distance
φ is latitude,
λ is longitude,
R is earth's radius (mean radius = 3,950 miles)

The final result of these calculations were three matrices which contained straight-line distances (in miles) between all geographies relevant to this analysis. A sample of the matrix between Counties and MSAs can be seen in Figure 1.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
DISTANCES				FID	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
				GEOID	40340	39580	39660	40380	39740	39820	39900	40060	40140	40220	40420	40580	40660	41860	40900
				NAME	Rochester,	Raleigh, N(	Rapid City,	Rochester,	Reading, P	Redding, C	Reno, NV	Richmond,	Riverside-S	Roanoke, V	Rockford, I	Rocky Mou	Rome, GA	San Francis	Sacramento
				LAT	43.95601	35.75724	44.19149	43.14908	40.4163	40.76377	40.619	37.46186	34.55168	37.28615	42.33162	35.94101	34.26316	37.77411	38.78046
FID	GEOID	NAME	LAT	LONG	-92.33809	-78.46086	-102.8999	-77.52207	-75.926	-122.0405	-119.6591	-77.47316	-116.1297	-79.94691	-89.04208	-77.79849	-85.21428	-122.2741	-120.9976
0	31039	Cuming	41.9164	-96.7874	265.4876	1071.407	346.2104	982.3997	1087.322	1307.712	1187.657	1069.384	1162.993	949.9633	397.819	1098.009	820.6776	1376.585	1288.692
1	53069	Wahkiakum	46.29113	-123.4335	1514.675	2418.66	1006.544	2232.759	2384.431	388.2129	435.1055	2405.865	896.5467	2293.79	1708.404	2443.643	2153.666	591.4573	533.4813
2	35011	De Baca	34.34241	-104.412	925.3134	1466.876	685.2676	1562.89	1611.557	1060.12	939.9544	1517.759	667.4426	1381.825	996.8575	1503.073	1094.112	1023.767	968.5329
3	31109	Lancaster	40.78417	-96.68776	311.8894	1045.579	394.2849	995.8082	1086.932	1321.906	1199.87	1052.917	1144.083	928.7818	409.3384	1074.136	772.422	1379.143	1294.015
4	31129	Nuckolls	40.17638	-98.04718	392.1925	1107.106	372.2713	1076.327	1162.822	1257.881	1134.763	1120.711	1063.911	993.9633	490.6107	1136.992	814.5574	1307.768	1224.352
5	46099	Minnehaha	43.67418	-96.79144	222.8541	1113.742	305.9695	965.6805	1090.922	1302.361	1186.399	1097.707	1208.817	986.6767	402.2446	1137.18	898.0571	1388.9	1297.361
6	48327	Menard	30.88978	-99.82064	990.7157	1275.294	934.2332	1485.96	1487.755	1413.628	1295.154	1351.74	979.97	1217.082	989.3536	1313.933	880.8882	1362.368	1314.775
7	6091	Sierra	39.5804	-120.516	1475.634	2294.23	958.2317	2218.533	2335.394	114.7291	84.85439	2309.14	423.1944	2182.846	1643.832	2324.999	1971.236	156.7385	60.99392
8	21053	Clinton	36.72748	-85.13601	626.5954	377.8885	1063.578	599.1154	558.599	1993.341	1869.448	425.2328	1739.284	288.8666	439.4921	411.9041	170.3265	2030.318	1951.688
9	39063	Hancock	41.00194	-83.66654	486.4214	458.9523	1000.276	348.1806	407.2917	1988.236	1868.939	411.7664	1816.69	324.9566	292.2113	472.0334	473.2241	2056.857	1969.919
10	48189	Hale	34.07051	-101.8269	850.8134	1325.85	701.6428	1447.34	1484.382	1198.219	1076.313	1381.314	816.2731	1245.034	896.9588	1362.554	948.7605	1169.802	1111.932
11	1027	Clay	33.26909	-85.86055	816.3663	454.8545	1184.522	818.1442	737.7725	2046.417	1921.278	553.9634	1731.479	433.7684	649.6739	494.0583	78.07384	2058.129	1987.44

Figure 1: Sample of straight-line distance matrix between Counties and MSAs

On-Road Distances

On-road distances were calculated using a second series of steps, outlined here and again repeated 3 times to provide data on the three different geographic areas being reached. First, shapefiles for the counties, MSAs, UAs and airports were downloaded from the Census TIGERfiles website (78) and a workspace was created in ESRI ArcMap that displayed each layer. Second, each county, MSA and UA polygon was converted in its geographic centroid point (i.e. the locational center of each area) using ArcMap's built-in conversion tools, creating three new point layers. Third, the FHWA National Highway Planning Network (NHPN) line shapefile was downloaded (79) and added to the ArcMap workspace. This shapefile includes all the major primary and secondary roads in the US, made up of interstates and state highways, and is stored as a geodatabase to work with network analyses in ArcMap. Fourth, using the ArcMap and ArcCatalog software, a network file was generated that is necessary for ArcMap to calculate travel distances. This network file generates information about travel times, distances, and intersection choices for any trips made using the NHPN line shapefile. Fifth, the OD Matrix function in the Network Analyst toolbar of ArcMap was used to determine the travel distance from every county centroid to every MSA, UA and airport centroid/point. However, when ArcGIS uses Network Analyst to calculate on-road distances, it does not create a standard origin-destination matrix with rows corresponding to counties and columns corresponding to MSAs, similar to what can be seen in Figure 3. Instead, ArcGIS creates a table with a separate row for each individual combination between a county and an MSA, a sample of which can be seen in Figure 2. With 3,141 counties and 389 MSAs, this meant that there were a little over 1.2 million rows in the table holding the on-road distances. Sixth, due to limitations in the number of rows that can be exported at one time, these tables were exported from ArcMap to Excel in pieces, reassembled and restructured (using Excel VBA) to match the format seen in Figure 1.

	A	B	C	D	E	F	G
1	FID	ObjectID	Name	OriginID	Destinatio	Destinat_1	Total_Mile
2	0	1	Cuming - Location 97	1	97	1	30.23406861
3	1	2	Cuming - Location 1141	1	1141	2	63.60312933
4	2	3	Cuming - Location 791	1	791	3	70.62625921
5	3	4	Cuming - Location 1067	1	1067	4	89.32730619
6	4	5	Cuming - Location 1076	1	1076	5	90.01045169
7	5	6	Cuming - Location 91	1	91	6	93.3409667
8	6	7	Cuming - Location 792	1	792	7	94.98246274
9	7	8	Cuming - Location 1081	1	1081	8	95.73468915
10	8	9	Cuming - Location 1442	1	1442	9	96.66855369
11	9	10	Cuming - Location 925	1	925	10	99.56243223

Figure 2: Sample of ArcGIS Network Analyst table output

The final result of these calculations were three matrices which contained on-road distances (in miles) between every county and (a) MSA, (b) UA, and (c) airport. A sample of the matrix between Counties and MSAs can be seen in Figure 3.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	**DISTANCES**				**FID**	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
2					**GEOID**	40340	39580	39660	40380	39740	39820	39900	40060	40140	40220	40420	40580	40660	41860	40900
3					**NAME**	Rochester,	Raleigh, N	Rapid City,	Rochester,	Reading, P	Redding, C	Reno, NV	Richmond,	Riverside-S	Roanoke, V	Rockford, I	Rocky Mou	Rome, GA	San Franci	Sacrament
4					**LAT**	43.95601	35.75724	44.19149	43.14908	40.4163	40.76377	40.619	37.46186	34.55168	37.28615	42.33162	35.94101	34.26316	37.77411	38.78046
5	**FID**	**GEOID**	**NAME**	**LAT**	**LONG**	-92.33809	-78.46086	-102.8999	-77.52207	-75.926	-122.0405	-119.6591	-77.47316	-116.1297	-79.94691	-89.04208	-77.79849	-85.21428	-122.2741	-120.9976
6	0	31039	Cuming	41.9164	-96.7874	327.825	1241.872	398.7309	1045.301	1145.22	1574.665	1352.872	1218.44	1554.971	1096.631	432.4373	1276.018	985.2535	1619.439	1522.806
7	1	53069	Wahkiakum	46.29113	-123.4335	1756.427	2808.971	1229.921	2632.193	2732.112	529.8098	612.1404	2787.577	1208.891	2663.73	1983.219	2843.117	2531.104	739.38	711.9011
8	2	35011	De Baca	34.34241	-104.412	1126.142	1576.766	876.3271	1681.245	1699.538	1420.986	1235.976	1636.031	1032.848	1482.738	1165.077	1610.912	1167.204	1411.267	1333.862
9	3	31109	Lancaster	40.78417	-96.68776	384.9253	1192.203	488.705	1050.83	1141.589	1526.189	1304.396	1170.81	1501.11	1046.962	451.2446	1226.349	914.3368	1570.963	1474.33
10	4	31129	Nuckolls	40.17638	-98.04718	492.7861	1260.085	470.2133	1158.364	1226.821	1488.161	1266.368	1254.896	1398.633	1131.048	559.1054	1294.231	960.4861	1532.935	1436.302
11	5	46099	Minnehaha	43.67418	-96.79144	229.1335	1315.053	311.9325	1101.222	1201.141	1594.775	1372.982	1281.993	1634.675	1169.813	450.6376	1349.2	1101.021	1639.549	1542.916
12	6	48327	Menard	30.88978	-99.82064	1146.825	1354.942	1108.51	1629.046	1636.909	1799.898	1621.582	1453.143	1258.773	1299.85	1164.374	1395.813	950.4467	1670.282	1674.679
13	7	6091	Sierra	39.5804	-120.516	1717.102	2620.481	1228.039	2470.868	2569.867	210.9588	176.5688	2599.088	667.0385	2475.241	1871.283	2654.628	2324.273	216.4495	108.1851
14	8	21053	Clinton	36.72748	-85.13601	773.6359	456.6454	1247.227	692.3455	671.0553	2302.745	2080.952	512.9152	2098.901	359.6224	532.2688	490.7916	214.1089	2345.111	2234.553
15	9	39063	Hancock	41.00194	-83.66654	567.3994	571.2886	1073.648	367.53	450.1829	2229.233	2007.44	529.212	2156.555	426.0477	326.0324	605.4347	566.9297	2274.008	2177.374
16	10	48189	Hale	34.07051	-101.8269	1042.055	1443.268	824.1802	1579.8	1598.092	1553.796	1368.786	1502.534	1165.659	1349.241	1080.99	1477.415	1033.707	1544.078	1466.672
17	11	1027	Clay	33.26909	-85.86055	994.4914	482.2471	1419.298	987.1308	835.355	2436.269	2251.259	607.9064	2109.618	497.9642	771.9286	523.1175	99.36169	2464.003	2353.444

Figure 3: Sample of on-road distance matrix between Counties and MSAs

6: CALCULATING LONG DISTANCE ACCESS MEASURES

In this section, the process of calculating the access measures is discussed and a discussion of how the calculated access measures are distributed geographically across the United States is provided. The comprehensive set of access measures was calculated through a series of steps using the opportunity factor data and the distance data that was generated in the previous two sections. The full set of access measures can be seen in Table 3. There are two types of access measures calculated in this thesis: *individual attribute access measures*, which describe each county's accessibility related to the 13 unique long distance attributes (colored blue in Table 3), and *aggregated factor access measures*, which combine the attributes for each factor into 4 single summarized access measures (colored orange in Table 3).

In this section, a hypothetical example is used to illustrate the methodology used in calculating the long distance access measures. In this example, three theoretical counties accessing four different MSAs are considered. The Economic Activity factor is simplified with just two attributes: Total Number of Employers and Total Annual Payroll ($1000). The equation used in calculations, the basic data for each attribute in each MSA, and the distance between counties and MSAs from this example can be seen in Figure 4. Within the figure, the orange outline highlights the data that corresponds with β and the red outline highlights where the distance data is used in the equation. Additionally, Figure 5 gives a spatial representation of this hypothetical example in a diagram. The data in the orange circles corresponds with the attribute data from Figure 4, and the distances along each red line correspond with the distances from Figure 4.

$$Access\ Score_i = \sum \left[\beta * d^b * e^{(c*d)} \right]$$

Attribute Values				
	MSA			
	A	B	C	D
Total Number of Employers	500	800	1000	200
Total Annual Payroll ($1000)	1000	2000	9000	500

Travel Distances				
County	**MSA**			
	A	B	C	D
1	50	100	200	300
2	500	200	300	100
3	50	100	800	1000

Figure 4: Example Data for Access Measure Calculations

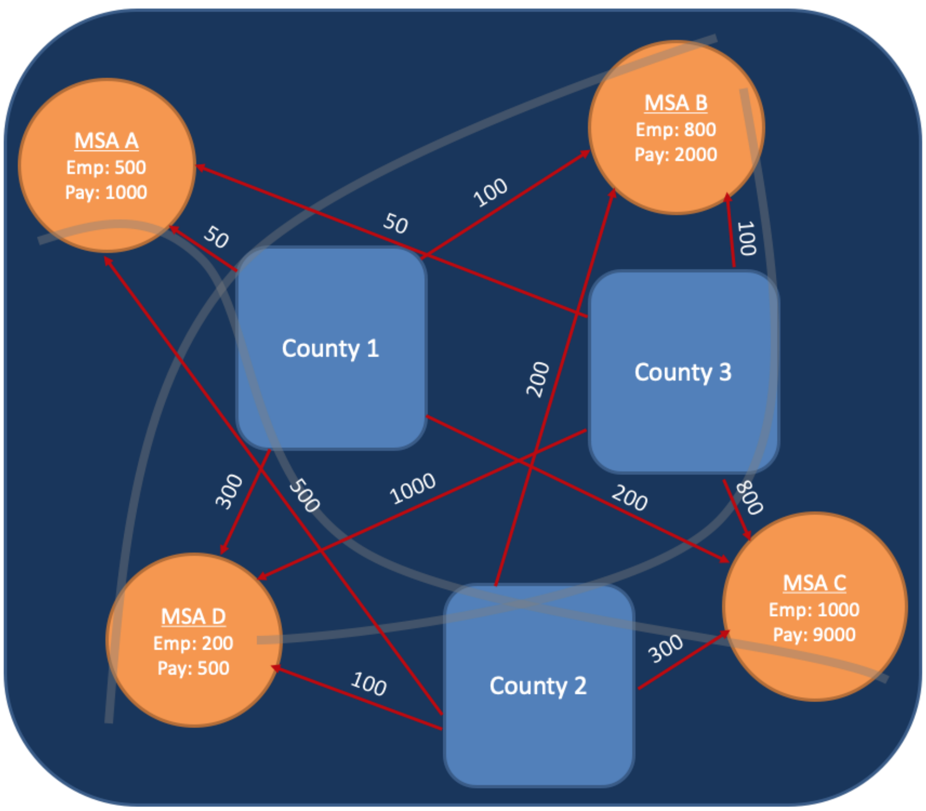


Figure 5: Spatial Diagram of Example Data

The first step is to calculate the individual County to MSA components and then sum those components for each county. The relevant data from the diagram can be seen in Figure 6, and a walkthrough of the calculation of one of these components can be seen in Figure 7. This specific calculation, which is circled in black in Figure 7, looks at the effect that the Total Number of Employers from *MSA A* has on long distance travel demand in *County 1*. Therefore, the Total Number of Employers from *MSA A* has been circled in blue in Figure 6, and the distance from *County 1* to *MSA A* has been circled in orange. Where these values fit in to the equation used to carry out this calculation can be seen with the corresponding orange and blue circles in Figure 7.

The result of the calculation of this component is 0.200, which then goes into the table for Total Number of Employers and is used in the next calculation (illustrated by green arrow). This calculation is also done for *MSAs B, C, and D* and then the four components are summed to get the raw Total Number of Employers Individual Attribute Access Score for *County 1*, which in this example turned out to be 0.307 (illustrated by blue arrow).

This process is repeated for each county and each attribute. It is important to note that the scale of these raw individual attribute access measures are dependent on the original opportunity factor attribute value describing the MSAs, so they can range from zero to infinity. This raises issues for combining individual attribute access scores into aggregate access scores, since it is possible that the range of values could vary wildly from score to score.

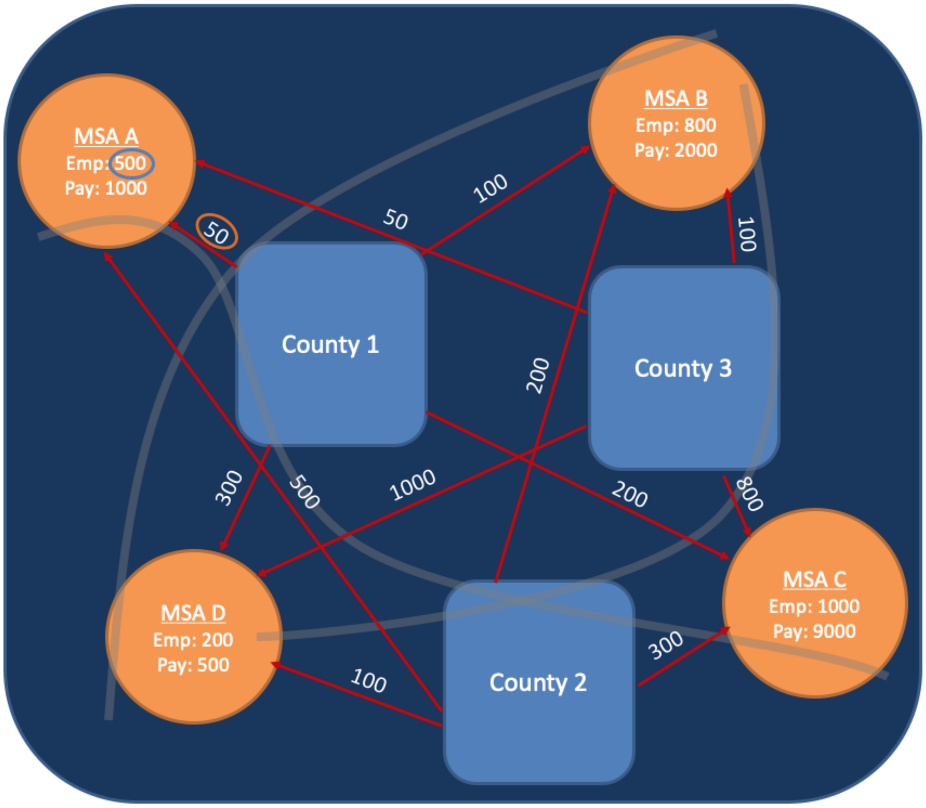


Figure 6: Spatial Diagram with Relevant Data Highlighted

$$Access\ Score_i = \sum [\beta * d^b * e^{(c*d)}]$$

$$500 * 50^{(-0.421)} * e^{[(-0.0022)*50]} = 0.200$$

$$0.200 + 0.080 + 0.025 + 0.002 = 0.307$$

For: Total Number of Employers

County	MSA A	MSA B	MSA C	MSA D	SUM
1	0.200	0.080	0.025	0.002	0.307
2	0.002	0.020	0.011	0.020	0.053
3	0.200	0.080	0.002	0.000	0.282

For: Total Annual Payroll

County	MSA A	MSA B	MSA C	MSA D	SUM
1	0.400	0.200	0.225	0.006	0.831
2	0.004	0.050	0.100	0.050	0.204
3	0.400	0.200	0.014	0.001	0.615

Figure 7: Step 1 Calculations

Once the raw individual attribute access scores have been calculated, the next steps are to normalize the scores and then aggregate the two individual access measures. The normalization process ensures that every individual access score value is scaled between 0 and 100. Zeros represent a county with the smallest access score of a specific attribute, 100 represents a county with the largest access measure value, and all other counties are scaled proportionally between these two limits. This process is important to ensure that access measures with different variable units (both within and across factors) can be compared and combined equitably.

In this example, a walkthrough of the normalization process for one of the components can be seen in Figure 8. This specific calculation, which is circled in black at the bottom of Figure 8, normalizes the raw score for the Total Number of Employers attribute for *County 3*. First, the sums from the previous step are reformatted in an easy-to-understand form for carrying out Step 2. Next, the normalization equation seen in Figure 8 is utilized to normalize the raw score. In this calculation, V_{Raw} in the normalization equation is 0.282, as is illustrated by the green arrow. Since the attribute being normalized is Total Number of Employers, the maximum and minimum values in the normalization equation are 0.307 and 0.053, respectively. The number resulting from this calculation is multiplied by 100 to get a normalized score of 89.98, which is then placed in the proper location of the normalized table (illustrated by blue arrow).

