Equitable Access to Nutrition in Utah

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Abstract

Convenient access to high-quality nutrition is a critical element of public health as well as an important interface between communities and the transportation system. In this research, we seek to construct a detailed picture of the nutrition environment in three communities in Utah, alongside the community members' ability to access that environment through multiple transportation modes. In doing so we construct a utility-based accessiblity model enabled by modern mobility device data. This model reveals the tradeoffs between the quality and price of goods on one hand and the distance traveled to reach them on the other. We then apply this model to a series of potential access-improving policies: building a new store, improving an existing store, and improving the non-automobile transport network between residents and existing stores. The results show that new or improved store locations bring substantially higher benefits than improvements to the transportation system, at likely lower costs. The report recommends that UDOT work to increase the availability of community-sized grocery stores in low-access areas, and consider activity-based methods of measuring resource access.

Keywords: Accessibility, Access to nutrition, Passive location data

1. Introduction

The Utah Department of Transportation (UDOT) recently adopted a new mission to "Enhance the Quality of Life through Transportation," alongside a four-part framework: Better Mobility, Good Health, Connected Communities, and Strong Economies (UDOT, 2023a). A critical role of the transportation system in accomplishing all elements of UDOT's mission is ensuring that all Utah households have adequate access to quality nutrition and other community resources. Access to quality nutrition is shown to have a correlation with mental and physical well being (Francis et al., 2012), and there are many communities that do not have good accessibility to quality nutrition, with the main options being either more expensive for quality goods, or no quality goods available.

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"Accessibility" is an abstract concept without a specific quantitative definition (Handy & Niemeier, 1997). However, using accessibility as a policy measure requires comparative quantification, and transportation and public health researchers have constructed several quantitative measures. Some commonly used measures include:

- Nearest destination: How close is the nearest grocery store?
- Opportunities within a travel time: How many grocery stores can be reached within 30 minutes?

These types of measures require the researcher to make a series of assumptions and assertions: why is 30 minutes chosen instead of 40? Is that time by transit or highway or walking? Should these definitions change for individuals in different socioeconomic groups? And do people always go to the closest grocery store to begin with? How much further are people willing to travel to go to a store that is cheaper or that has a wider variety of goods? A measure that combines all of these different considerations is desirable.

1.1. Objectives

The objective of this project is to develop an understanding of what variables and attributes are desirable in grocery stores for populations in different areas of Utah, in order to help identify where to make improvements to increase equitable access to nutrition in Utah. The proposed logit model methodology is developed from a connection between three extensive data sources:

- A detailed survey of the nutrition market in three Utah communities
- Location-based services data derived from mobile phone records revealing which grocery stores are frequented by residents of different neighborhoods
- Multi-modal network data providing detailed mobility data by car, walking, and public transit.

These data will be combined in order to develop accurate logit models that demonstrate the variables that are significant to grocery store choice in Utah. These models could then be used to find accessibility to stores and impact transportation policy to improve quality of life for all communities in Utah.

1.2. Outline

This document is organized in a typical manner. Chapter 2 presents a review of transportation organizations' efforts to improve general health outcomes in their communities, followed by a specific review of research exploring the relationship between nutrition access and health. The methodology for data collection and modeling is described in Chapter 3 and a description of the nutrition environment and choice models estimates follows in Chapter 4. Chapter 5 presents a series of scenarios to which we apply the models estimated in Chapter 4, illustrating the interrelated elements of nutrition quality and transportation infrastructure in developing more complete access to nutrition. The document concludes in Chapter 6 with a list of limitations and a pair of recommendations to UDOT.

2. Literature Review

This chapter presents an overview of existing transportation energy policies related to health broadly, followed by a review of the literature on access to nutrition specifically.

2.1. Existing Transportation and Health Policies

Transportation policy impacts the way our transportation systems function in cities, and along with that, impacts the way that we live our lives as well. For example, transportation policy that demands a certain level of safety on roadways creates a better, safer, travel network for those using the roads. Also, policy that puts the pedestrian first helps improve the quality and quantity of sidewalks and bike ways in cities, improving active transportation. There are many different types of policies that can be established, whether they be required by federal law, or established through the individual decisions of local or state governments. Because these policies make such a big impact on the way we live it is important to discover what types of policies exist currently, where there are areas that are missing in policy and practice, and discover how this research can help to bridge the gap between identified need and practical application.

How UDOT and other departments of transportation (DOTs) approach their responsibility to improve quality of life beyond providing mobility is a relatively recent concern. In this section, we discuss how DOTs have begun incorporating public health concerns into their policy making and project prioritization processes.