The final step is to calculate each county's aggregated economic activity factor access measure. With each attribute having been considered equally important, and each factor being comprised of different numbers of attributes, the aggregate measures are calculated simply by taking the mean of the normalized individual attribute access measures. These values can be seen in the final column of the table at the bottom of Figure 8.

For: Total Number of Employers

County	MSA A	MSA B	MSA C	MSA D	SUM
1	0.200	0.080	0.025	0.002	0.307
2	0.002	0.020	0.011	0.020	0.053
3	0.200	0.080	0.002	0.000	0.282

For: Total Annual Payroll

County	MSA A	MSA B	MSA C	MSA D	SUM
1	0.400	0.200	0.225	0.006	0.831
2	0.004	0.050	0.100	0.050	0.204
3	0.400	0.200	0.014	0.001	0.615

County	Raw: Total Number of Employers	Raw: Total Annual Payroll ($1000)
1	0.307	0.831
2	0.053	0.204
3	0.282	0.615

Calculation for Total Number of Employers for County 3:

$$V_{Norm} = \frac{V_{Raw} - Min}{Max - Min} \times 100\%$$

$$\frac{0.282 - 0.053}{0.307 - 0.053} \times 100\% = 89.98$$

County	Normalized: Total Number of Employers	Normalized: Total Annual Payroll ($1000)	Normalized: Aggregate
1	100.00	100.00	100.00
2	0.00	0.00	0.00
3	89.98	65.53	77.80

Figure 8: Steps 2 and 3 Calculations

The final results of this example are shown in tabulated form in Figure 9 and in diagram form in Figure 10. In the updated diagram, each county's aggregated economic activity access measure is included. Additionally, the values are circled by color in both Figures 9 and 10 to show how the data corresponds to the diagram. The process demonstrated in this example was used to calculate the 26 individual attribute access measures and 8 aggregated factor access measures outlined in Table 3. The summary statistics of these measures can be seen in Table 4.

County	Raw		Normalized		
	Total Number of Employers	Total Annual Payroll ($1000)	Total Number of Employers	Total Annual Payroll ($1000)	Aggregate
1	0.307	0.831	100.00	100.00	100.00
2	0.053	0.204	0.00	0.00	0.00
3	0.282	0.615	89.98	65.53	77.80

Figure 9: Example Raw and Normalized Attribute Scores

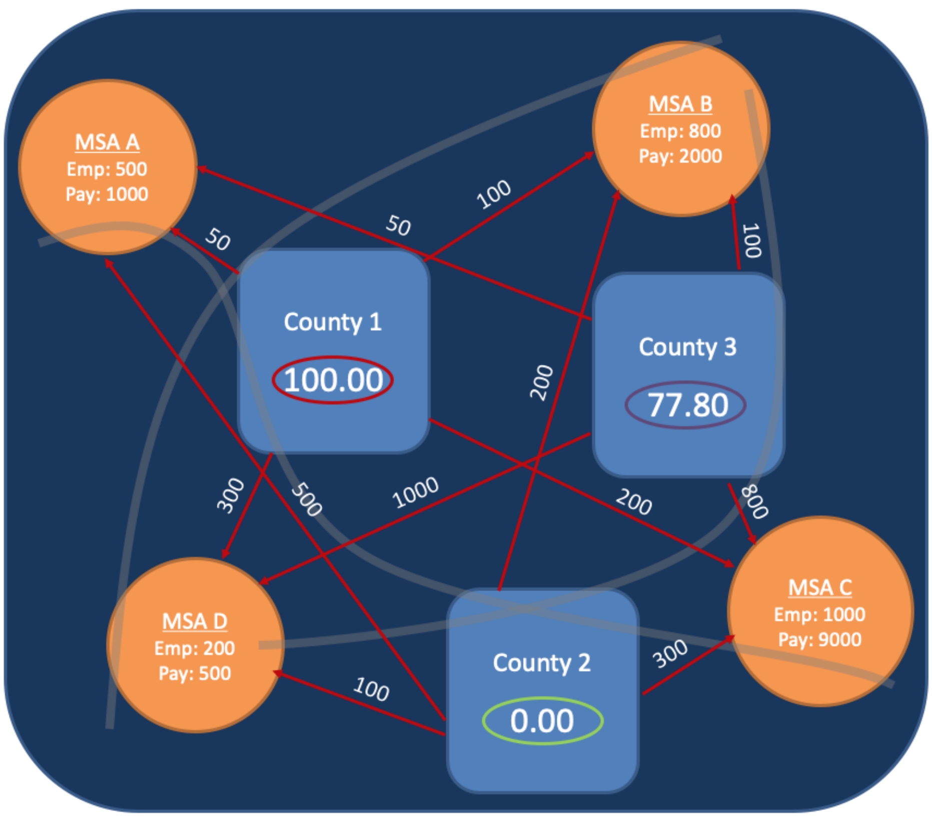


Figure 10: Spatial Diagram with Final Calculation Results Highlighted

Table 3: County Access Measures

STRAIGHT LINE DISTANCES	ON ROAD DISTANCES
Economic Activity	**Economic Activity**
Aggregated Economic Activity Factor Measure	Aggregated Economic Activity Factor Measure
Total Number of Employers	Total Number of Employers
Total Employment	Total Employment
Total Annual Payroll ($1000)	Total Annual Payroll ($1000)
Breadth of Specialized Industries	Breadth of Specialized Industries
Intensity of Specialized Industries	Intensity of Specialized Industries
Leisure Activity	**Leisure Activity**
Aggregated Leisure Activity Factor Measure	Aggregated Leisure Activity Factor Measure
Total Number of Leisure Center Employers	Total Number of Leisure Center Employers
Total Leisure Center Employment	Total Leisure Center Employment
Total Leisure Center Annual Payroll ($1000)	Total Leisure Center Annual Payroll ($1000)
Intensity of Leisure Industry Specialization	Intensity of Leisure Industry Specialization
Airport Activity	**Airport Activity**
Aggregated Airport Activity Factor Measure	Aggregated Airport Activity Factor Measure
Relative Number of Annual Enplanements	Relative Number of Annual Enplanements
Livable Activity	**Livable Activity**
Aggregated Livable Activity Factor Measure	Aggregated Livable Activity Factor Measure
Total Number of Trips Per Week	Total Number of Trips Per Week
Percentage of Weekly Travel by Transit	Percentage of Weekly Travel by Transit
Area Served by Transit	Area Served by Transit

Table 4: Summary Statistics of Individual Attribute and Aggregated Factor Access Measures

	Minimum	Maximum	Mean	Median	Std. Dev.
STRAIGHT LINE DISTANCES					
Economic Activity					
Aggregated Economic Activity Factor Measure	0.21	79.70	35.70	35.95	17.00
Total Number of Employers	0.00	100.00	19.64	18.13	11.54
Total Employment	0.00	100.00	23.09	21.61	12.41
Total Annual Payroll ($1000)	0.00	100.00	19.64	17.30	12.11
Breadth of Specialized Industries	0.00	100.00	47.76	50.02	23.75
Intensity of Specialized Industries	0.00	100.00	52.32	54.38	22.85
Leisure Activity					
Aggregated Leisure Activity Factor Measure	0.00	83.11	22.22	21.29	11.75
Total Number of Leisure Center Employers	0.00	100.00	9.51	8.18	6.70
Total Leisure Center Employment	0.00	100.00	10.97	9.62	7.29
Total Leisure Center Annual Payroll ($1000)	0.00	100.00	8.25	7.03	6.21
Intensity of Leisure Industry Specialization	0.00	100.00	34.93	34.51	17.78
Airport Activity					
Aggregated Airport Activity Factor Measure	0.00	100.00	4.45	1.28	8.19
Relative Number of Annual Enplanements	0.00	100.00	4.45	1.28	8.19
Livable Activity					
Aggregated Livable Activity Factor Measure	0.00	94.36	24.84	21.25	15.44
Total Number of Trips Per Week	0.00	100.00	22.28	18.27	15.32
Percentage of Weekly Travel by Transit	0.00	100.00	27.39	24.49	16.09
Area Served by Transit	0.00	100.00	31.02	26.24	18.99

Table 4 (continued): Summary Statistics of Individual Attribute and Aggregated Factor Access Measures

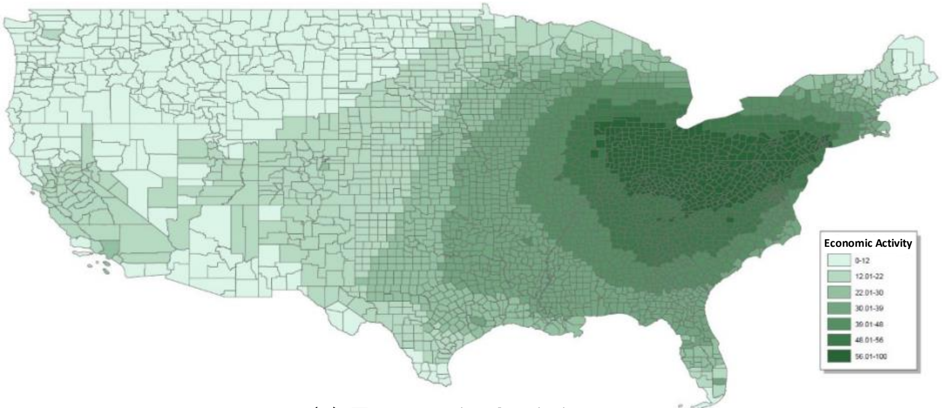
	Minimum	Maximum	Mean	Median	Std. Dev.
ON-ROAD DISTANCES					
Economic Activity					
Aggregated Economic Activity Factor Measure	0.07	87.36	32.97	32.37	16.46
Total Number of Employers	0.00	100.00	18.70	17.06	11.15
Total Employment	0.00	100.00	22.03	20.66	12.07
Total Annual Payroll ($1000)	0.00	100.00	18.04	16.03	11.25
Breadth of Specialized Industries	0.00	100.00	51.81	53.54	26.27
Intensity of Specialized Industries	0.00	100.00	54.26	57.59	24.86
Leisure Activity					
Aggregated Leisure Activity Factor Measure	0.00	92.37	15.67	14.48	8.99
Total Number of Leisure Center Employers	0.00	100.00	10.60	9.44	6.94
Total Leisure Center Employment	0.00	100.00	10.58	9.31	7.24
Total Leisure Center Annual Payroll ($1000)	0.00	100.00	8.03	6.96	6.20
Intensity of Leisure Industry Specialization	0.00	100.00	33.47	32.44	17.32
Airport Activity					
Aggregated Airport Activity Factor Measure	0.00	100.00	3.47	0.00	7.30
Relative Number of Annual Enplanements	0.00	100.00	3.47	0.00	7.30
Livable Activity					
Aggregated Livable Activity Factor Measure	0.13	100.00	12.51	11.21	7.75
Total Number of Trips Per Week	0.00	100.00	4.26	3.55	3.34
Percentage of Weekly Travel by Transit	0.00	100.00	20.75	19.07	12.54
Area Served by Transit	0.00	100.00	22.50	19.75	13.62

To have a visual representation of long distance access, each of the 8 aggregated component access scores were mapped across the United States. The maps associated with straight-line distances can be seen in Figure 5 and the maps associated with on-road distances can be seen in Figure 6.

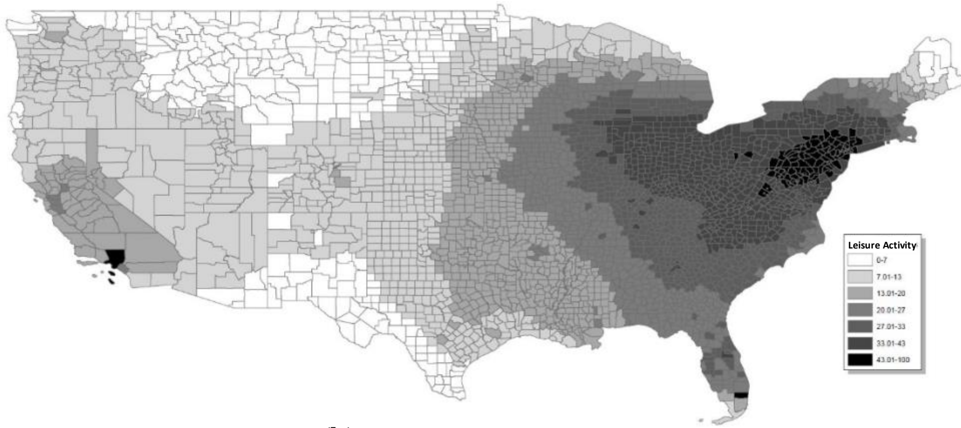
When looking at the straight-line distance maps in Figure 5, there tend to be clear geographic areas that have higher scores that show where counties are highly connected to many urban areas, MSAs or airports with high attraction levels. For example, the leisure, economic, and livable activity access measure has high scores clustered around the densely populated and developed northeast corridor, with scores decreasing as it radiates out from that cluster. This can also be seen with scores radiating out from the southern California area for economic activity and leisure activity and from the Bay Area for livable activity. In addition, the airport activity access scores are higher surrounding the large and medium airports.

However, when looking at the on-road distance maps in Figure 6, the trends are not as clean. The leisure, economic, and livable activity access scores still certainly favor the eastern half of the United States where there is more dense development, with a particular bias towards the northeast corridor, but many low-score counties can be seen throughout, breaking up the trend. This can also be seen with the airport activity access score, which still has visible clusters around airports, but also has nearby counties with lower scores than previously.

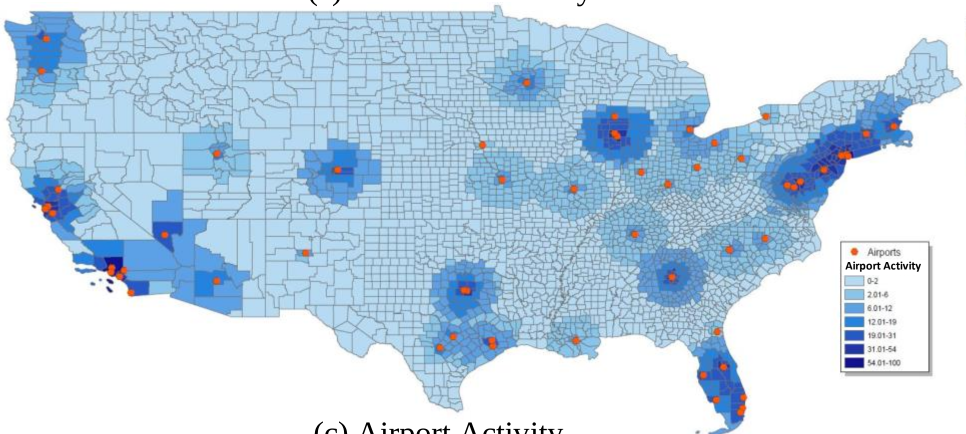
There are two main conclusions from these figures. First, considering that the only difference in calculation between the two sets of maps is whether a straight-line distance or an on-road distance was used, it is likely that there is a disconnect in how much access a county is perceived to have and how much access a county actually has. Clearly there are counties that are nearby to airports, for example, but lack major roadways to reach them quickly. True on-road measures show that access is not equitable across neighboring counties, and straight-line distances often oversimplify these relationships. Second, the same color bands are used in both figures, but the straight-line maps demonstrate more diverse representation across each band. Counties in the on-road maps show a higher number of counties with middling access scores, showing that many counties share similar average levels of access and a few counties have significantly higher access levels. To better understand this disconnect, it is important to further investigate trends among these four measures.



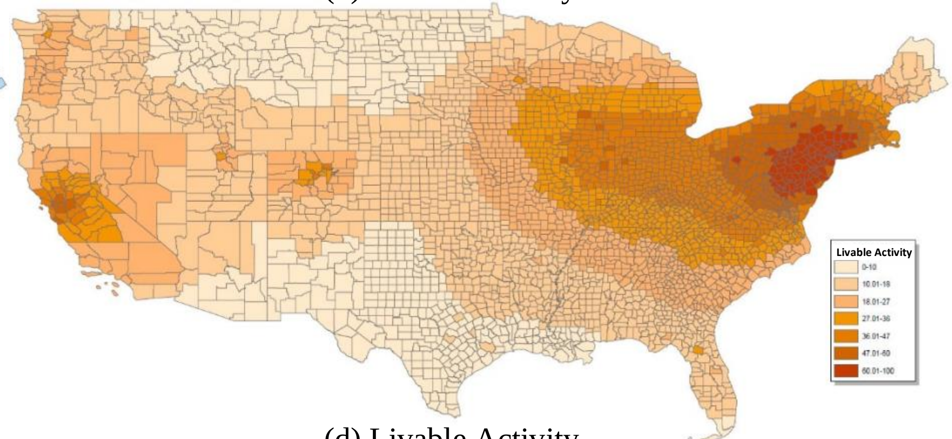
(a) Economic Activity



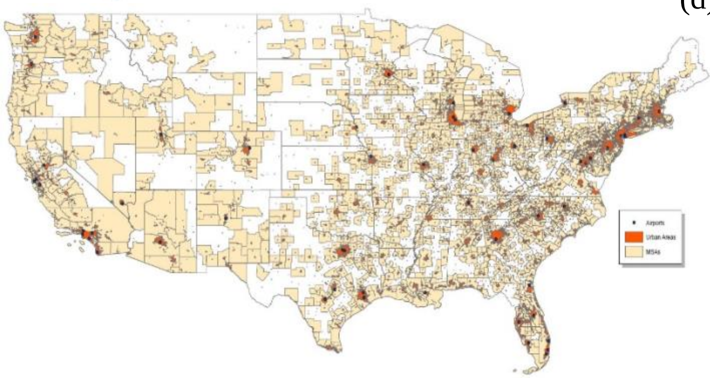
(b) Leisure Activity



(c) Airport Activity

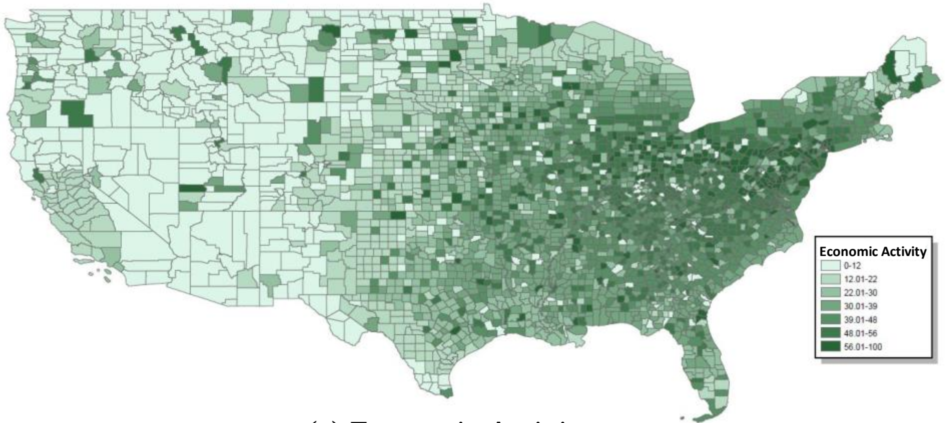


(d) Livable Activity

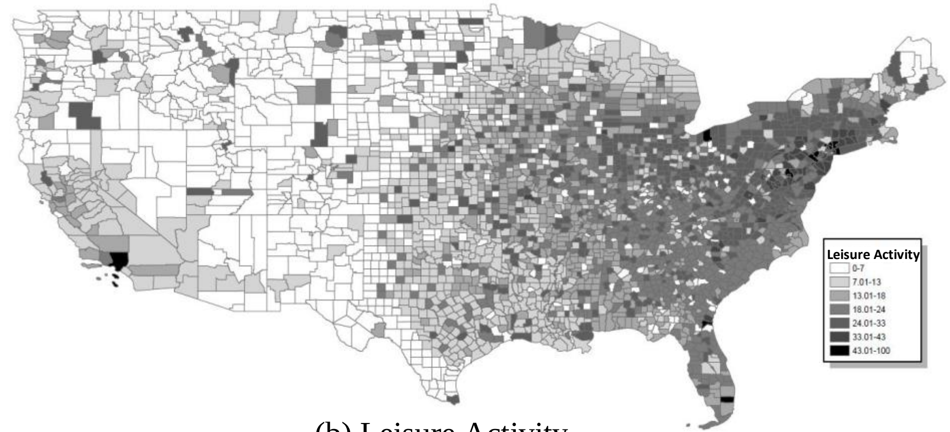


(e) Attraction Geographies

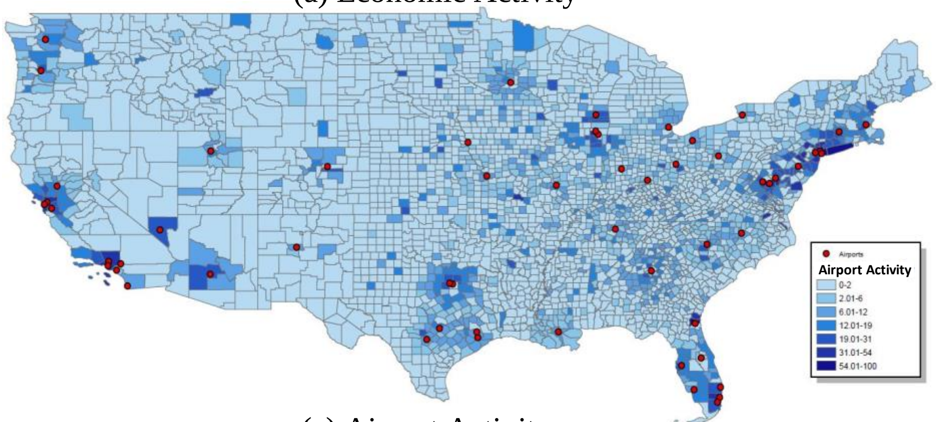
Figure 11: Aggregated Access Scores (Straight-Line Distances) Mapped



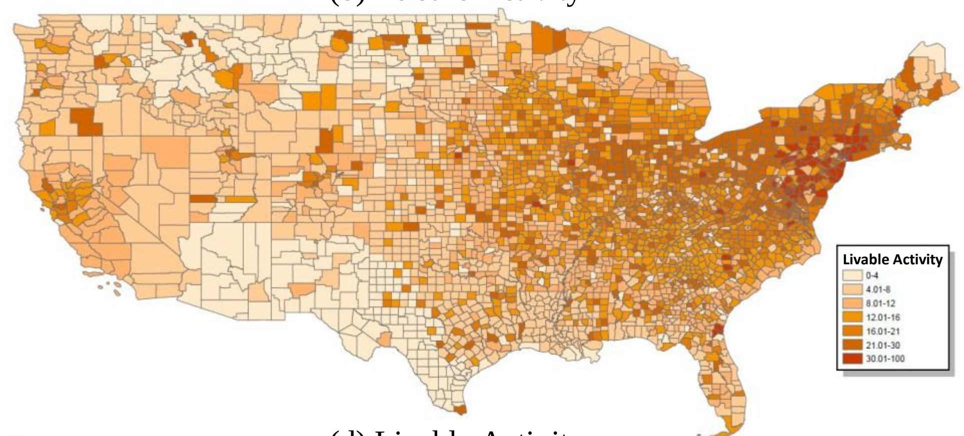
(a) Economic Activity



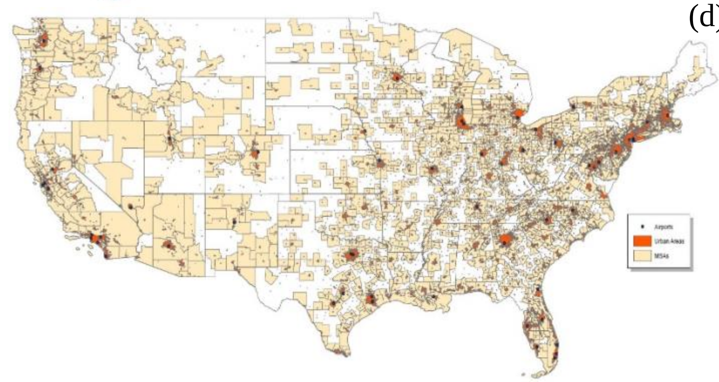
(b) Leisure Activity



(c) Airport Activity



(d) Livable Activity



(e) Attraction Geographies

Figure 12: Aggregated Access Scores (On-Road Distances) Mapped

7: ASSESSING ACCESS MEASURE TRANSFERABILITY

In this section, preliminary assessments of the previously calculated distances and access measures are provided. Before conducting more complex assessments with these access measures, it is important to consider how (a) on-road and straight-line distances are related and (b) how the different attribute and factor access measures compare with each other. Similarities between these two considerations indicate the transferability of the distances or access measures.

For the first assessment, categories for every 250 miles were created and on-road distances and straight-line distances were grouped into these categories by frequency. The frequencies were then used to create a bubble graph, which can be seen in Figure 7. The orange line on the graph represents where an origin-destination would fall if that origin-destination's on-road and straight-line distance were exactly the same. Therefore, origin-destinations that fall above the orange line have a longer on-road distance than straight-line distance, while origin-destinations that fall below the orange line have a longer straight-line distance than on-road distance.

As expected, a majority of origin-destinations had slightly longer on-road distances than straight-line distances. The average difference in on-road distances and straight-line distances was 149.22 miles, with the median value and standard deviation of that measurement being 129.96 and 73.01 miles, respectively. In fact, there was a small minority of origin-destinations (less than 1%, illustrated by upper black triangle in Figure 7) that had noticeably longer on-road than straight-line distances. This is likely best explained by how some origin-destinations can have difficult topography to traverse, and subsequently do not have a very straight on-road path to get from origin to destination.

The more surprising result of this analysis was the presence of another small minority of origin-destinations (approximately 6.5%) that had a longer straight-line distance than on-road distance. Within this minority, the average difference in distances was 40.06 miles, and the median and standard deviation of the difference were 28.85 and 31.37 miles, respectively. Of this group, the majority (approximately 5.8%, illustrated by the red polygon in Figure 7) can be explained by how the two distances were calculated. Straight-line distances were calculated from the center point of an origin to the center point of a destination. On-road distances were calculated by finding the nearest point on the road network to the center point and then calculating the distance from there. It is likely that a portion of the on-road distances were calculated to be shorter because the starting and ending points for the on-road calculation may have been closer to each other than they had been when calculating the corresponding straight-line distance. This is a consequence of how ArcGIS's Network Analyst tool calculates distances. In western states, where county geography is quite large and the road network can be less dense, these effects could have become quickly magnified, particularly among origin-destinations that were relatively close to each other.

While this phenomena caused by the difference in the starting points used for calculations of straight-line and on-road distances is something to be aware of, the phenomena is considered in this thesis to be negligible, mainly due to how the calculated distances are used throughout access measure calculations. In the equation from NCHRP Report 735, distance values are subject to exponents that are less than 1. This means that rather than each individual calculation applying a typical *exponential* effect on distances, where discrepancies can have an increasing effect as each calculation builds on itself, each individual calculation is instead applying something more akin to a typical *square root* effect on distances. This means that as the thousands of calculations are conducted and summed, the effects of discrepancies on final outcomes is being minimized. Therefore, with millions of calculations having been done to calculate the access measures, the effect of the aforementioned phenomena is considered negligible.

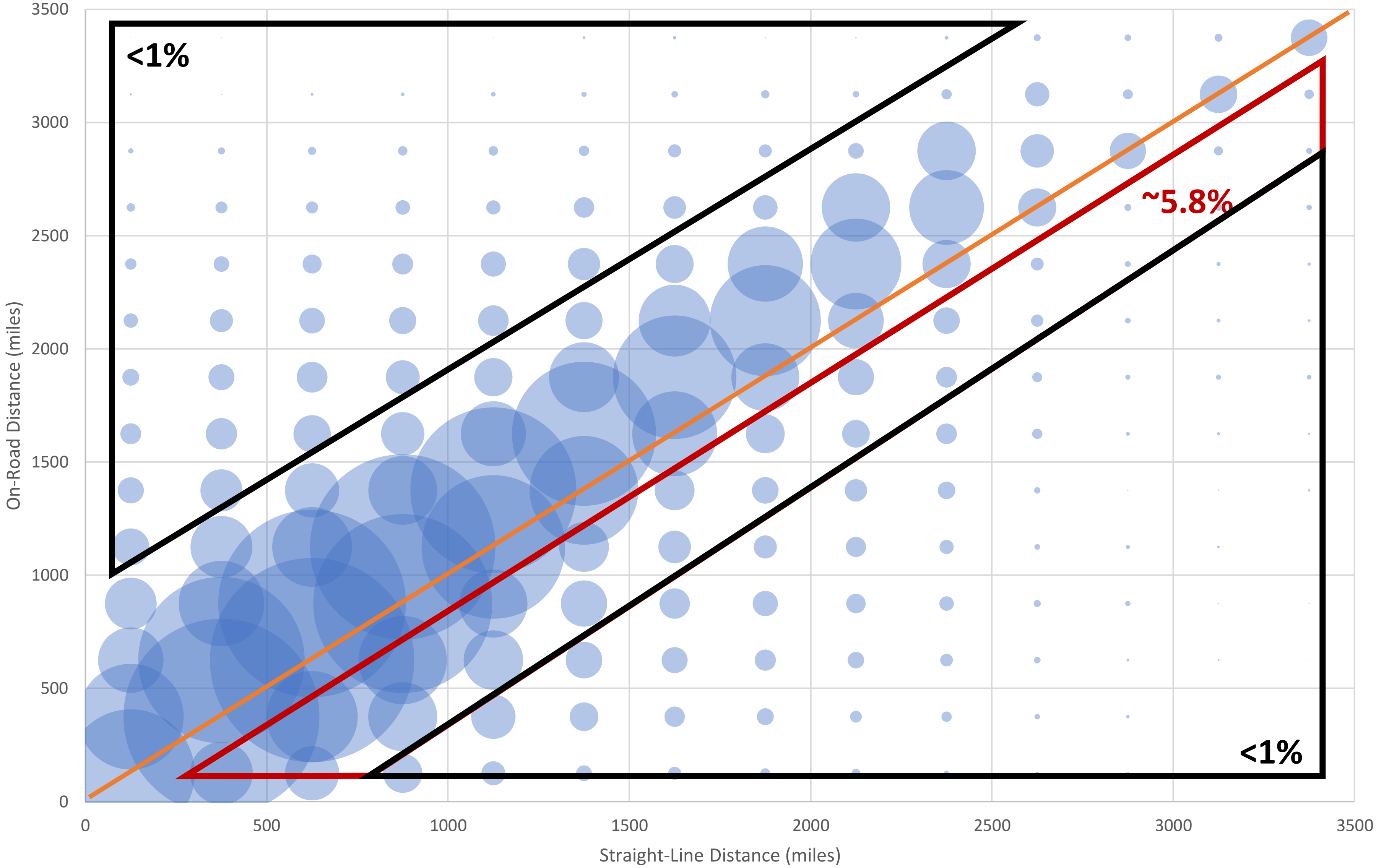


Figure 13: Comparing On-Road vs. Straight-Line Distances

Next, correlation tables were created to see how well each of the individual attributes and aggregated factor access scores correlated with each other (Tables 5 and 6). A number of inferences were drawn, across both straight-line and on-road measures:

- All of the individual economic attribute access measures were highly correlated with other individual attribute access measures describing the economic activity factor
- All of the individual leisure attribute access measures were highly correlated with other individual attribute access measures describing the leisure activity factor
- All of the individual livable attribute access measures were highly correlated with other individual attribute access measures describing the livable activity factor
- The majority of these individual economic, leisure, and livable attribute access measures were highly correlated with those individual attribute access measures across these other factors
- Individual airport attribute access measures were not correlated with the other sets of access measures

This means that (a) any single attribute access measure can be selected to successfully describe the same trends across each factor, (b) any economic, leisure or livable factor measure can be selected to characterize general access trends (even though actual values may differ, as will be seen in the next section), and (c) airport accessibility is distinctly different from the other three and should be included as a separate access variable in analyses.

Table 5: On-Road Access Measures Correlation Table

		Economic					Leisure				Air	Livable			Aggregated			
		Total Number of Employers	Total Employment	Total Annual Payroll ($1000)	Intensity of Specialized Industries	Breadth of Specialized Industries	Total Number of Leisure Employers	Total Leisure Center Employment	Intensity of Leisure Industry Specialization	Total Leisure Annual Payroll ($1000)	Relative Number of Annual Enplanements	Total Number of Trips Per Week	Percentage of Weekly Travel by Transit	Area Served by Transit	Economic	Leisure	Airport	Livable
Economic	Total Number of Employers	1	0.99	0.99	0.83	0.87	0.95	0.95	0.95	0.90	0.45	0.73	0.91	0.85	0.95	0.99	0.45	0.89
	Total Employment		1	0.98	0.87	0.90	0.94	0.93	0.96	0.88	0.44	0.72	0.90	0.84	0.97	0.98	0.44	0.88
	Total Annual Payroll ($1000)			1	0.80	0.84	0.94	0.95	0.92	0.90	0.47	0.74	0.90	0.85	0.93	0.97	0.47	0.89
	Intensity of Specialized Industries				1	0.98	0.70	0.66	0.90	0.58	0.15	0.51	0.71	0.63	0.96	0.80	0.15	0.68
	Breadth of Specialized Industries					1	0.74	0.72	0.95	0.63	0.18	0.57	0.76	0.69	0.98	0.85	0.18	0.74
Leisure	Total Number of Leisure Employers						1	0.98	0.85	0.98	0.58	0.71	0.85	0.81	0.84	0.97	0.58	0.84
	Total Leisure Center Employment							1	0.85	0.98	0.60	0.72	0.86	0.82	0.83	0.97	0.60	0.85
	Intensity of Leisure Industry Specialization								1	0.77	0.31	0.69	0.87	0.83	0.97	0.95	0.31	0.85
	Total Leisure Annual Payroll ($1000)									1	0.63	0.70	0.82	0.80	0.75	0.93	0.63	0.81
Air	Relative Number of Annual Enplanements										1	0.39	0.42	0.41	0.29	0.49	1.00	0.42
Livable	Total Number of Trips Per Week											1	0.86	0.88	0.64	0.74	0.39	0.91
	Percentage of Weekly Travel by Transit												1	0.92	0.83	0.90	0.42	0.99
	Area Served by Transit													1	0.77	0.86	0.41	0.94
Aggregated	Economic														1	0.93	0.29	0.81
	Leisure															1	0.49	0.88
	Airport																1	0.42
	Livable																	1

Table 6: Straight-Line Access Measures Correlation Table

		Economic					Leisure				Air	Livable			Aggregated			
		Total Number of Employers	Total Employment	Total Annual Payroll ($1000)	Intensity of Specialized Industries	Breadth of Specialized Industries	Total Number of Leisure Employers	Total Leisure Center Employment	Intensity of Leisure Industry Specialization	Total Leisure Annual Payroll ($1000)	Relative Number of Annual Enplanements	Total Number of Trips Per Week	Percentage of Weekly Travel by Transit	Area Served by Transit	Economic	Leisure	Airport	Livable
Economic	Total Number of Employers	1	0.99	0.99	0.81	0.86	0.92	0.95	0.94	0.90	0.48	0.84	0.91	0.83	0.93	0.98	0.48	0.89
	Total Employment		1	0.98	0.85	0.89	0.91	0.94	0.95	0.88	0.46	0.82	0.90	0.82	0.95	0.98	0.46	0.88
	Total Annual Payroll ($1000)			1	0.79	0.83	0.92	0.95	0.92	0.90	0.49	0.86	0.92	0.84	0.90	0.96	0.49	0.90
	Intensity of Specialized Industries				1	0.97	0.59	0.64	0.88	0.55	0.12	0.54	0.68	0.58	0.97	0.83	0.12	0.62
	Breadth of Specialized Industries					1	0.66	0.70	0.94	0.61	0.16	0.62	0.75	0.66	0.99	0.90	0.16	0.70
Leisure	Total Number of Leisure Employers						1	0.99	0.80	1.00	0.65	0.83	0.86	0.81	0.75	0.89	0.65	0.86
	Total Leisure Center Employment							1	0.85	0.98	0.65	0.85	0.88	0.82	0.79	0.92	0.65	0.88
	Intensity of Leisure Industry Specialization								1	0.77	0.33	0.80	0.87	0.82	0.96	0.99	0.33	0.85
	Total Leisure Annual Payroll ($1000)									1	0.68	0.83	0.84	0.80	0.71	0.86	0.68	0.85
Air	Relative Number of Annual Enplanements										1	0.50	0.45	0.45	0.26	0.43	1	0.48
Livable	Total Number of Trips Per Week											1	0.93	0.98	0.69	0.84	0.50	0.98
	Percentage of Weekly Travel by Transit												1	0.91	0.81	0.90	0.45	0.98
	Area Served by Transit													1	0.72	0.85	0.45	0.96
Aggregated	Economic														1	0.94	0.26	0.76
	Leisure															1	0.43	0.89
	Airport																1	0.48
	Livable																	1

8: RELATING ACCESS MEASURES & REGIONAL EQUITY CHARACTERISTICS

In this section, the access measures are compared to assess how access measures are distributed (a) regionally, (b) by county density, (c) across disadvantaged populations, and (d) relative to long distance travel demand. The following comparisons were done with both straight-line and on-road aggregated factor access measures to additionally determine which is more adept at capturing equity-type variation. Additional comparisons with other regional characteristics can be found in Appendix A.

How are access measures distributed regionally?

To assess each measure by region, the country was divided into the four major regions, as defined by the U.S. Census Bureau: the Northeast, the Midwest, the South, and the West. The accessibility measures were each grouped into these four categories before Probability Distribution Functions (PDFs) were calculated and graphed for all eight (Figure 8).

When looking at these graphs, it becomes evident that the Northeast region of the United States tends to have higher scores than any other region with every measure, whether straight-line or on-road distances were used. The Midwest and South regions appear to have similar scores throughout, with the South having slightly better scores throughout. In addition, the west has the lowest of the four, for all measures. The straight-line and on-road distance economic activity and airport curves are relatively similar. However, the straight-line leisure and livable version of the curves have generally higher scores than their on-road counterparts.

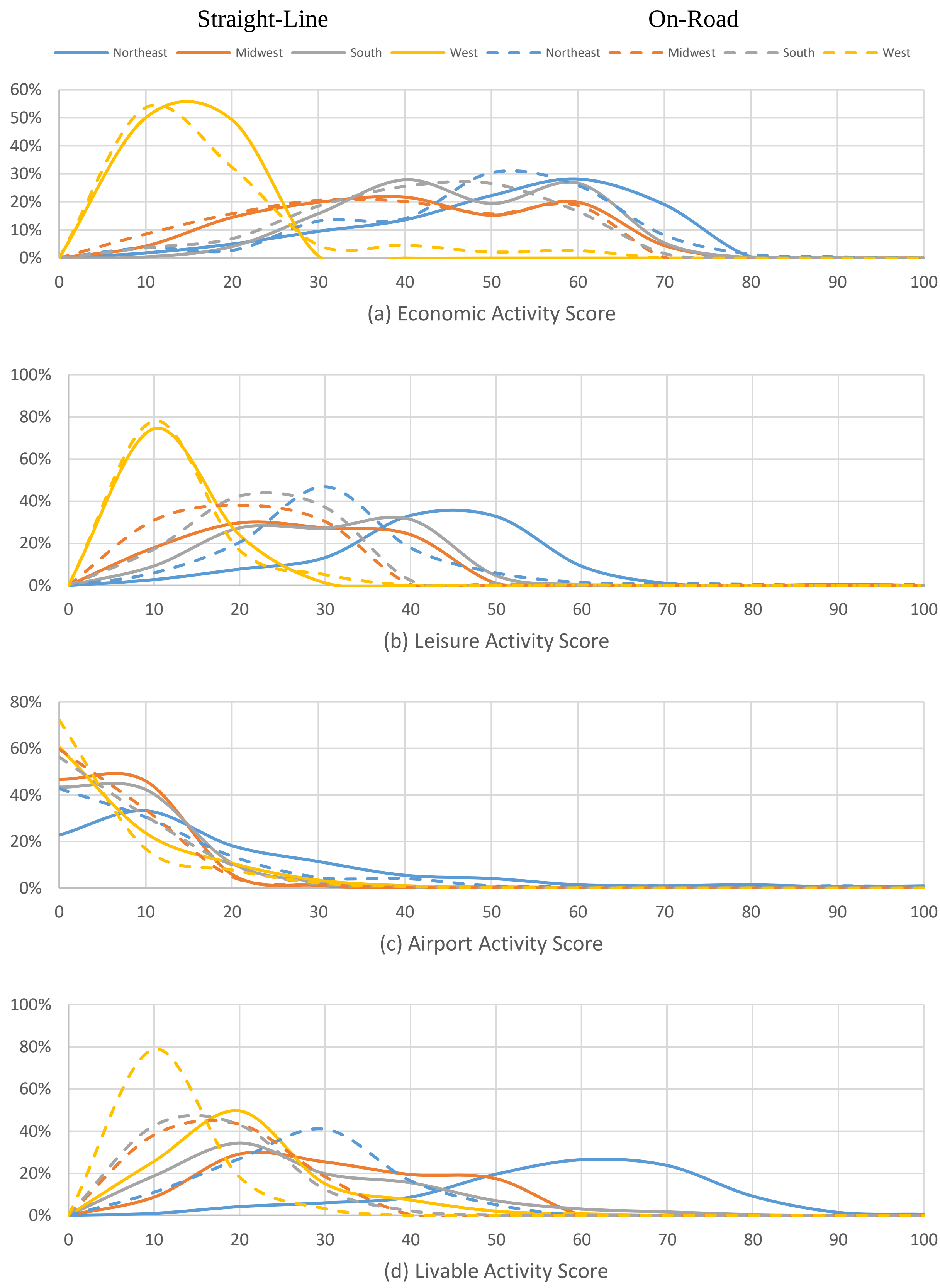


Figure 14: Aggregated Access Scores by Region of the United States

How are access measures distributed by county density?