Transportation impacts public health across several different sectors identified in the literature, which have been grouped together into four general topics: Traffic Safety, Pollution, Active Transportation, and Access to Community Resources. These four topics mirror the focus points of the UDOT mission, with Traffic Safety and Pollution corresponding to Good Health, Active Transportation corresponding to Better Mobility, and Access to Community Resources corresponding to Connected Communities and Strong Economies.

2.1.1. Traffic Safety

Arguably the area where most attention has been given in terms of a public health perspective informing transportation decision making concerns vehicle and roadway safety. This attention is deserved, as transportation safety is a major public health concern. In 2021 there were 329 total fatalities and 1734 serious injuries resulting from car crashes in Utah, the highest mark in a decade (UDOT, 2023b); though crashes in 2022 were marginally lower, they still greatly exceeded the annual rates prior to 2020.

Efforts to improve traffic safety in policy take various forms. One of the strategies to improve safety focuses on educating the public to minimize reckless and distracted driving. Research clearly shows the danger of both reckless and distracted driving and we have recently seen a national focus on eliminating distracted driving National Highway Traffic Safety Administration (2022). In response, Utah has implemented the Zero Fatalities program, focusing on decreasing the number of roadway fatalities to zero by educating the public on deadly driving behaviors, including distracted driving, aggressive driving, drowsy driving, impaired driving, and not wearing seat belts (Zero Fatalities, 2022). Zero Fatalities has different age-specific educational materials for students and teachers. These age groups include pre-drivers, newly licensed teenagers, experienced drivers, and even driving instructors. But, educating the public does not solve all safety concerns; if the roadways themselves are not safe for the drivers, there needs to be a change to those roadways as well.

Efforts to change the roadways have focused on improving facilities design to enhance safety for cars as well as for bikes and pedestrians (Charreire et al., 2021; Jarry & Apparicio, 2021; Monfort et al., 2021). In 2012 the Federal Highway Administration established a federal aid program titled the Safe System Approach that focuses on different programs including the Strategic Highway Safety Plan (SHSP), Highway Safety Improvement Program (HSIP), Railroad-Highway Crossings Program (RHCP), and High Risk Rural Roads (HRRR) (Finkel et al., 2020). Of these four programs included in the safe system approach, the HSIP is the only one mandated and implemented in every state, including Utah. The HSIP gives federal funding for projects, plans, activities, and reports that improve safety of highways.

Vision Zero (Vision Zero Network, 2022) is a safety program funded by a non-profit organization that has been implemented in many communities and combines improving facilities and educating the public. Vision Zero is a tool to help communities create action plans and strategies. In order to be involved in Vision Zero the following must be true:

- the community must have a clear goal and plan with a process in place to accomplish the goals (including a target date for when the community will reach zero fatalities)
- the community leader must declare that they are joining the Vision Zero community to strive for zero fatalities on the roadway.

This program is a multinational road traffic safety program with the potential to greatly improve traffic safety in communities where it is implemented. The Vision Zero focus is to eliminate traffic fatalities and severe injuries with a clear strategy or plan. A map showing the communities involved is in Figure 1. Vision

Zero has not been implemented in any communities in Utah. Two major differences between Vison Zero and Utah's Zero Fatalities program are that Zero Fatalities does not yet have a specific target date of when the state will reach zero fatalities, and Vision Zero typically includes many stakeholders such as transportation professionals, policy makers, public health officials, police, and community members.