In addition to categorizing each measure by region, another way to assess the measures was to classify the measures by whether a county was urban or rural. This was done using the U.S. Census Bureau classification system, which states that "Counties with less than 50 percent of the population living in rural areas are classified as urban; 50 to 99.9 percent are classified as suburban; 100 percent rural are classified as rural". The accessibility measures were each grouped into these three categories before Probability Distribution Functions (PDFs) were calculated and graphed for all eight (Figure 9).

Again, across all the different access measures, straight-line and on-road distributions tended to mimic similar shapes, however the straight-line measures included wider distributions with more counties that had higher scores.

Both urban and suburban counties mimicked similar access patterns, with two variations: more suburban counties provide higher economic access scores and more urban counties provide higher leisure access scores. This makes sense, as urban areas are closer to destinations with higher scores and suburban areas are connected to more destinations with a variety of scores.

Unfortunately, the results also emphasize that rural counties offer significantly less accessibility of all types, especially when on-road distances are considered.

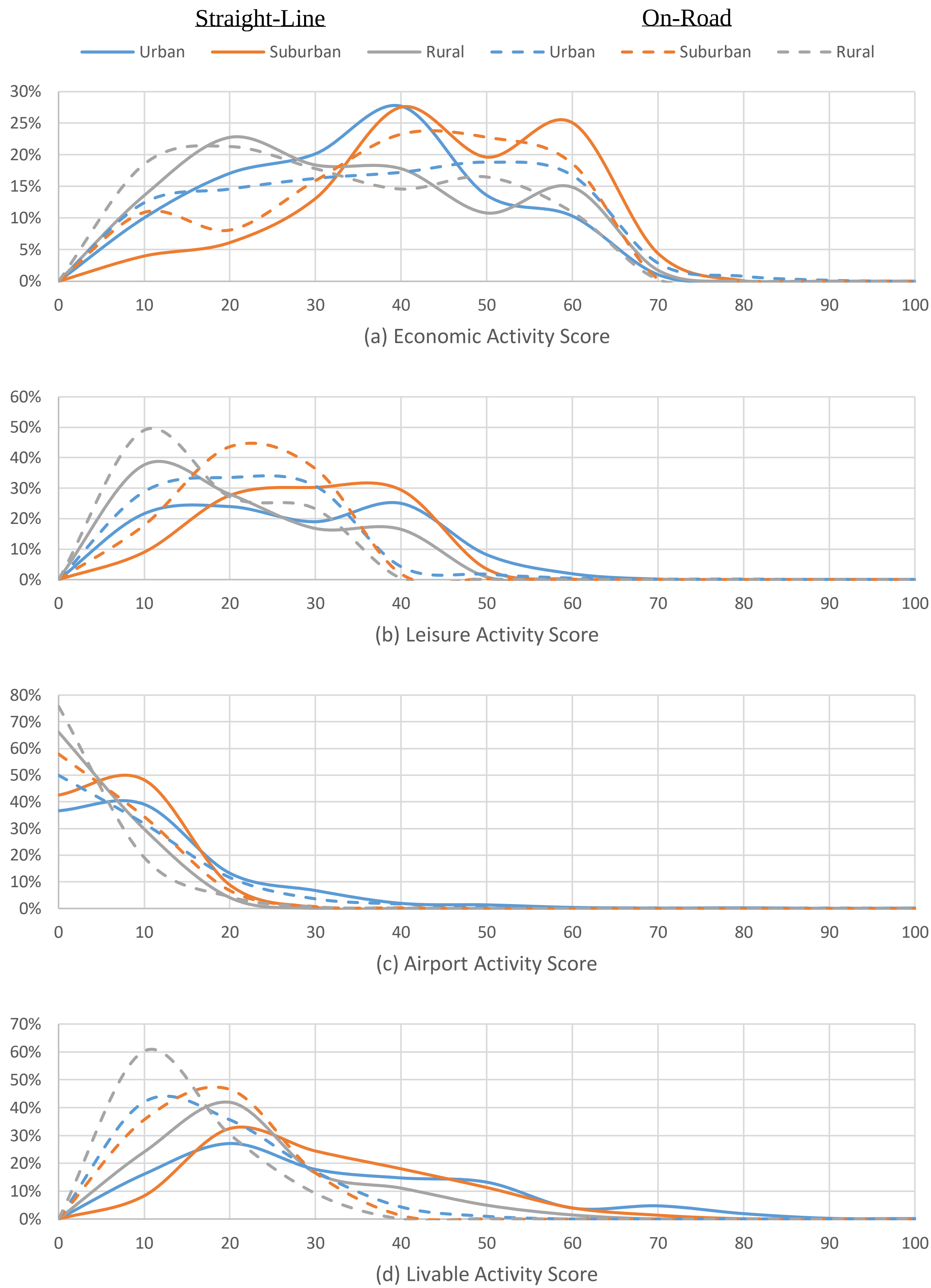


Figure 15: Aggregated Access Scores by Density Level

How are access measures distributed across disadvantaged populations?

Another important topic discussed in the literature is how disadvantaged populations are influenced by accessibility. Median household income in each county was used as a proxy for identifying economically disadvantaged counties, and the counties were divided into four quartiles based on median household income. Probability Distribution Functions (PDFs) were calculated and graphed for all eight measures (Figure 10).

These graphs exhibit the same pattern where the straight-line distributions seem to be more exaggerated versions of the on-road distributions.

Interestingly, counties with the top 75% of median incomes share similar distributions in terms of economic, leisure, and livable activity accessibility. However, counties with the highest 25% of household incomes have noticeably higher airport access than any other economic group. Interestingly, counties with the lowest quartile of median income have more of a peak in the middle of their distributions, meaning that the majority of these lower income counties have about the same middling access scores. This means that residents of these counties do not have poor access scores, but they neither have high access scores found in some of their fellow counties with higher incomes.

In addition to the PDF's that were calculated and graphed for all eight measures, scatter plots that plotted median household income versus each of the eight measures were also created to see if there were any other trends that might emerge. No major trends were observed for any of the eight measures that were graphed.

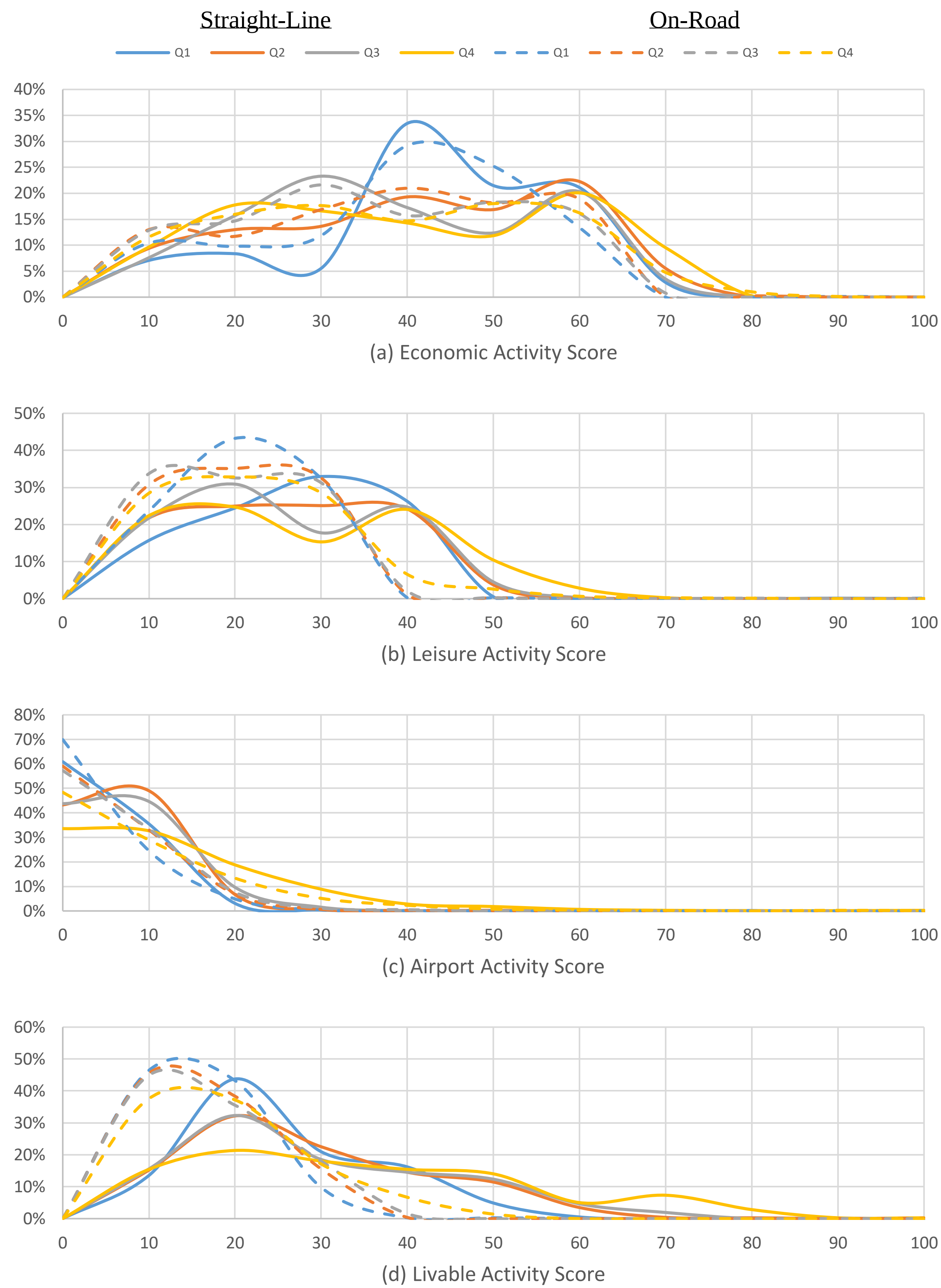


Figure 16: Aggregated Access Score by Median Household Income

How are access measures distributed relative to long distance travel demand?

The last assessment considers how accessibility measures relate to long distance travel demand (an important application of these measures). The number of long distance trips of 50-miles or more out of each county was collected from the Travel Analysis Framework (TAF) developed by FHWA (80). FHWA estimated the total number of long distance trips from each county using the 1995 American Travel Survey (ATS). Even though this is an older dataset, it provided much more detailed information about tripmaking. Counties were categorized into three groups based on the bottom third, middle third, and top third of the distribution of travel demand for counties: low demand, medium demand and high demand (Figure 11). It is hypothesized that counties with higher volumes of long distance tripmaking should have higher accessibility scores.

Interestingly, counties with medium and high demand have similar patterns of accessibility. In fact, counties that make at least medium levels of long distance trips have higher levels of access across all four measures, and this is true of both on-road and straight-line distance calculations. Counties with low demand demonstrate noticeably lower access scores across all four metrics as well. Again, it can be seen that the spread of access scores for high/medium tripmaking counties is much wider and higher than those access scores for low tripmaking counties (where they are clustered around a lower access score). These results are consistent with expectations that accessibility to economic, leisure, airport and livable activities are related to long distance travel making.

Scores appear smoother and higher for all four scores when straight-line distances were used instead of on-road distances, but an obvious trend is still observed with both types of measures: the higher the travel demand, the better the scores. This can be seen with all four measures, although it is not as striking when looking at economic activity. The main question that arises out of this is whether a county has higher long distance travel demand levels *because* it has better long distance access or if the better long distance access *was provided* to meet the higher long distance travel demand.

In addition to the PDF's that were calculated and graphed for all eight measures, scatter plots that plotted travel demand versus each of the measures were created to see if any other trends might emerge. No major trends were observed for the measures that were graphed.

Summary

Across all four graphs, the access score measure distribution shapes are similar with some subtle variations that highlight differences across region, density, economic group, and travel patterns. This further emphasizes that while the measures may be similar, they are capturing variability across counties and all four measures should be included in analyses. While it has been shown that there is correlation between the factors, we also see that each factor is important to differentiating between regions, communities, demographic groups, etc.

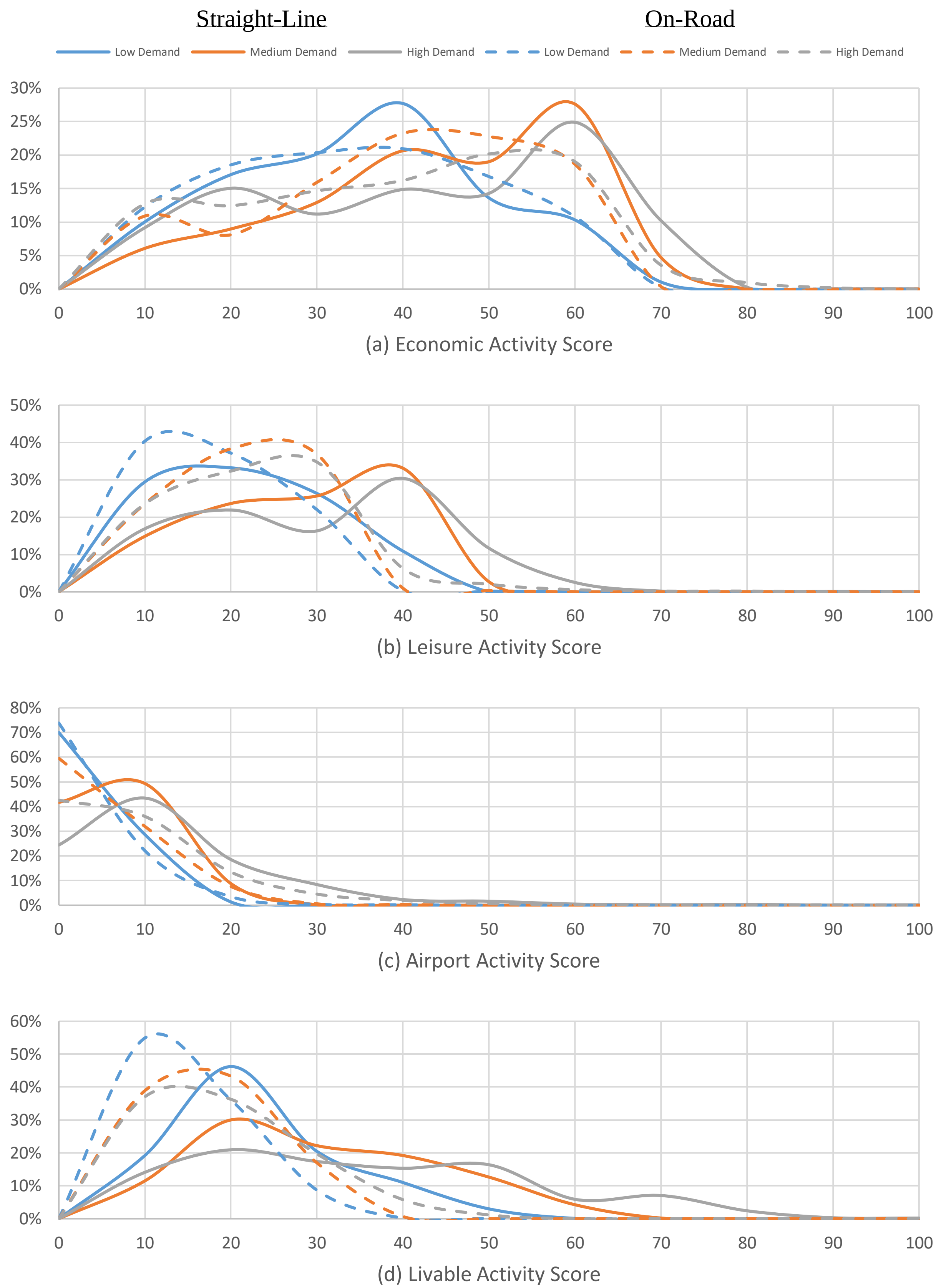


Figure 17: Aggregated Access Scores by Travel

9: RELATIONSHIPS BETWEEN ACCESS MEASURES & LONG DISTANCE TRAVEL

In this section, in one last assessment, a series of multiple linear regression analyses are performed to determine (a) if the long distance access measures were influential in predicting long distance travel demand and (b) if, so, which measure(s) were most influential. Again, the Travel Analysis Framework (TAF) long distance trip generation counts for each county, developed by FHWA (80), were used as the dependent variable for these regressions.

Six regression models using the Ordinary Least Squares (OLS) methodology were created and compared. These models used demographic information, individual attribute scores, and aggregated access scores, the results of which can be seen in Tables 7 to 12. The first model only includes demographic variables and provides a strong fit (R-squared of 0.872). Tables 8, 9 and 10 are regressions with only accessibility scores, which do not provide a strong fit and demonstrate that, at most, accessibility can account for 48.8% of behavior and demographics of counties are important for capturing the rest of the variation. Tables 11 and 12 showcase the final regressions where demographics are joined with accessibility measures. Neither model dramatically increases the model fit, but the straight-line attribute accessibility variables are most significant.

Additionally, it was apparent from the results of the analysis that straight-line variables had higher correlations with total external trips than related on-road variables, especially relative to demographic variables. This would suggest that access measures created using straight-line distance variables are more useful, however it is important to note that these results come from analyses using data for all counties in the United States. This lends credence to the idea that straight-line distance access measures are acceptable for macro-level analyses that look at the entire United States, but do not speak to the nuances that may occur from state to state on a micro-level. As can be seen from the maps previously produced, individual counties can have very different results based on if straight-line or on-road distances were used. In states with mountainous topography where these differences may be most prevalent, such as states in the Appalachian Mountains like West Virginia, access measures using on-road distances may be more useful.