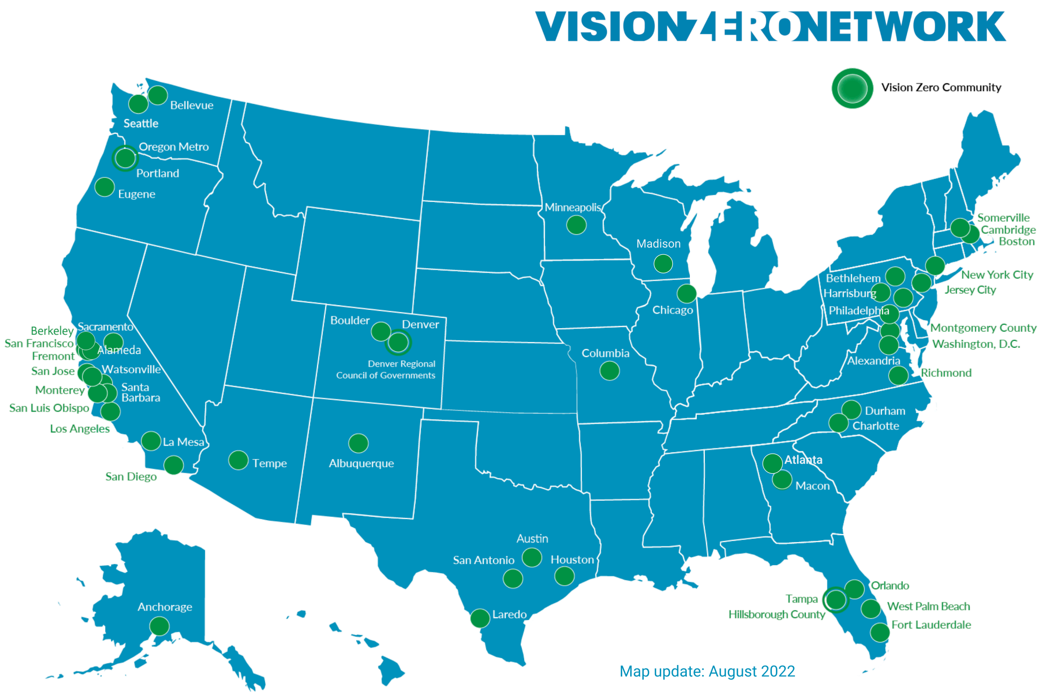


Figure 1: Vision Zero communities in the United States.

2.1.2. Pollution and Environmental Justice

Another place where transportation and public health intersect is pollution and related environmental justice issues. A large percentage of airborne pollution comes from vehicle emissions including over 55% of nitrogen oxides (NOx), less than 10% of volatile organic compounds (VOC), and less than 10% of particulate matter (PM). Vehicle emissions are of the largest contributors to PM2.5 levels around the globe. Studies have shown the impact of fine particulate matter (PM2.5) and ozone levels on health and have found about 36,000 deaths a year attributed to these levels Fann et al. (2013). In addition, PM2.5 has been linked to various health defects such as respiratory and cardiac symptoms, and exacerbate many other health conditions (Schraufnagel et al., 2019).

Vehicle pollution has been addressed differently across states. California has a Zero-Emission Vehicles (ZEVs) strategy to increase the access of electric vehicle chargers along the roadway networks, support local transit transitions to zero-emission technology, and support the development of zero-emission freight technology. Delaware established a Strategic Implementation Plan for Climate Change, Sustainability and Resilience for Transportation, and Massachusetts has begun a new Low Emission Vehicle Program requiring most new vehicles to be equipped with advanced emission control systems. Utah has implemented a Noise Abatement Policy to decrease noise pollution which complies with federal regulation according to NEPA to be environmentally responsible.

On a national level, however, the Clean Air Act directs the Environmental Protection Agency to set certain quality standards for pollutants in the air (Environmental Protection Agency, 2023). States are required to meet these standards or develop a plan to improve pollution levels. The map in Figure 2 shows counties in each state that do not meet the standard for the identified air pollutants. As can be seen, there are several counties in Utah that do not meet the federal air quality standards for certain particulates, so there are opportunities for improvement.

One problem with fine particulate matter and vehicle pollution is that it has differential effects related to demographics, with some communities experiencing more severe health disparities (Chakraborty, 2022). In order to more equitably address some of these pollution problems, the EPA has established guidance related to Environmental Justice to "determine any disproportionately high and adverse human health or environmental effects to low-income, minority, and tribal populations". This guidance is met through the National Environmental Policy Act (NEPA), which requires an impact assessment for every federal action – including most transportation infrastructure projects – that could have an impact on the environment. A report describing any potential environmental or health impacts or findings of no significant impact must be submitted. This process and legislation is intended to protect communities that could be more adversely affected by new transportation projects or improvements.

In some ways these national and state measures have helped, and recent evidence that shows a decrease in air pollution related deaths in the U.S. (Choma et al., 2021). However, more work needs to be done in order to further decrease pollution related death and disease. This is true for existing facilities that can be improved to be more equitable and less polluted as well as any new policies or projects that can be designed to limit or decrease pollution.