Table 7: Demographics Model

VARIABLE	COEFFICIENT
DEMOGRAPHICS	
POPULATION AGES 16 AND UP	8.313E-05***
PERCENTAGE EMPLOYED	-0.040
MEAN COMMUTE TIME	-0.044
POPULATION AGES 15 AND LESS	1.608E-05
MEDIAN HOUSEHOLD INCOME	9.442E-06
URBAN AREA	1.401***
SUBURBAN AREA	0.641
NORTHEAST REGION	-4.667***
MIDWEST REGION	-4.535***
SOUTH REGION	-3.914***
R2:	0.872

Table 8: Aggregated Access Scores Model

VARIABLE	COEFFICIENT
AGGREGATED ACCESS SCORES	
ON-ROAD	
ECONOMIC ACTIVITY MEASURE	-0.803***
LEISURE ACTIVITY MEASURE	2.022***
AIRPORT ACTIVITY MEASURE	-0.218***
LIVABLE ACTIVITY MEASURE	-0.658***
STRAIGHT-LINE	
ECONOMIC ACTIVITY MEASURE	-0.286***
LEISURE ACTIVITY MEASURE	0.483**
AIRPORT ACTIVITY MEASURE	1.372***
LIVABLE ACTIVITY MEASURE	-0.234***
R2:	0.302

* - SIGNIFICANT AT A 90% CONFIDENCE LEVEL
** - SIGNIFICANT AT A 95% CONFIDENCE LEVEL
*** - SIGNIFICANT AT A 99% CONFIDENCE LEVEL

Table 9: On-Road Scores Model

VARIABLE	COEFFICIENT
ON-ROAD DISTANCE ATTRIBUTES	
ECONOMIC ACTIVITY	
TOTAL NUMBER OF EMPLOYERS	-6.138***
TOTAL EMPLOYMENT	3.477***
TOTAL ANNUAL PAYROLL ($1000)	1.016***
INTENSITY OF SPECIALIZED INDUSTRIES	-0.269***
BREADTH OF SPECIALIZED INDUSTRIES	-0.455***
LEISURE ACTIVITY	
TOTAL NUMBER OF LEISURE CENTER EMPLOYERS	4.88***
TOTAL LEISURE CENTER EMPLOYMENT	-6.457***
INTENSITY OF SPECIALIZED LEISURE INDUSTIRES	1.486***
TOTAL LEISURE CENTER ANNUAL PAYROLL ($1000)	4.964***
AIRPORT ACTIVITY	
RELATIVE NUMBER OF ANNUAL ENPLANEMENTS	0.431***
LIVABLE ACTIVITY	
TOTAL NUMBER OF TRIPS PER WEEK	0.886***
PERCENT OF WEEKLY TRAVEL BY TRANSIT	-0.849***
AREA SERVED BY TRANSIT	-0.01
R2:	0.330

Table 10: Straight-Line Scores Model

VARIABLE	COEFFICIENT
STRAIGHT-LINE DISTANCE ATTRIBUTES	
ECONOMIC ACTIVITY	
TOTAL NUMBER OF EMPLOYERS	-9.014***
TOTAL EMPLOYMENT	6.555***
TOTAL ANNUAL PAYROLL ($1000)	0.291
INTENSITY OF SPECIALIZED INDUSTRIES	-0.234***
BREADTH OF SPECIALIZED INDUSTRIES	-0.296**
LEISURE ACTIVITY	
TOTAL NUMBER OF LEISURE CENTER EMPLOYERS	7.553***
TOTAL LEISURE CENTER EMPLOYMENT	-1.172
INTENSITY OF SPECIALIZED LEISURE INDUSTIRES	0.716***
TOTAL LEISURE CENTER ANNUAL PAYROLL ($1000)	-1.904*
AIRPORT ACTIVITY	
RELATIVE NUMBER OF ANNUAL ENPLANEMENTS	0.586***
LIVABLE ACTIVITY	
TOTAL NUMBER OF TRIPS PER WEEK	0.392**
PERCENT OF WEEKLY TRAVEL BY TRANSIT	-0.931***
AREA SERVED BY TRANSIT	-0.037
R2:	0.488

* - SIGNIFICANT AT A 90% CONFIDENCE LEVEL
** - SIGNIFICANT AT A 95% CONFIDENCE LEVEL
*** - SIGNIFICANT AT A 99% CONFIDENCE LEVEL

Table 11: Demographics and Aggregated Access Scores Model

VARIABLE	COEFFICIENT
DEMOGRAPHICS	
POPULATION AGES 16 AND UP	8.403E-05***
PERCENTAGE EMPLOYED	-0.045
MEAN COMMUTE TIME	-0.017
POPULATION AGES 15 AND LESS	1.305E-05
MEDIAN HOUSEHOLD INCOME	-2.116E-05
URBAN AREA	1.801***
SUBURBAN AREA	1.071**
NORTHEAST REGION	-3.488***
MIDWEST REGION	-2.752***
SOUTH REGION	-1.389*
AGGREGATED ACCESS SCORES	
ON-ROAD	
ECONOMIC ACTIVITY MEASURE	0.002
LEISURE ACTIVITY MEASURE	-0.014
AIRPORT ACTIVITY MEASURE	0.001
LIVABLE ACTIVITY MEASURE	-0.003
STRAIGHT-LINE	
ECONOMIC ACTIVITY MEASURE	0.009
LEISURE ACTIVITY MEASURE	-0.248***
AIRPORT ACTIVITY MEASURE	0.066*
LIVABLE ACTIVITY MEASURE	0.139***
R2:	0.873

Table 12: Demographics and Straight-Line Scores Model

VARIABLE	COEFFICIENT
DEMOGRAPHICS	
POPULATION AGES 16 AND UP	8.936E-05***
PERCENTAGE EMPLOYED	0.001
MEAN COMMUTE TIME	-0.049
POPULATION AGES 15 AND LESS	-1.372E-05
MEDIAN HOUSEHOLD INCOME	-4.608E-05**
URBAN AREA	1.082**
SUBURBAN AREA	0.561
NORTHEAST REGION	-3.645***
MIDWEST REGION	-3.014***
SOUTH REGION	-1.755*
STRAIGHT-LINE DISTANCE ATTRIBUTES	
ECONOMIC ACTIVITY	
TOTAL NUMBER OF EMPLOYERS	-1.236***
TOTAL EMPLOYMENT	1.676***
TOTAL ANNUAL PAYROLL ($1000)	0.027
INTENSITY OF SPECIALIZED INDUSTRIES	-0.102**
BREADTH OF SPECIALIZED INDUSTRIES	-0.117
LEISURE ACTIVITY	
TOTAL NUMBER OF LEISURE CENTER EMPLOYERS	-0.146
TOTAL LEISURE CENTER EMPLOYMENT	0.016
INTENSITY OF SPECIALIZED LEISURE INDUSTIRES	-0.022
TOTAL LEISURE CENTER ANNUAL PAYROLL ($1000)	-0.304
AIRPORT ACTIVITY	
RELATIVE NUMBER OF ANNUAL ENPLANEMENTS	0.016
LIVABLE ACTIVITY	
TOTAL NUMBER OF TRIPS PER WEEK	0.219***
PERCENT OF WEEKLY TRAVEL BY TRANSIT	-0.16***
AREA SERVED BY TRANSIT	-0.027
R2:	0.876

* - SIGNIFICANT AT A 90% CONFIDENCE LEVEL
** - SIGNIFICANT AT A 95% CONFIDENCE LEVEL
*** - SIGNIFICANT AT A 99% CONFIDENCE LEVEL

10: CONCLUSIONS

The objective of this thesis was to assess the quality of long distance accessibility measures for counties across the United States. Thirteen different attribute scores and four different aggregated scores for counties were calculated using either on-road or straight-line distances. The four different aggregated scores were then mapped across the United States using each type of distance to assess any geographic trends. Next, the scores were grouped into different types of demographics and prominent industries before then being analyzed to see if specific groups of people were receiving better access than others.

In general, the four scores using straight-line distances were clustered around the northeast corridor and California, with scores slowly getting lower further away from those clusters. The same trend was present when using on-road distances, but the scores were more scattered and less uniform. The regression analysis revealed that the individual attribute scores were better at predicting the total long distance trips leaving the county than the aggregated access scores were, as the model using aggregate scores had an R-squared of 0.302 and the model using individual scores had an R-squared of 0.488. The analysis also indicated that scores using straight-line distances had a higher correlation with total external trips than scores using on-road distances, when looking at things from a macro-level perspective.

A key trend observed from these results was that measures that use straight-line distances may not be completely accurate, as many counties that had good access scores with straight-line distances were revealed to have lower scores once driving distances were considered. Additionally, the finding that lower income counties have lower airport activity and livable activity access scores indicates that lower income populations have less access to non-automobile modes of travel at their destinations.

One possible application for future work is for Departments of Transportation and Metropolitan Planning Organizations to incorporate this research into their statewide models and analyses. In general, measures using straight-line distances are likely to perform better for national-level analyses, while measures using on-road distances are likely to perform better for state- or region-level analyses. This thesis developed useful long distance accessibility measures, but also developed a general framework to create measures that are suited for long distance access. Beyond just using the accessibility measures developed in this thesis, analysts with DOTs and MPOs can easily create and test their own long distance accessibility measures that use different opportunity factor data from what was used in this thesis.

Researchers interested in equity could use the information from these access measures in future work. In the future, additional attributes should be considered for the access scores. Possible attributes could involve attempts to characterize how the perception of costs at a destination, such as the cost of gas, hotel expenses, tolls, etc., affects long distance travel volumes. Further research into additional attributes could possibly provide further detail to each of the aggregated access scores and improve the results of long distance travel models. This could help strengthen the results of this study and improve the accuracy of planners' long distance travel modeling efforts. This work also has some limitations. Namely, the viability of using these measures for much smaller analyses (such as for specific counties surrounding a major city) was not explored in this thesis. More investigation into how well straight-line distance scores perform as compared to on-road distance scores during analyses using smaller geographies could prove to be beneficial.

REFERENCES

1. Kneebone, E. and N. Holmes. *The growing distance between people and jobs in metropolitan America*. Metropolitan Policy Program at Brookings, 2015.
2. Downs, A. *Traffic: Why it's Getting Worse, What Government Can Do*. Policy Brief #128, The Brookings Institution, 2004.
3. Sweet, M. Traffic Congestion's Economic Impacts: Evidence from US Metropolitan Regions. *Urban Studies*, 2014. 51: 2088-2110.
4. Frank, L. D., J. F. Sallis, and B. Saelens. The Development of a Walkability Index: Application to the Neighborhood Quality of Life Study. *British Journal of Sports Medicine*, 2009. 44: 924-33.
5. The Effects of Urban Patterns on Ecosystem Function. (Marina Alberti)
6. Redding, S. J., and M. A. Turner. Transportation Costs and the Spatial Organization of Economic Activity. *Handbook of Regional and Urban Economics*, 2015. 5: 1339-1398.
7. Litman, T. A.. *Evaluating Accessibility for Transport Planning: Measuring People's Ability to Reach Desired Goods and Activities*. Victoria Transportation Policy Institute, 2019.
8. Mohamad, S., A. Shafaghat, and T. H. Khan. Accessibility measurement techniques in urban studies: a comprehensive review. *Journal of Biodiversity and Environmental Sciences*, 2017. 10: 20176663-2222
9. Envall, P. Accessibility Planning: a chimera? The Universty of Leeds Institute for Transport Studies, 2007.
10. Litman, T. A. Measuring Transportation: Traffic, Mobility and Accessibility. *ITE Journal*, 2003. 73(10)(10).

11. Wong, W. E. *Proceedings of the 4th International Conference on Computer Engineering and Networks*. Springer, 2014.

12. Blackmar, C. E., C. Bhat, and J. LaMondia. *Comparing Transit Accessibility Measures: A Case Study of Access to Healthcare Facilities*. The University of Texas at Austin, 2010.

13. Makri, M-C., and C. Folkesson. Accessibility Measures for Analyses of Land Use and Travelling with Geographical Information Systems. *Urban Transport Systems, Proceedings from the 2nd KFB Research Conference in Lund, Sweden (Bulletin 187)*. June 7-8, 1999.

14. Wachs, M., and T. G. Kumagai. Physical accessibility as a social indicator. *Socio-Economic Planning Sciences*, 1973. 7(5): 437-456.

15. Dalvi, M.Q., and K.M. Martin. The measurement of accessibility: Some preliminary results. *Transportation*, 1976. 5: 17-42.

16. Baradan, S., and F. Ramjerdi. Performance of Accessibility Measures in Europe. *Journal of Transportation and Statistics*, 2001. 4(2): 31-48.

17. Talen, E., and L. Anselin. Assessing Spatial Equity: An Evaluation of Measures of Accessiblity to Public Playgrounds. *Environment and Planning A*, 1998. 30: 595-613.

18. El-Geneidy, A. and D. Levinson. *Access to Destinations Development of Accessibility Measures, Report #1*. Minneapolis: Department of Civil Engineering, University of Minnesota, 2006.

19. Church, R. and J. Marston. Measuring Accessibility for People with a Disability. *Geographical Analysis*, 2003. 35.

20. Iacono, M., K. Krizek, and A. El-Genidy. *Access to Destinations: How Close is Close Enough? Estimating Accurate Distance Decay Functions fro Multiple Modes and Different Purposes, Report #4*. Minneapolis: Department of Civil Engineering, University of Minnesota, 2008.
21. LaMondia, J. J., L. Aultman-Hall, and E. Greene. Long Distance Work and Leisure Travel Frequencies: Ordered Probit Analysis Across Non-Distance-Based Definitions. *Transportation Research Record*, 2014. 2413(1): 1-12.
22. Gustafson, P. Work-Related Travel, Gender and Family Obligations. *Work Employment and Society*, 2006. 20(23): 513-530.
23. Jeong, Y.-J., A. M. Zvonkovic, Y. Sano, and A. C. Acock. The Occurrence and Frequency of Overnight Job Travel in the USA. *Work*, *Employment and Society*, 2013. 27: 138-152.
24. Presser, H. B., and J. M. Hermsen. Gender Differences in the Determinants of Work-Related Overnight Travel Among Employed Americans. *Work and Occupations*, 1996. 23(1): 87-115.
25. Mallett, W. J. Long Distance Travel by Low-Income Households. In *Transportation Research Circular E-C026: Personal Travel: The Long and Short of It*, Transportation Research Board of the National Academies, Washington, D.C., 2001, 169-177.
26. Limtanakool, N., M. Dijst, and T. Schwanen. On the Participation in Medium- and Long Distance Travel: A Decomposition Analysis for the UK and the Netherlands. *Journal of Economic and Social Geography*, 2006. 97(4): 389-404.
27. Dangschat, J. and J. Blasius. Lebensstile in der Stadt. *Lebensstile in den Städten*, 1994. 335-354.

28. Kesselring, S. Pioneering mobilities: new patterns of movement and motility in a mobile world. *Environment and Planning Part A*. 38: 269-279.

29. Schubert, H. J. Enträumlichung durch Beziehungslockerung—Zur Konstruktion des Raumes durch soziale Netzwerke. *Lebensstile und Raumerleben*, Institut für Regionalentwicklung und Strukturplanung, Berlin. 45–59.

30. Stead, D., J. Williams, and H. Titheridge. Land use, transport and people: identifying the connections. *Achieving Sustainable Urban Form*, Routledge, London, 2000. 174-186.

31. Hong, J., Q. Shen, and L. Zhang. How do built-environment factors affect travel behavior? A spatial analysis at different geographic scales. *Transportation*, 2014. 41: 419-440.

32. De Abreu e Silva, J., T. F. Golob, and K. Goulias. Effects of Land Use Characteristics on Residence and Employment Location and Travel Behavior of Urban Adult Workers. *Transportation Research Record*, 2006. 1977: 121-131.

33. Boarnet, M. and R. Crane. The influence of land use on travel behavior: specification and estimation strategies. *Transportation Research Part A*, 2001. 35(9): 823-845.

34. Cao, X., P. L. Mokhtarian, and S. L. Handy. Neighborhood design and vehicle type choice: Evidence from Northern California. *Transportation Research Part D: Transport and Environment*, 2006. 11(2): 133-145.

35. Cervero, R. Mixed land-uses and commuting: evidence from the American Housing Survey. *Transporation Research Part A*, 1996. 30(5): 361-377.

36. Frank, L. D., B. E. Saelens, K. E. Powell, and J. E. Chapman. Stepping towards causation: do built environments or neighborhood and travel preferences explain physical activity, driving and obesity? *Social Science Medicine*, 2007. 65: 1898-1914.

37. Ewing, R. and R. Cervero. Travel and the built environment: a synthesis. *Transportation Research Record*, 2001. 1780(1): 87-114.

38. Fesenmaier, D. R. Integrating activity patterns into destination choice models. *Journal of Leisure Research*, 1988. 20(3): 175-191.

39. Eymann, A. and G. Ronning. Microeconometric models of tourists' destination choice. *Regional Science and Urban Economics*, 1997. 27: 735-761.

40. LaMondia, J., T. Snell, and C. R. Bhat. Traveler Behavior and Values Analysis in the Context of Vacation Destination and Travel Mode Choices: Eurpoean Union Case Study. *Transportation Research Record*, 2010. 2156(1): 140-149.

41. Bargeman, B., and H. van der Poel. The Role of Routines in the Vacation Decision-Making Process of Dutch Vacationers. *Tourism Management*, 2006. 27: 707-720.

42. Eugenio-Martin, J. L. *Modelling Determinants of Tourism Demand as a 5-Stage Process: A Discrete Choice Methodological Approach*. Technical Paper. Departamento de Analisis Economico Aplicado, Universidad de Las Palmas de Gran Canaria, Canary Islands, 2008.

43. Johnson, P. and J. Ashworth. Modelling tourism demand: A summary review. *Leisure Studies*, 1990. 9: 145-161.

44. Nicolau, J. L. and F. J. Más. The influence of distance and prices on the choice of tourist destinations: The moderating role of motivations. *Tourism Management*, 2006. 27(5): 982-996.

45. Lamondia, J. L., and C. Bhat. A study of visitors' leisure travel behavior in the northwest territories of Canada. *Transportation Letters*, 2011. 3(1): 1-19.

46. Jang, S. and L. A. Cai. Travel motivations and destination choice: A study of British outbound market. *Journal of Travel & Tourism Marketing*, 2002. 13(3): 111-133.

47. Cervero, R. Built environments and mode choice: toward a normative framework. *Transportation Research Part D: Transport and Environment*, 2002. 7(4): 265-284.

48. Rodriguez, D. A., J. Joo. The relationship between non-motorized mode choice and the local physical environment. *Transportation Research Part D: Transport and Environment*, 2004. 9(2): 151-173.

49. Wardman, M., M. Tight, and M. Page. Factors influencing the propensity to cycle to work. *Transportation Research Part A: Policy and Practice*, 2007. 41(4): 339-350.

50. Campbell, A. A., C. R. Cherry, M. S. Ryerson, and X. Yang. Factors influencing the choice of shared bicycles and shared electric bikes in Beijing. *Transportation Research Part C: Emerging Technologies*, 2016. 67: 399-414.

51. Glaeser, E. L. and J. D. Gottlieb. Urban Resurgence and the Consumer City. *Urban Studies*, 2006. 43(8).

52. Glaeser, E. L., J. Kolko, A. Saiz. Consumer city. *Journal of Economic Geography*, 2001. 1: 27-50.

53. Schiff, N. Cities and product variety: evidence from restaurants. *Journal of Economic Geography*, 2014. 15: 1085-1123.

54. Hamed, M. M., and F. L. Mannering. Modeling Travelers' Postwork Activity Involvement: Toward A New Methodology. *Transportation Science*, 1993. 27: 381-394.

55. Levinson, D. M. Space, money, life-stage, and the allocation of time. *Transportation*, 1999. 26: 141-171.

56. Sandow, E. and K. Westin. The preserving commuter – Duration of long distance commuting. *Transportation Research Part A Policy and Practice*, 2010. 44: 433-445.

57. Lucas, R. E. and E. Rossi-Hansberg. On the Internal Structure of Cities. *Econometrica*, 2002. 70: 1445-1476.

58. Green, A. E., T. Hogarth, and R. E. Shackleton. Longer distance commuting as a substitute for migration in Britain: a review of trends, issues and implications. *Population, Space, and Place*, 1999. 5: 49-67.

59. Lundholm, E. New Motives for Migration? On Interregional Mobility in the Nordic Context. Department of Social and Economic Geography. Umeå University, Sweden, 2007.

60. Lundholm, E., J. Garvill, G. Malmberg, and K. Westin. Forced or free movers? The motives, voluntariness and selectivity of interregional migration in the Nordic countries. *Population, Space and Place*, 2004. 10, 59-72.

61. de Neufville, R. *Airport Systems Planning*. The Maxmillan Press Ltd, London, 1976.

62. Harvey, G. Airport choice in a multiple airport region. *Transportation Research*, 1987. 21: 439-449.

63. Pantazis, N. and I. Liefner. The impact of low-cost carriers on catchment areas of established international airports: The case of Hanover Airport, Germany. *Journal of Transport Geography*, 2006. 14: 265-272.

64. Mason, K. The propensity of business travelers to use low cost airlines. *Journal of Transport Geography*, 2000. 8: 107-119.

65. Lian, J. I. and J. Rønnevik. Airport competition – Regional airports losing ground to main airports. *Journal of Transport Geography*, 2011. 19: 85-92.

66. Le-Klahn D. and C. M. Hall. Tourist use of public transport at destinations – a review. *Current Issues in Tourism*, 2015. 18: 785-803.

67. Thompson, K. and P. Schofield. An investigation of the relationship between public transport performance and destination satisfaction. *Journal of Transport Geography*, 2007. 15: 136-144.

68. Mandeno, T. G. Is Tourism a Driver for Public Transport Investment? Thesis, University of Otago, 2012.

69. Yang, Y. Analysis of public transport for urban tourism in China. The University of Hong Kong, Hong Kong, 2010.

70. Lyons, G. and K. Chatterjee. A Human Perspective on the Daily Commute: Costs, Benefits and Trade-offs. *Transport Reviews*, 2008. 28(2): 181-198.

71. *National Household Travel Survey*. Federal Highway Administration (FHWA), Washington, D.C., 2008.

72. *County Business Patterns Dataset*. United States Census Bureau, Washington, D.C., 2016.

73. *Understanding Location Quotient*. Economic Modeling Specialists Incorporated (EMSI), Moscow, Idaho. First Accessed: Feb 2019. (https://www.economicmodeling.com/wp-content/uploads/2007/10/emsi_understandinglq.pdf).

74. *The Employment Situation – December 2016*. Bureau of Labor Statistics, U.S. Department of Labor, Washington, D.C.

75. *Air Carrier Airport Activity Statistics and Ontime Performance Data*. Bureau of Transportation Statistics, U.S. Department of Transportation, Washington, D.C., 2016.

76. Cao, J. The association between light rail transit and satisfactions with travel and life: evidence from Twin Cities. *Transportation*, 2013. 40: 921-933.

77. *2016 Census Urban and Rural Classification and Urban Area Criteria*. United States Census Bureau, Washington, D.C.

78. *TIGER/Line Shapefiles*. United States Census Bureau, Washington, D.C. First Accessed: Feb 2019. (https://www.census.gov/cgi-bin/geo/shapefiles/index.php)

79. *National Highway Planning Network*. Federal Highway Administration (FHWA), Washington, D.C. First Accessed: Jun 2019. (https://www.fhwa.dot.gov/planning/processes/tools/nhpn/)

80. *Travel Analysis Framework: National Long Distance Passenger Origin Destination*. Office of Highway Policy Information, Federal Highway Administration (FHWA), Washington, D.C. First Accessed Feb 2019. (https://www.fhwa.dot.gov/policyinformation/analysisframework/01.cfm)

APPENDIX A: EXTRA RELATIONSHIP ANALYSIS FIGURES

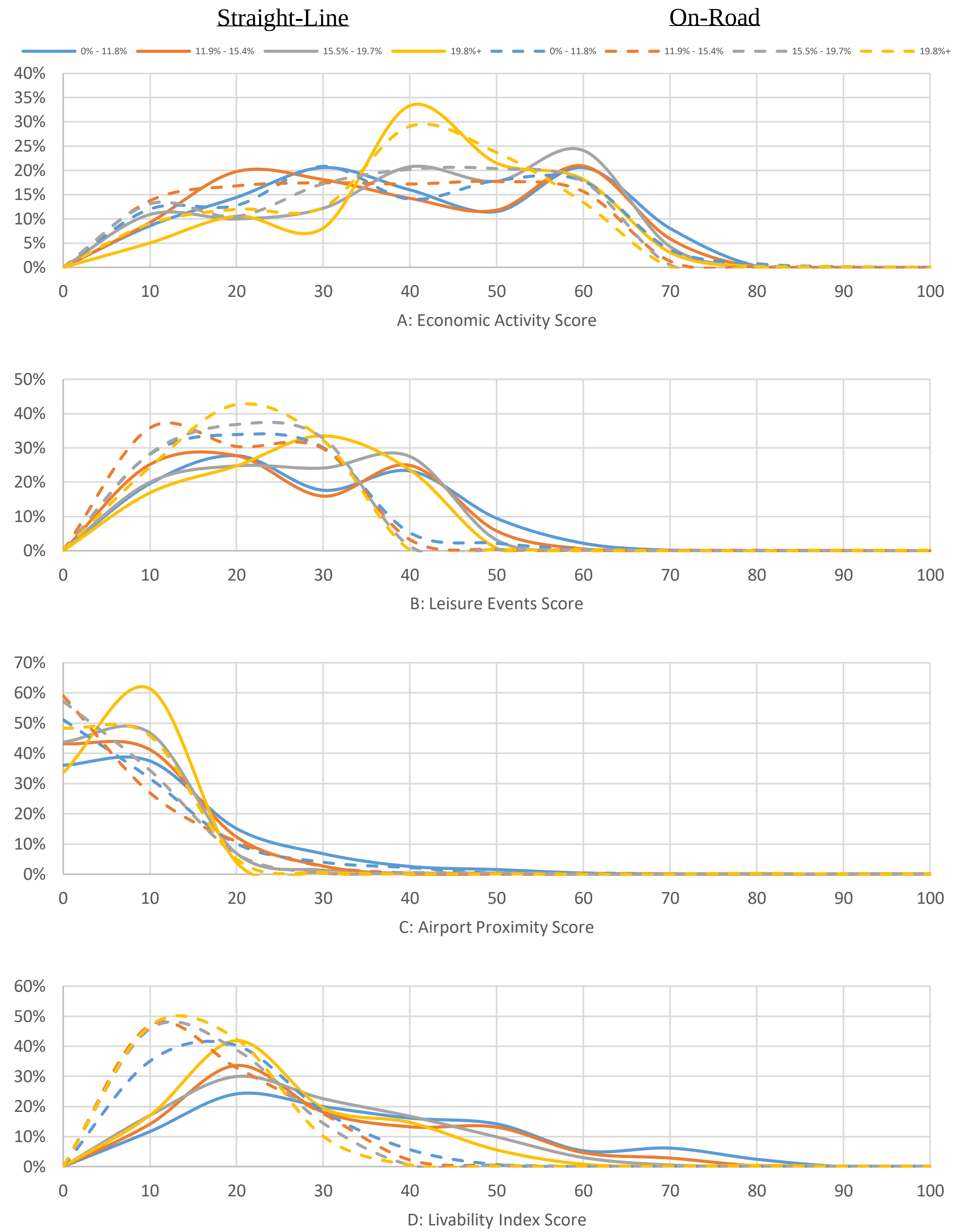


Figure A1: Average Access Score by Poverty Rate

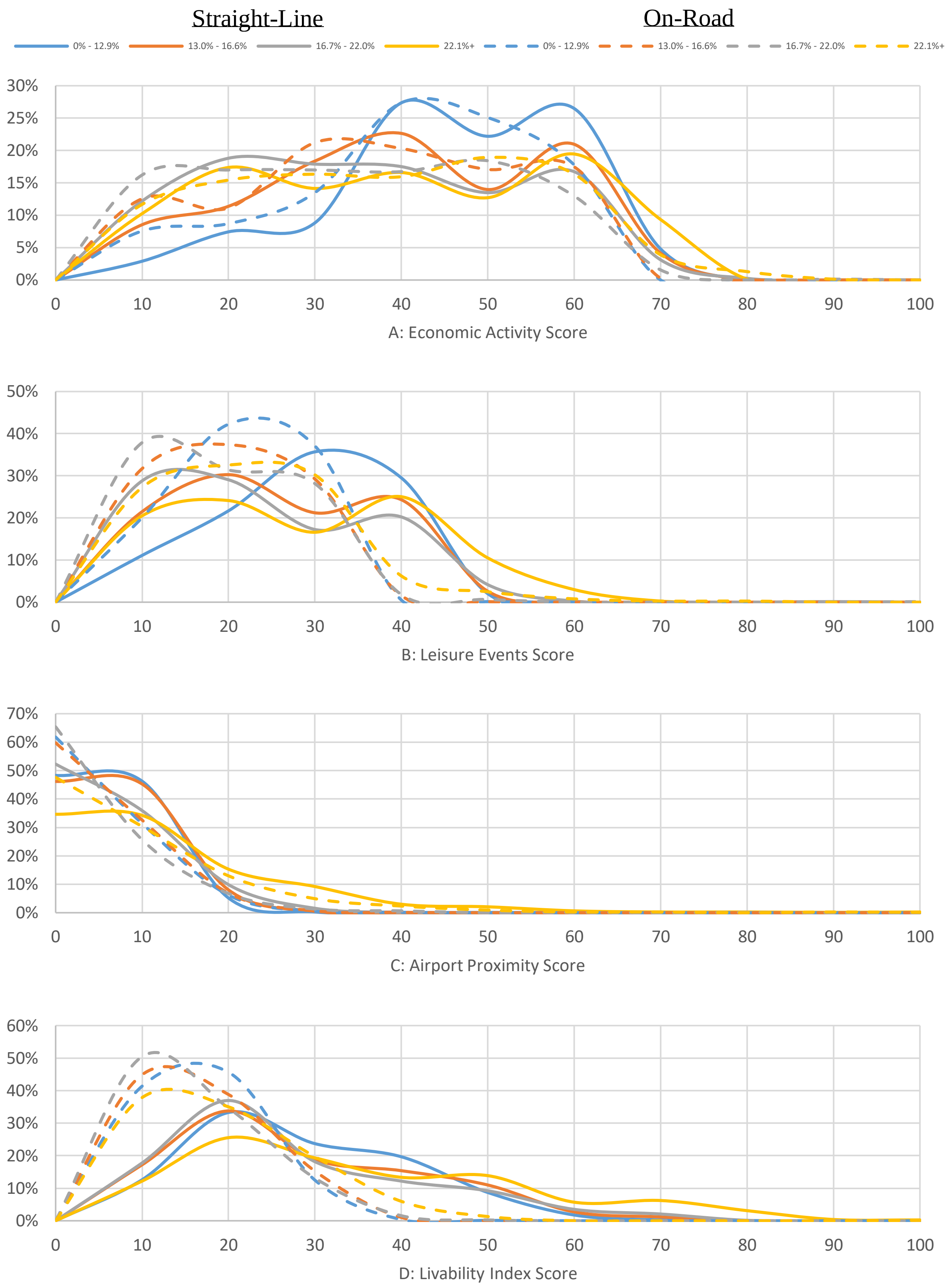


Figure A2: Average Access Score by Percent of Population with Bachelor's Degree or higher

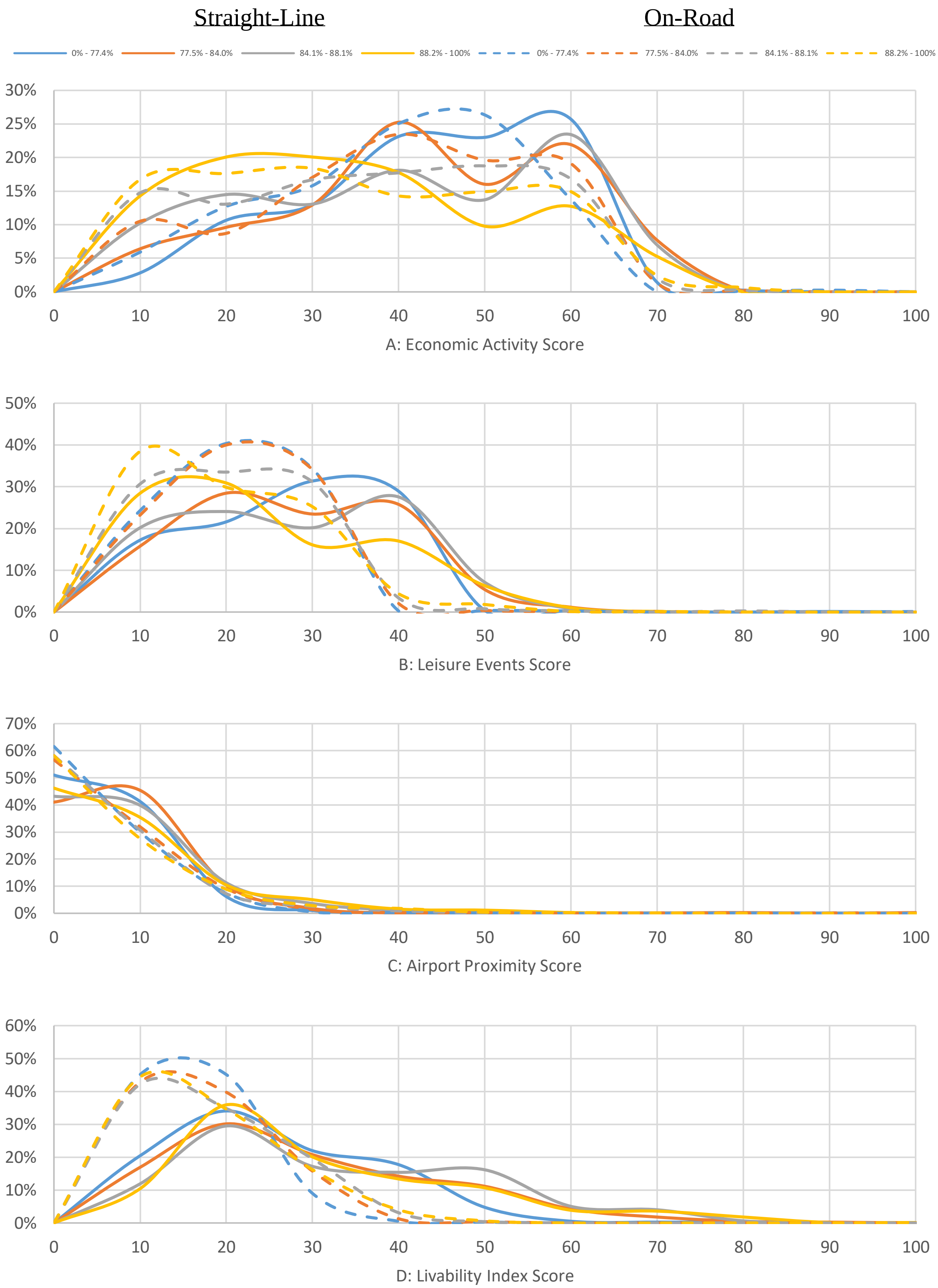


Figure A3: Average Access Score by Percent of Population with High School Diploma or higher