2.1.3. Active Transportation

Active transportation is an intersection of public health and transportation that includes walking and biking improvements, as well as public transportation. Both individual activity and public transportation system design are important when looking at active transportation. When looking at individual activity, direct correlations have been found between perceptions of well-being and social contact which comes through walking and biking and in relation to public transportation infrastructure a positive correlation was found

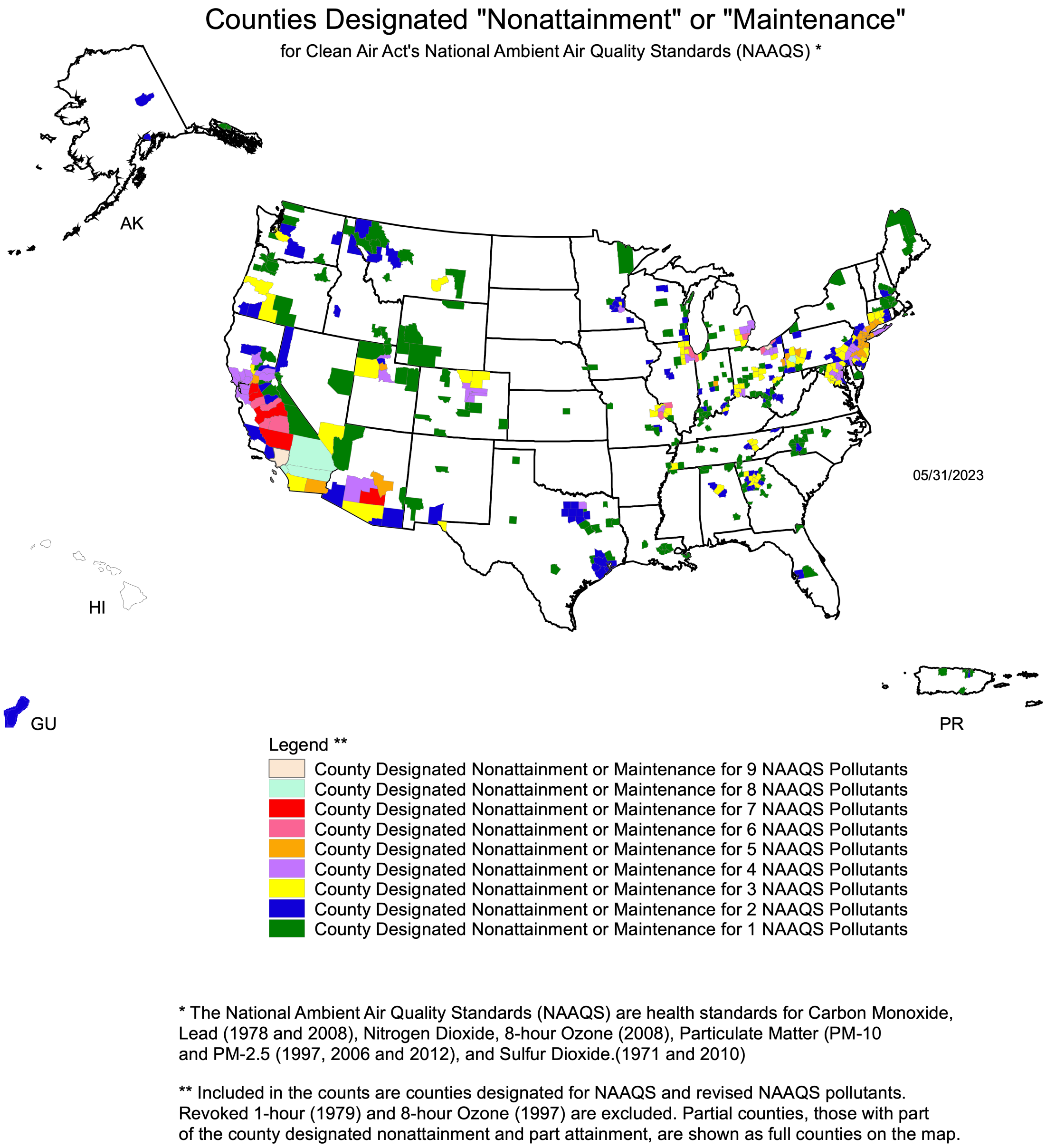
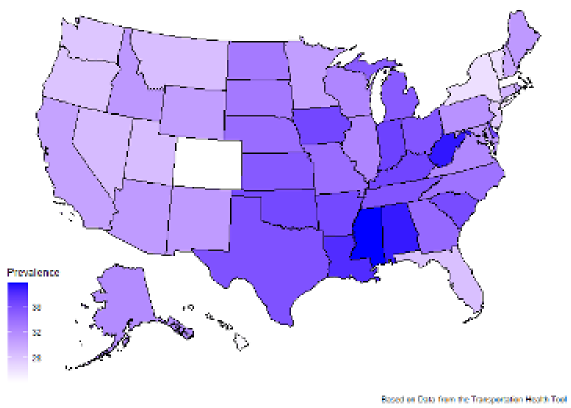


Figure 2: Nonattainment counties in the United States, identified by how many criteria pollutants are in nonattainment.

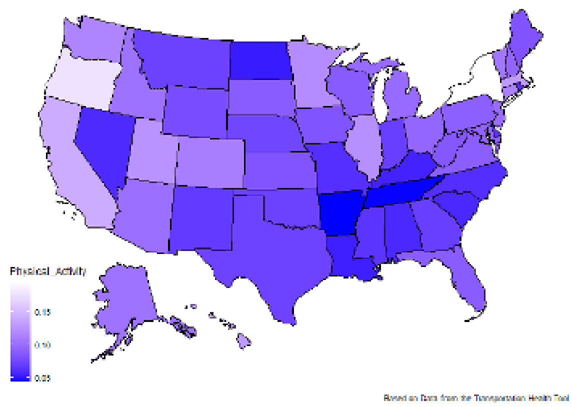
between quality of life and multimodal trips Gerike et al. (2019). In addition, correlations have been found between mode choice, the use of public transportation, and health, showing that the more a car was used for transport, the higher the BMI (Body Mass Index), supporting the connection between health and active transport and support- ing the improvement of public transportation infrastructure to encourage sustainable mobility Dons et al. (2018).

Active transportation measures and how they impact health can be somewhat difficult to track, but the best way to do so is by analyzing different data that has been collected in regards to health and transportation. To analyze the data on active transportation more completely, the US Department of Transportation (2022) has partnered with the Centers for Disease Control and Prevention (CDC) to develop the Transportation and Health Tool. This tool provides easy access to data of public health indicators and transportation in each US State and metropolitan area. These data include indicators such as obesity rates, percent of physical activity in trips taken, and how much federal funding was used to support active transportation infrastructure.

Using this data from 2017 in each state we created the maps show in Figure 3. Figure 3 (A) shows the obesity rates by state with 24.2% being the least in Colorado while (B) shows the estimated percent of trips that include physical activity (walking, bicycling, and walk-access public transport). As can be seen there does seem to be some pattern, with those states that have a higher physical activity, also having a lower obesity rate. There are a few outliers, such as Nevada, with a low obesity rate and a low physical activity percentage, but overall, there is a correlation coefficient between the two indicators of 0.64. It should be noted in this context that obesity is a complex disease with many contributing factors, of which physical activity is only one (Dhurandhar et al., 2021).



(a) Obesity



(b) Physical Activity

Figure 3: State-level rates of obesity and physical activity of trips.

Obesity is a problem in the United States, and with these graphs there does seem to be a correlation between increased active transportation and decreased obesity. In order to improve public health one goal could be to improve physical activity in transportation dramatically in states. The highest percentage of physical activity was in New York with about 20%. In order to improve this percentage to make 20% be a more normal value rather than the exception it is important that each state put more of an emphasis on public transportation and active transportation projects.

2.1.4. Accessibility to Resources

In addition to helping improve health, public transportation and active transportation project also improve accessibility to resources. Accessibility to resources has also been widely studied in the past and will be analyzed more completely later in this chapter. The main idea of equitable accessibility is to make sure that each race, economic background, and age has an equal transportation option or alternative to access different public goods and resources. Equitable accessibility can have a dramatic impact on public health and is an important part of transportation policy (Aggarwal et al., 2014). However, the presence of accessibility to resources in research and application in different states is somewhat limited.

At a minimum each state must adhere to the federal Americans with Disabilities Act (ADA) standard when designing roadways or other infrastructure. In addition, there is the federal complete streets policy that is implemented throughout the nation. According to Smart Growth America (2023), a non-profit organization that helps foster equitable and sustainable communities, there are 35 state governments that have adopted complete streets policies, with Utah being one of those states. Complete Streets requires streets to be planned, designed, and maintained to enable safe and comfortable access and travel for all users regardless of age, abilities and mode of transportation.

This map shown in Figure 4 gives a visual representation of which counties, cities, and towns have adopted a complete streets policy. As can be seen, even in the states that have adopted a policy, there are still massive regions that do not have that policy implemented that still need the impact of equitable accessibility in projects and policy.