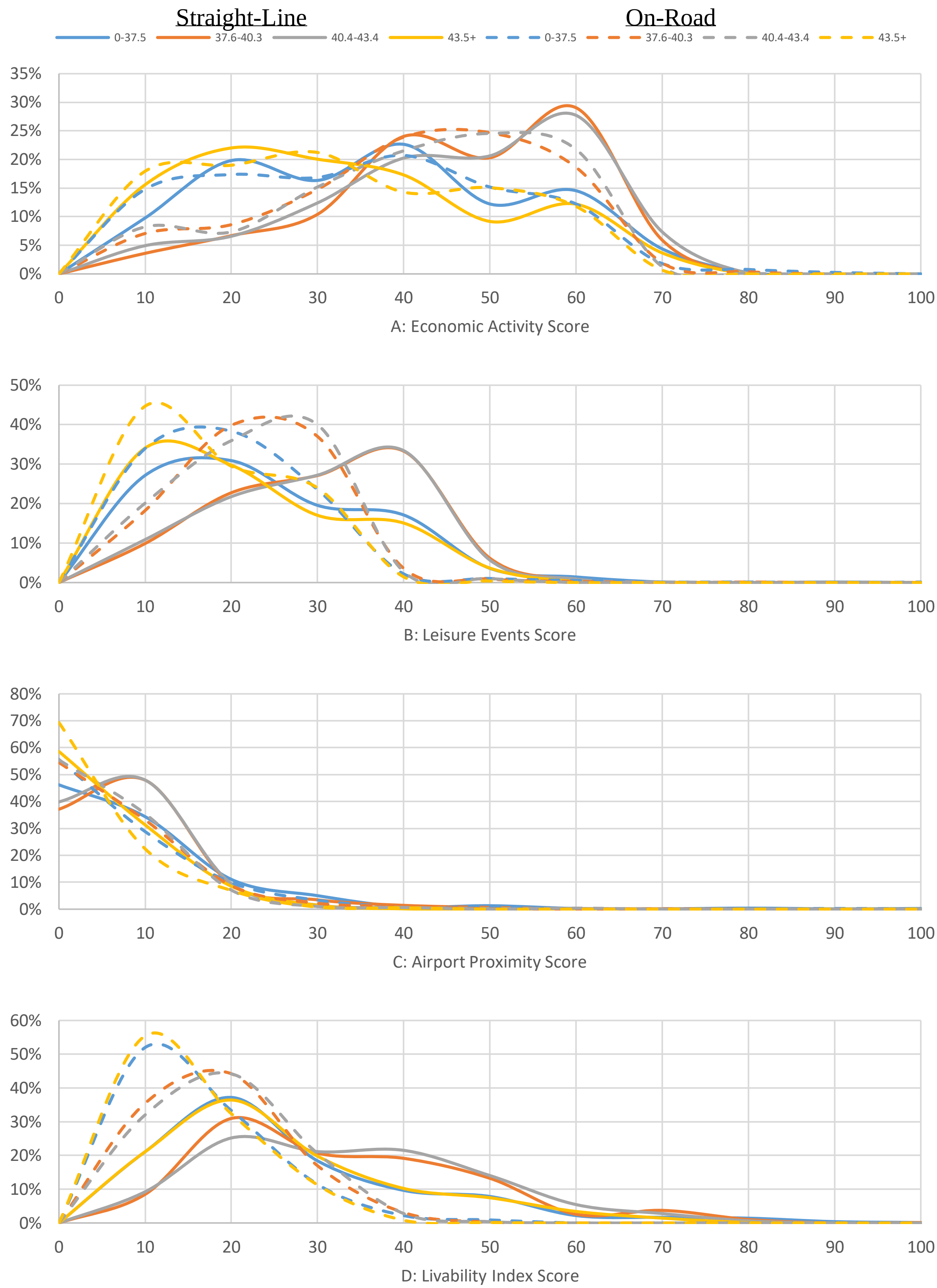


Figure A4: Average Access Score by Median Age

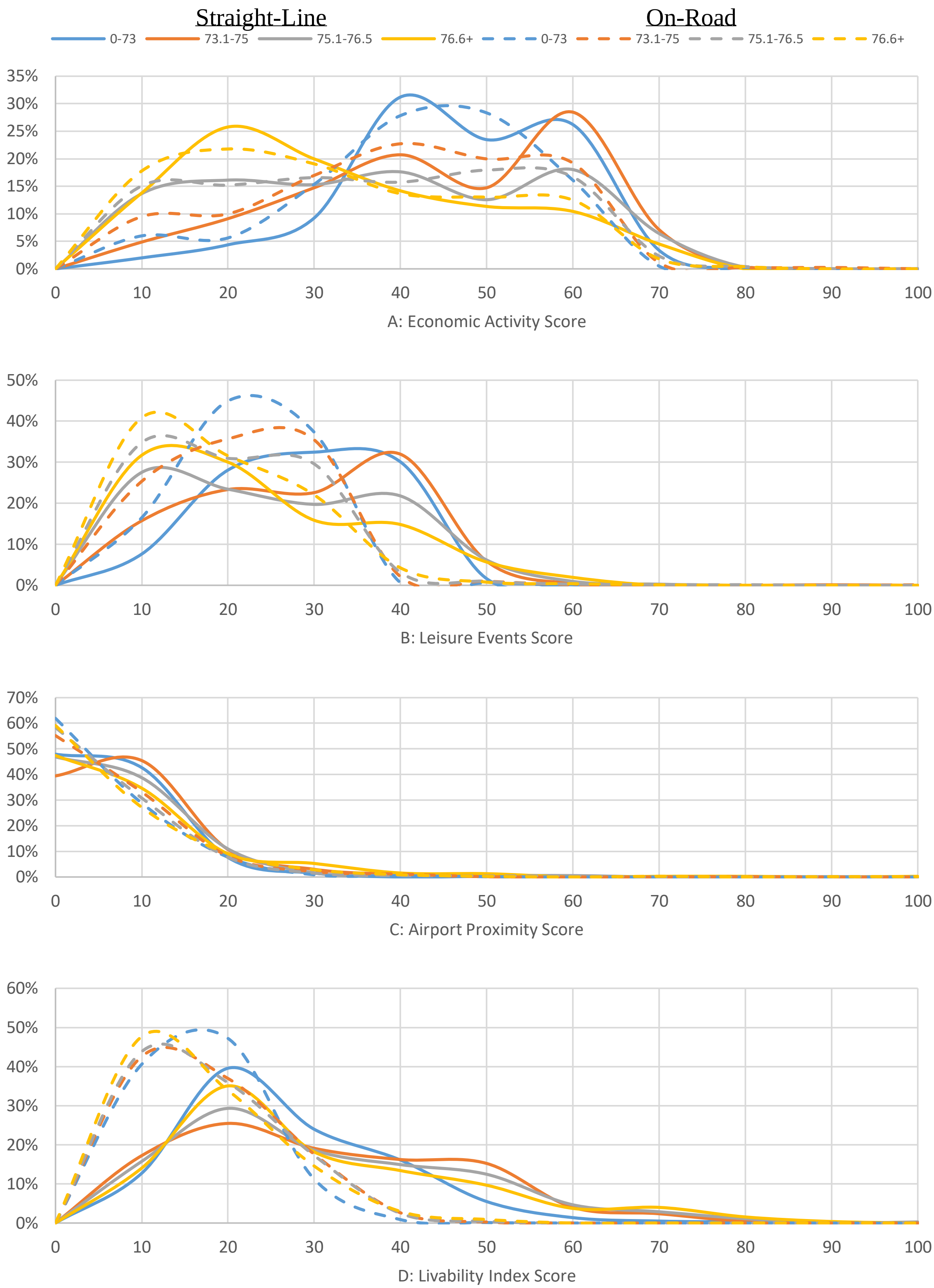


Figure A5: Average Access Score by Male Life Expectancy

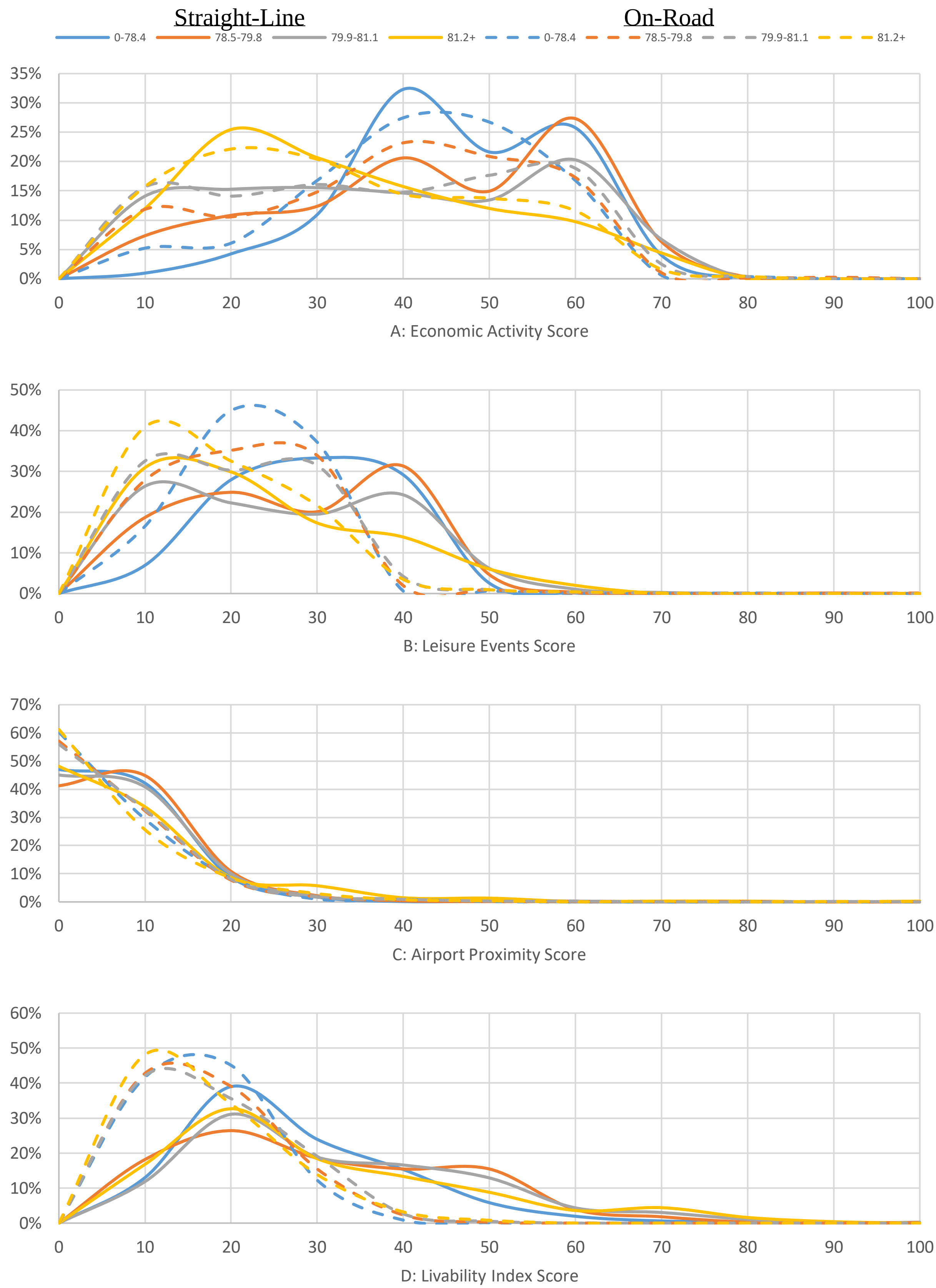


Figure A6: Average Access Score by Female Life Expectancy

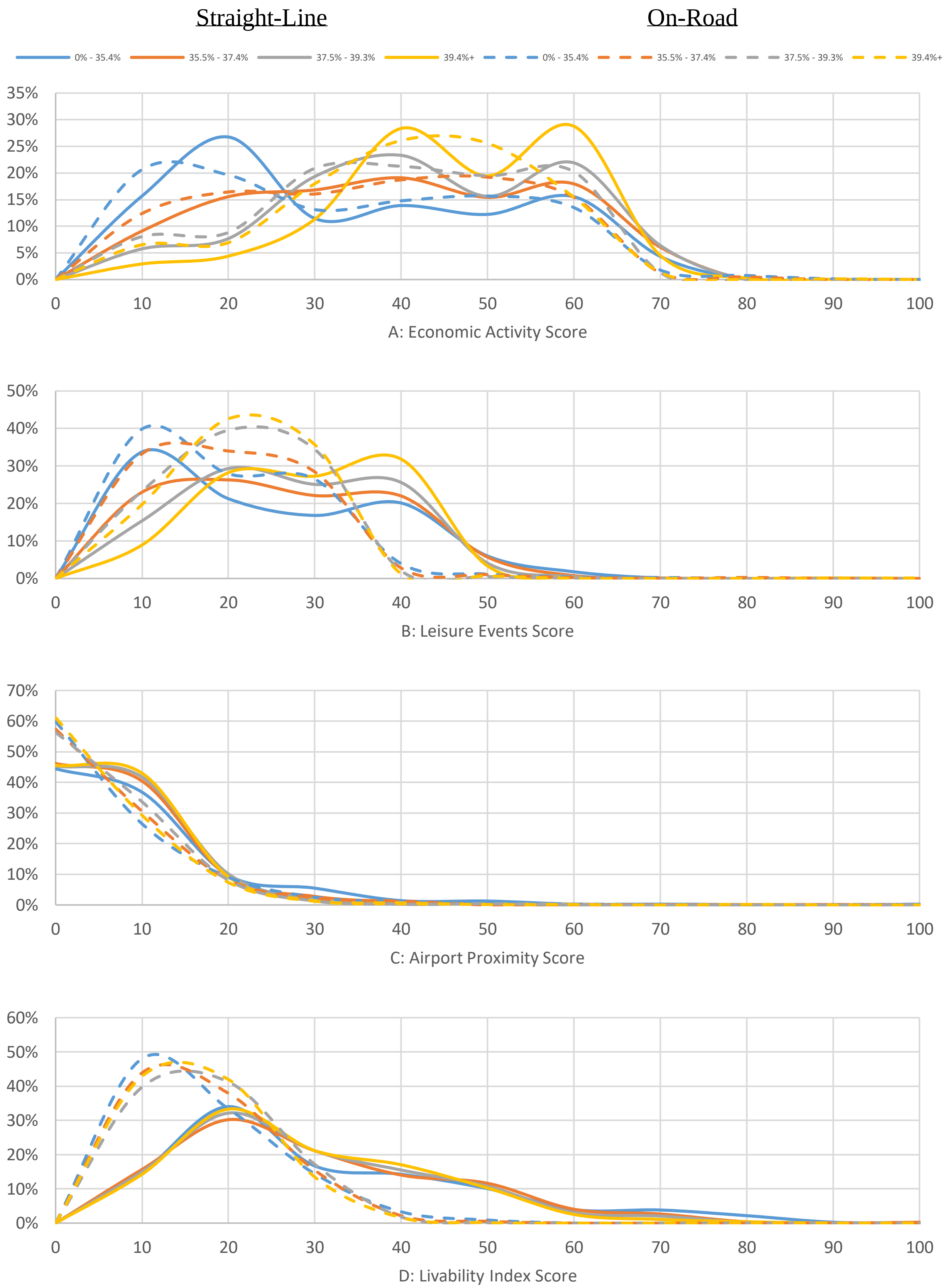


Figure A7: Average Access Score by Male Obesity Rate

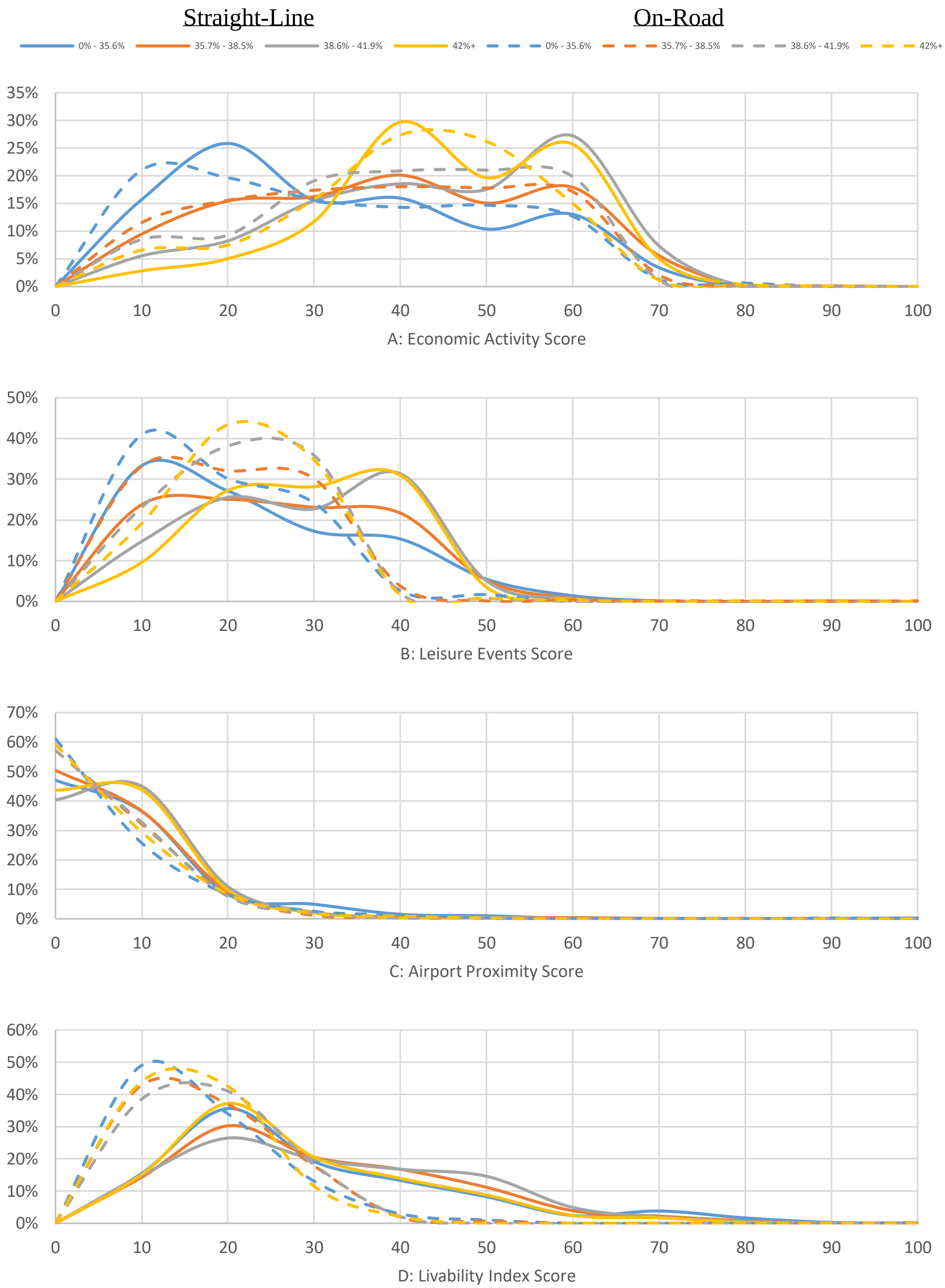


Figure A8: Average Access Score by Female Obesity Rate

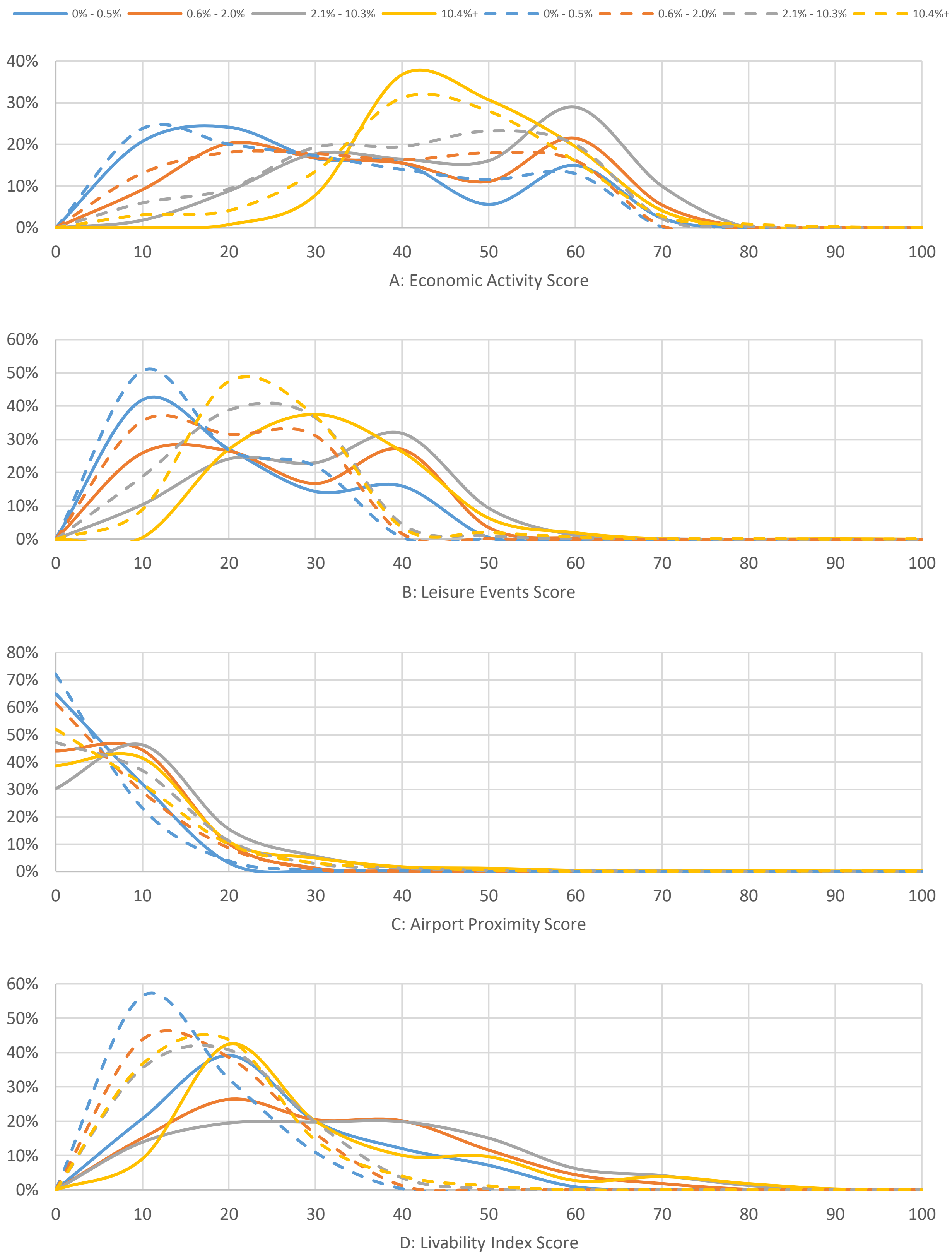


Figure A9: Average Access Score by Percent African American