2.2. Access to Nutrition

2.2.1. Access and Equity

Equitable access to community resources has been a topic of research and study, especially when looking at the impacts on measures of well-being and economic opportunity. Current social issues, economic opportunity and equity are significant topics that can help us ensure that each population demographic can have

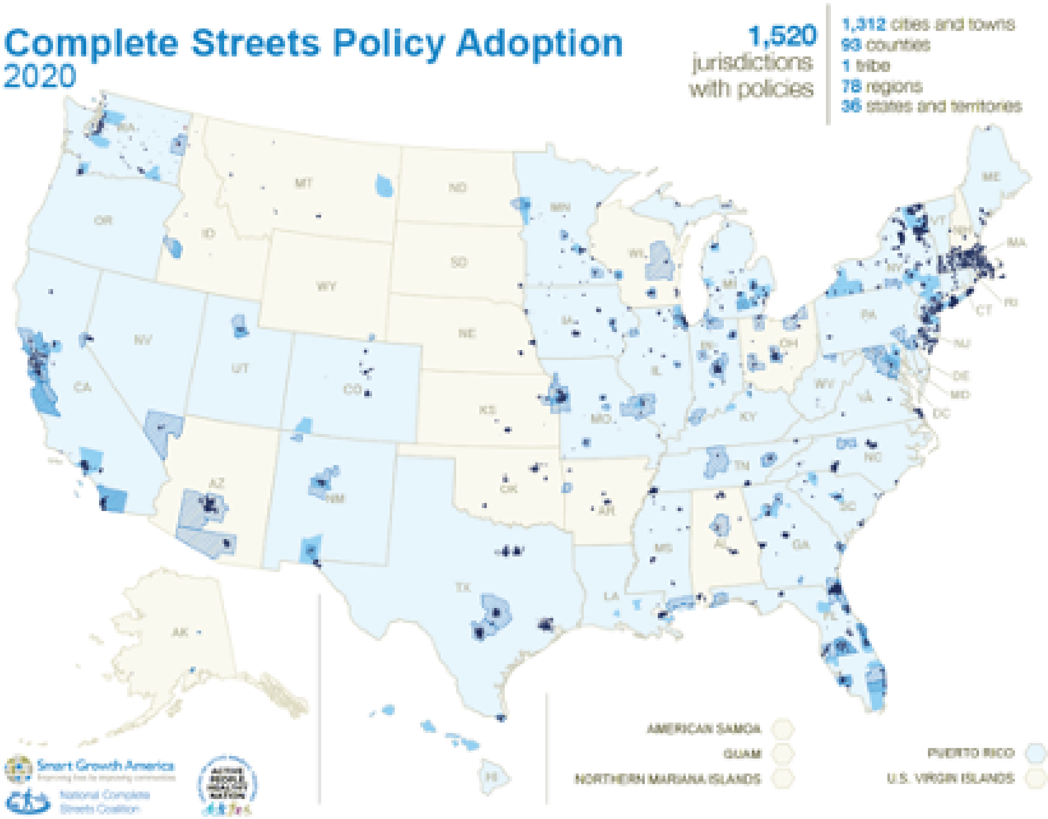


Figure 4: Jurisdictions with complete streets policies in the United States.

similar opportunities. Equity as a term is being fair and impartial, different from equality. Equality is providing the exact same thing to all people, whereas equity would provide different things to different people because of their circumstances in order to create a fair system. Lower-income populations frequently sit at a different level of advantage than higher-income populations, including when looking at accessibility Witten et al. (2003). It is important to discover how different transportation policies can improve accessibility to create better equity. Creating equitable societies and equitable transportation policies is important in order to remove any discrimination already present in the transportation network. In this way states can decrease the disparity that is common when looking at different neighborhoods and demographics. Perhaps there are low-income neighborhoods that do not have the same economic opportunity or resource accessibility as high-income neighborhoods. If we increase the accessibility of low-income neighborhoods, could that then increase the quality of life and health for those neighborhoods as well?

In addition to economic opportunity, the connection between well-being and opportunity is also significant, discovering who has access to which resources and how that access corresponds to their health Schwanen et al. (2015). A subjective sense of positive well-being correlates with increased access to more community resources: increased access was specifically connected with variety of resources, not necessarily number of the same type of resource. This increased access is true for both high- and low-income populations. However, high-income demographics frequently tend have better access to a variety of resources because of such variables as available child care, a transportation source available, or even time available to do things Liu et al. (2022) . In addition, increased access to resources such as parks or other greenspace have been found to decrease likelihood of mental health disorders, as well as improve physical activity Madzia et al. (2019). Different age groups each have a different response to access to greenspace. However, among all age groups there is a positive correlation.In addition to health impacts, lack of accessibility also affects economic opportunity when considering access to employment, affordable care, and other stores and shops Hu (2015).