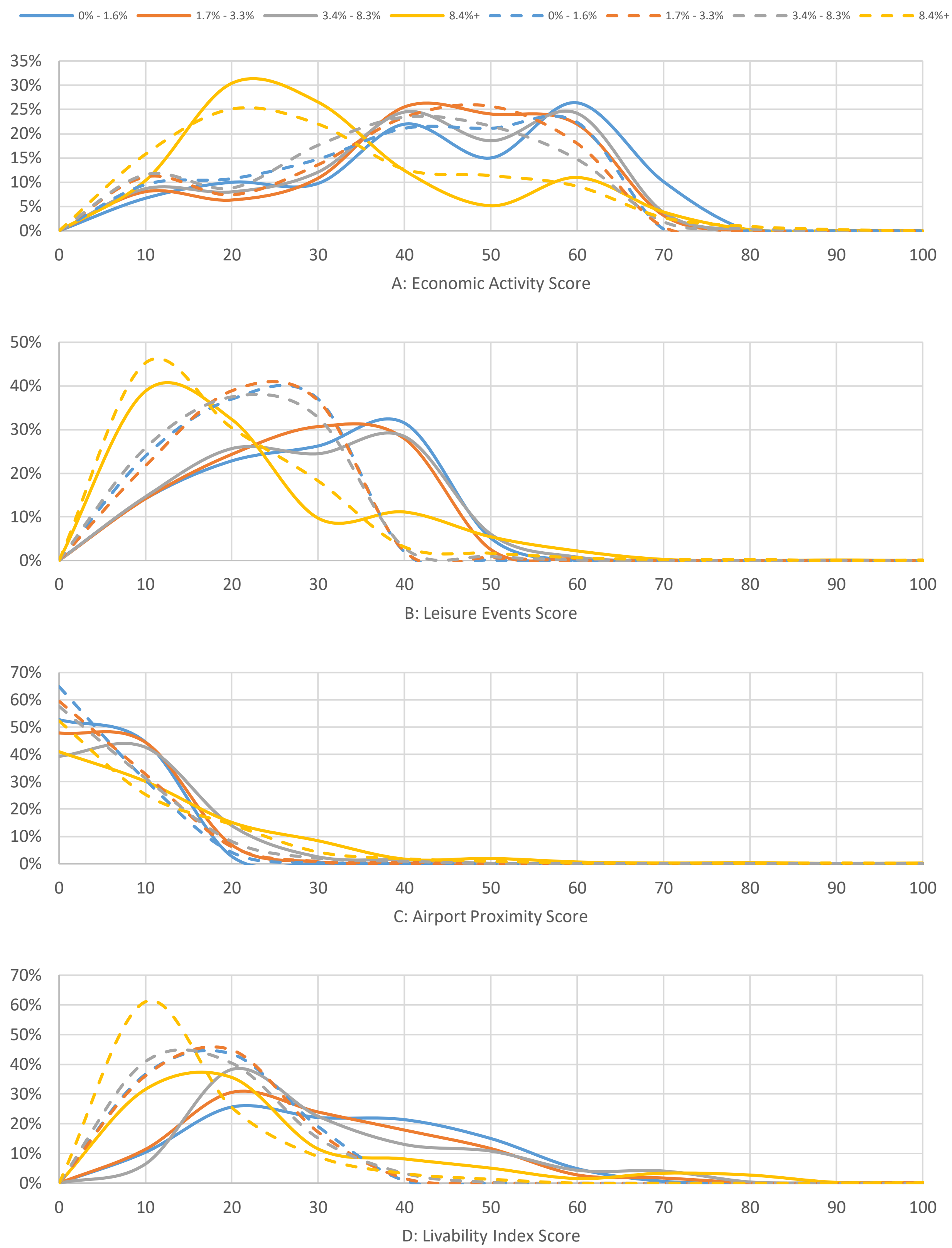


Figure A10: Average Access Score by Percent Hispanic

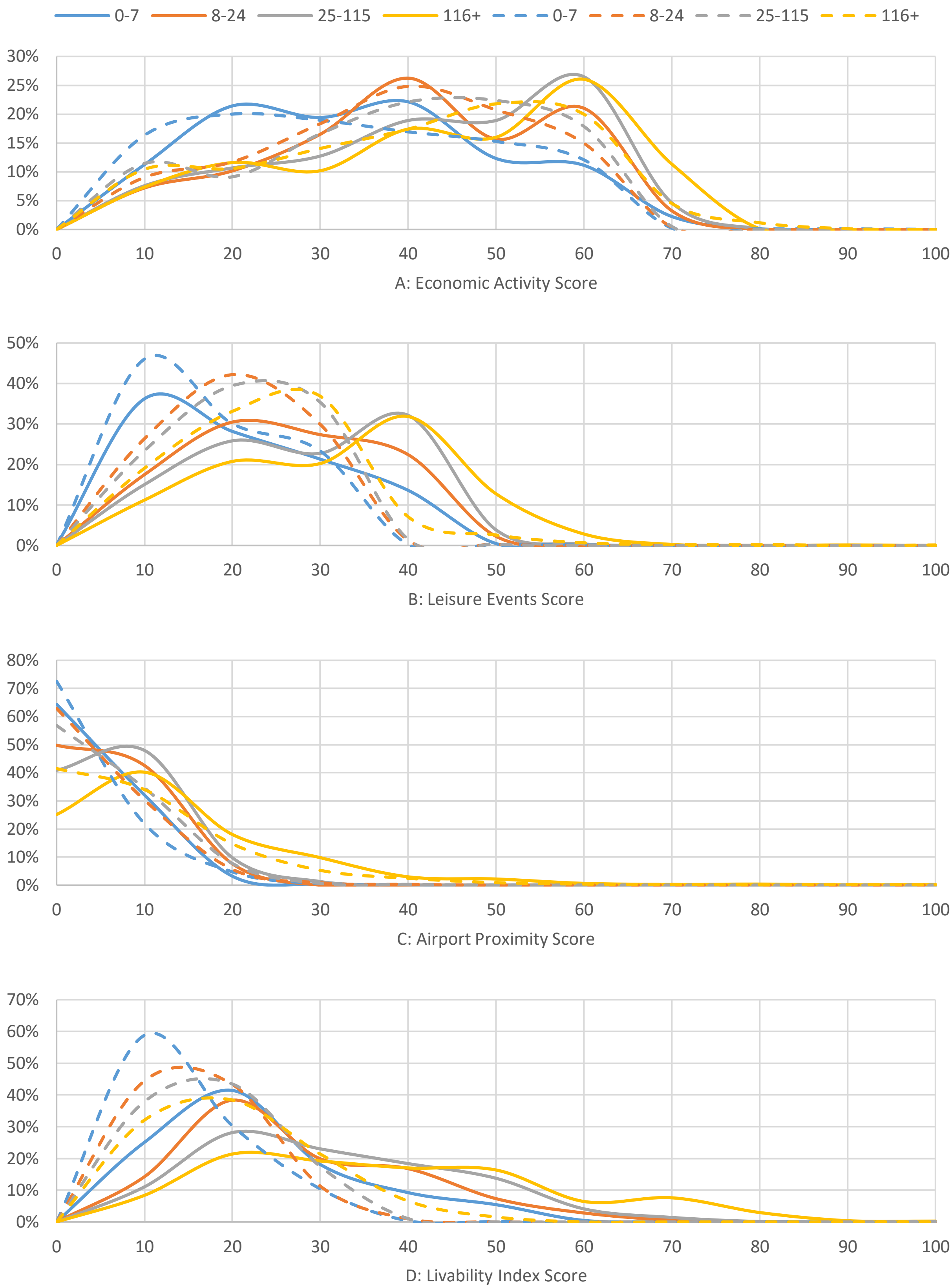


Figure A11: Average Access Score by Total Physicians

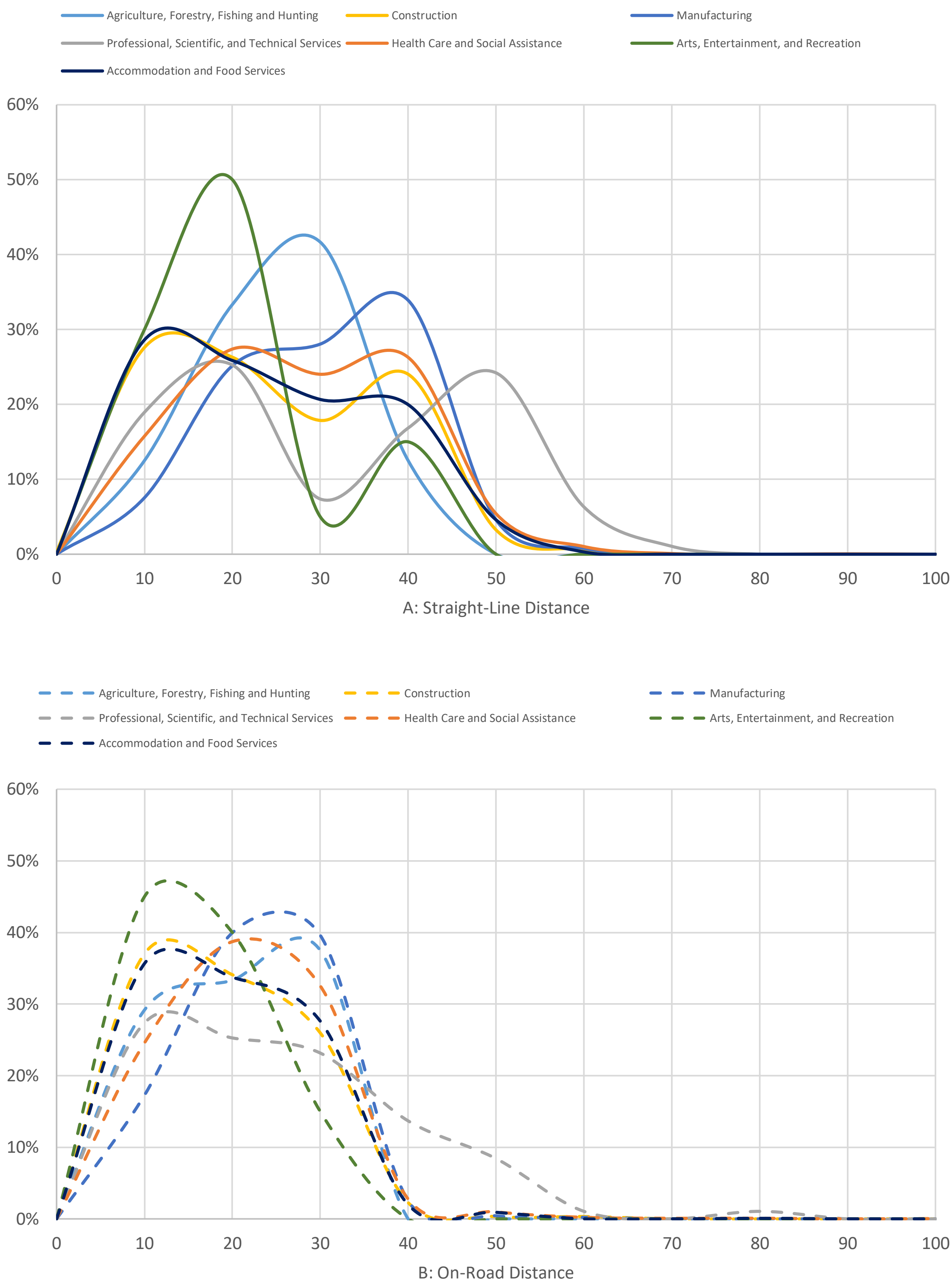
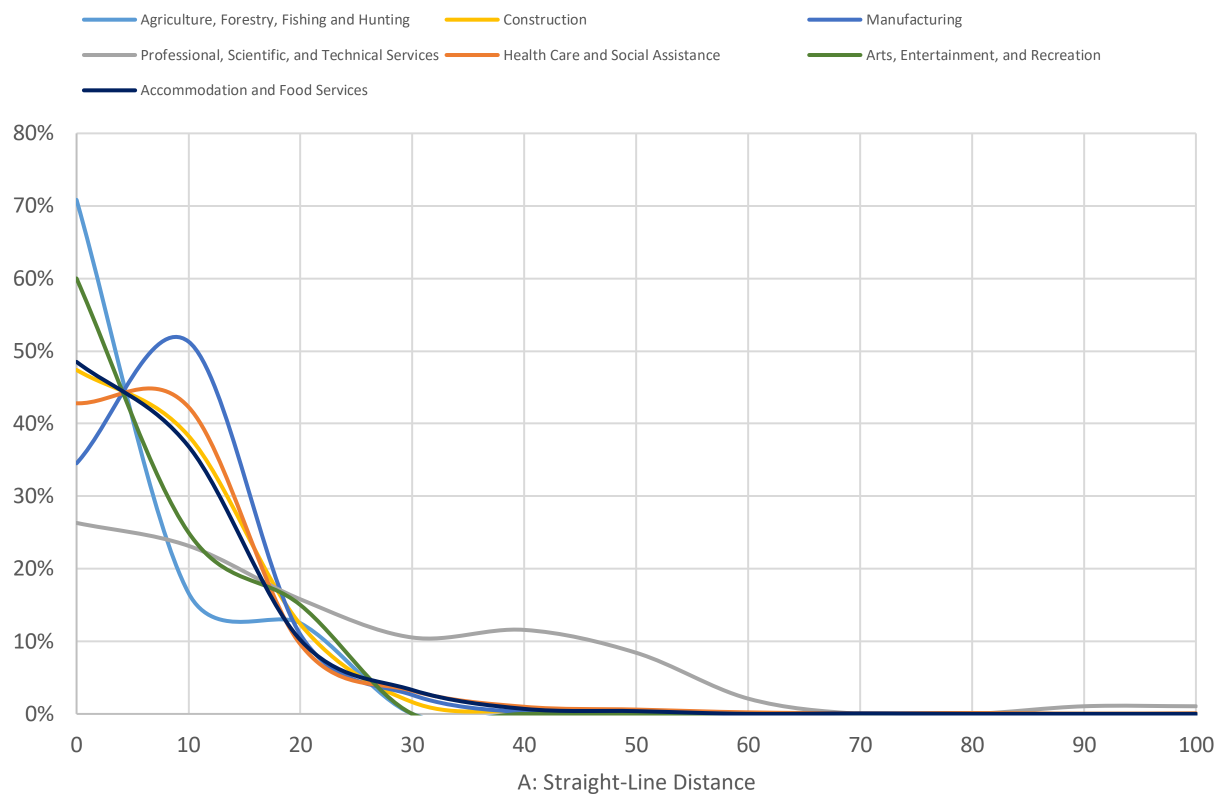


Figure A12: Leisure Events Score by Prominent Industry



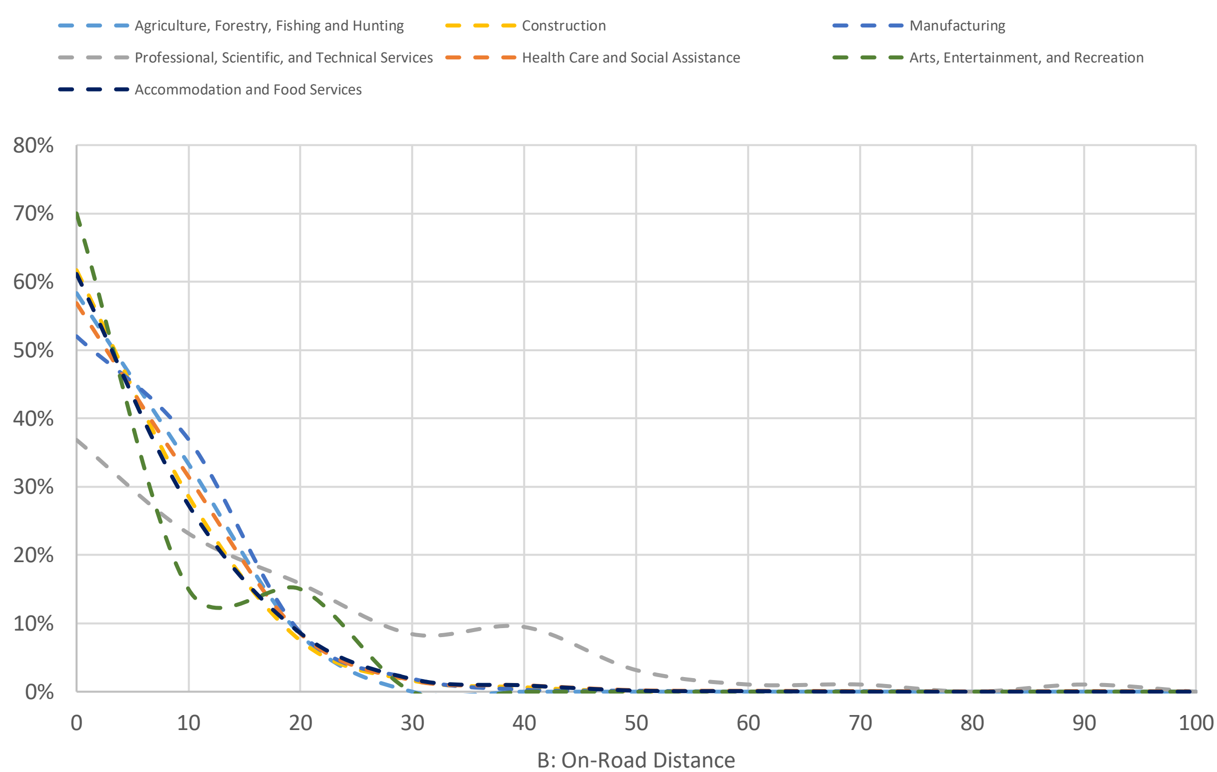
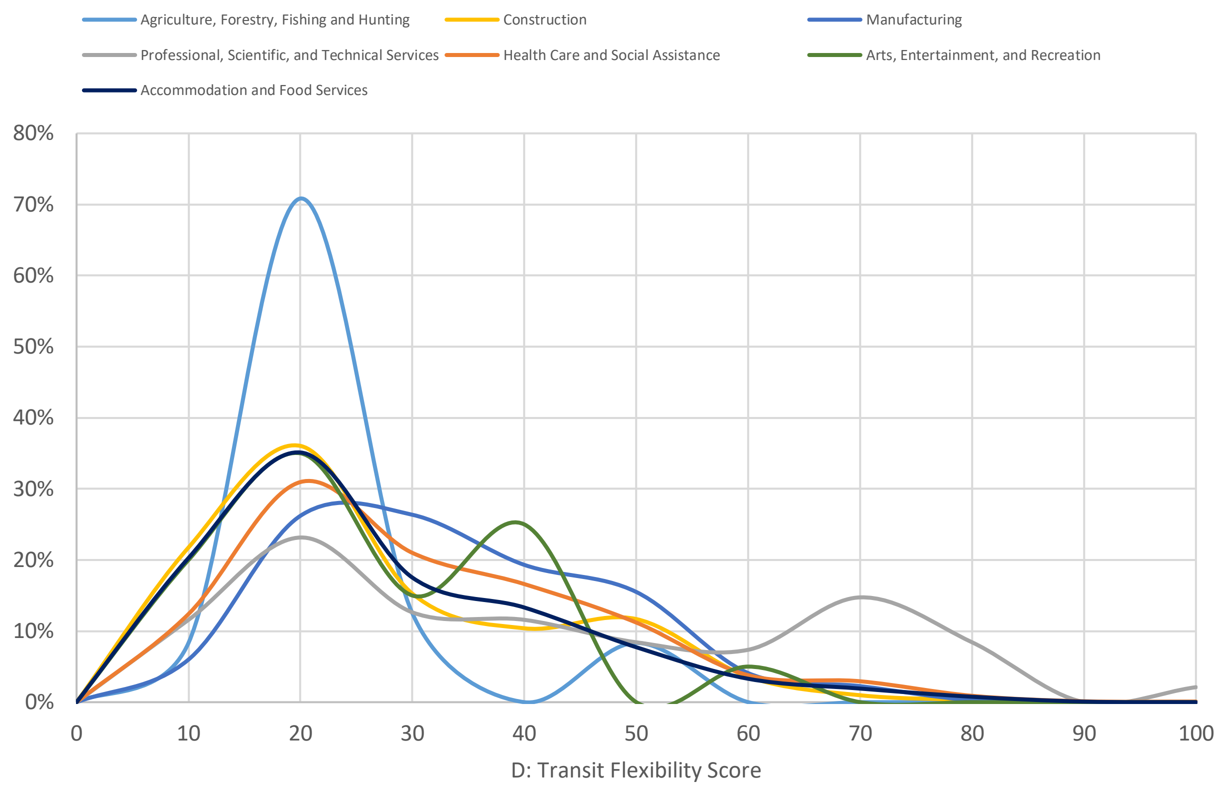


Figure A13: Airport Proximity Score by Prominent Industry



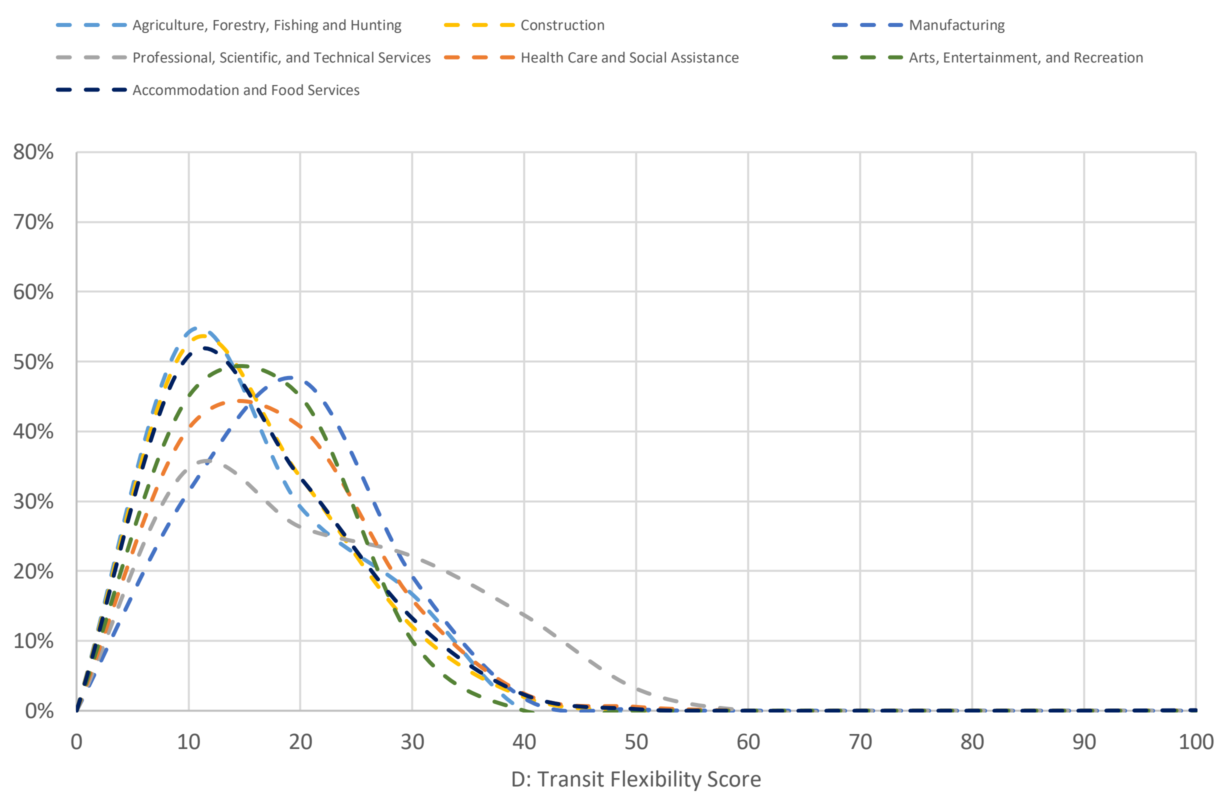


Figure A14: Livability Index by Prominent Industry