2.2.2. Food Deserts and Swamps

While there are many different community resources that can be the center of study, such as libraries, green space, hospitals, etc., this project will focus on the resource of grocery stores and discovering any correlation between accessibility to good nutrition environments such as healthy grocery stores and the demographic makeup of specific block groups, such as economic bracket and different ethnic groups. Lack of accessibility to grocery stores can have an effect on physical health and well-being (Aggarwal et al., 2014). This access is related directly with consumption of healthy foods, as well as indirectly with perceived sense of well-being.

Much of the current research that has been done has shown a different level of accessibility for different demographics, such as low income populations. Low income populations have been shown to frequently have less access to fresh fruits and vegetables Losada-Rojas et al. (2021). This may not be directly correlated to the physical distance from a grocery store, but the store that was chosen for these demographics. In a study analyzing grocery store choice in Seattle it was found that in some instances, there is a closer store with better produce, but for some reason it was not chosen and instead a store that was further away was chosen that did not have the same quantity and variety of fresh produce. This was found again in a different study, that frequently people will travel to a store that is not the closest store for different reasons Hillier et al. (2011). This study will help to determine that choice pattern and identify which variables are important when choosing a store to help improve accessibility more than simple distance measures.

However, areas that do not have any full service grocery stores however are also important to look at, with those areas being known as food swamps. These food swamps are an idea that there are locations where there is not healthy food available, so the only option that is readily accessible for food or meals would be fast food or convenience stores. There have been studies analyzing the different food swamp areas and what could be done to improve those areas, such as adding grocery stores or corner markets (Bao et al., 2020). These food swamps are areas that discriminate between those without readily available transit options and those with easy access to cars, creating a barrier to equity. In addition, these food swamp areas are especially significant when looking at the public health impacts of food accessibility and discovering how we can improve the quality of food available to those in every demographic to create an equitable solution to health differences.

Past research done clearly shows that location of store, quality of store, and price of store all have an impact on choice of grocery store and accessibility to grocery stores. This impacts the quality of life and overall health and well-being of individuals and shows the importance of discovering which variables are most significant in grocery store choice in order to improve accessibility and equity. What much existing research suffers from, however, is the wide variety of measures of access and the definitions used to describe a "grocery store." Certainly convenience stores do not typically provide the same variety and quality of goods, but simply excluding them from analyses ignores how many people obtain a large share of their daily and weekly nutrition, for better or worse. A measure that can incorporate multimodal access to stores as well as qualitatively describe the stores along a continuous array of measures is desirable.

3. Methods

This section describes how we construct a model of access to grocery stores in communities in Utah. We first describe the theoretical model, and then describe data collection efforts to estimate this model and apply it.

3.1. Model

A typical model of destination choice (Recker & Kostyniuk, 1978) can be described as a random utility maximization model where the utility of an individual i choosing a particular destination j is

$$U_{ij} = \beta_s f(k_{ij}) + \beta_x(X_j) \tag{1}$$

where $f(k_{ij})$ is a function of the travel impedance or costs from i to j and X_j represents the location attributes of j. The coefficients β can be estimated given sufficient data revealing the choices of individuals. The probability that individual at location i will choose alternative j from a choice set J can be estimated with a multinomial logit model (MNL) (McFadden, 1974),

$$P_i(j) = \frac{\exp(U_{ij})}{\sum_{j' \in J} \exp(U_{ij'})} \tag{2}$$

The overall fit of the model can be described with the Akaike Information Criterion (AIC) — which should be minimized — or by the McFadden likelihood ratio $\rho_0^2 = 1 - \ln \mathcal{L} / \ln \mathcal{L}_0$. In this ratio $\ln \mathcal{L}$ is the model log-likelihood and $\ln \mathcal{L}_0$ the log-likelihood of an alternative model where all destinations are equally likely; a higher ρ_0^2 value indicates more explanatory power relative to this null, random chance only model.

The idea of using destination choice logsums as accessibility terms is not new, and the theory for doing so is described in Ben-Akiva & Lerman (1985, p. 301). Effectively, the natural logarithm of the denominator in Equation 2 represents the consumer surplus — or total benefit — available to person i:

$$CS_i = \ln \left(\sum_{j \in J} \exp(U_{ij}) \right) \tag{3}$$

A difference in logsum measures may exist for a number of reasons that affect the utility functions described in Equation 1. For example, individuals at different locations or with different mobility will see different impedance values k_{ij} and therefore affected utility. Changes to the attributes of the destinations X_j will likewise affect the utility.

Despite the relative maturity of this theory, applications of utility-based access in the literature are still rare, outside of public transport forecasting analyses (Geurs et al., 2010). The rarity is likely explained by an unfamiliarity with destination choice models and the ready availability of simpler methods on one hand (Logan et al., 2019), and the difficulty in obtaining a suitable estimation dataset for particular land uses on the other (Kaczynski et al., 2016). This second limitation has been somewhat improved by a new methodology developed by Macfarlane et al. (2022) , relying on commercial location-based services data to estimate the affinity for simulated agents to visit destinations of varying attributes and distances.

Table 1: Demographic Statistics of Study Region

	Utah	Salt Lake	San Juan
Total population	627,098	655,830	7,091
Total households	171,538	216,731	2,090
Housing units per sq. km	599	831	103
Median income	79,453	64,868	58,586
Percent minority individuals	18	36	26

3.2. Data

In this research, we develop a unique dataset to estimate the destination choice utility coefficients for grocery store choice in three different communities in Utah. The three communities were selected to maximize potential observed differences in utility between community residents. The three communities are Utah County, West Salt Lake Valley, and San Juan County. Note that in this document we refer to the second community as "Salt Lake" even though this does not refer to the entire Salt Lake County nor to Salt Lake City, rather, we focus on communities in the western part of the valley, such as Magna, Kearns, and West Valley City.

Table 1 shows several key population statistics based on 2021 American Community Survey data for block groups in the three communities of interest. Utah County is a largely suburban county with high incomes and a low percentage of minority individuals. The Salt Lake region is more dense with somewhat lower incomes and household sizes but a high share of minority individuals. San Juan County is primarily rural, with a few small communities and a large reservation for the Navajo Tribe.

Estimating the utility model described in Equation 2 for grocery stores requires three interrelated data elements:

1. an inventory of grocery store attributes X_j,
2. a representative travel impedance matrix K composed of all combinations of origin i and destination j.
3. a database of observed person flows between i and j by which to estimate the β coefficients.

We describe each of these elements in turn in the following sections.

3.2.1. Store Attributes

The store attributes were collected using the Nutritional Environment Measures Survey — Stores (NEMS-S) tool (Glanz et al., 2007). This tool was developed to reveal significant differences in the availability and cost of healthy foods in an environment, and has been validated for this purpose. Beyond superficial attributes such as the store category (dollar store, convenience store, ethnic market, etc.) and the number of registers, the NEMS-S collects detailed information about numerous store offerings such as the availability of produce, dairy products, lean meats, juices, and canned and dry goods of various specific types. Of particular interest to the survey are availability and price differentials of lower-fat alternatives: for example, the survey instrument requests the shelf space allocated to milk products of various fat levels and the price of each product.

Student research assistants collected the store attributes by visiting grocery stores, dollar stores, ethnic markets, and other food markets in the three communities of interest described above. Stores were identified using internet-based maps combined with in-person validation and observation. The student researchers completed the NEMS-S instrument with the aid of a digital survey and a tablet computer. Each researcher who collected data was trained to use the survey at a control store in Provo, and the training data helped to eliminate the risk of surveyor bias. The store attributes were collected in the spring of 2021 for Utah County and spring of 2022 for Salt Lake and San Juan Counties. In Utah and Salt Lake Counties, we included dollar stores and grocery stores but did not include convenience stores. Given the rural nature of San Juan County, we made two adjustments to capture the entirety of the nutrition environment. First, we included convenience stores and trading posts if they were the only food market in a community. We also included full-service grocery stores in Cortez, Colorado, and Farmington, New Mexico in the San Juan data collection, as community conversations made it clear that many residents will drive these long distances for periodic shopping with greater availability and lower prices.

Using the information in the NEMS-S survey, two measures of a store can be calculated: an availability score based on whether stores stock particular items as well as lower-calorie options; and a cost score describing the spread between prices of these options. These score values are described in Lunsford et al. (2021), and we developed an R package to compute the scores; this package is available at https://github.com/byu-transpolab/nemsr. In the availability score each store is given a value for whether or not there are more healthful options available in the store, such as low-calorie chips, or low-fat milk. If the store does not have a more healthful option in a category it receives a lower score, so stores with more availability of healthful food options will receive a higher availability score. For the cost score, the measure is the price spread between healthful and less healful options: if the price of whole wheat bread is cheaper than white bread, the store receives positive points for the cost option, if the price is the same then zero points are awarded, and if the wheat bread is more expensive then the store receives negative points. Thus a store with a higher availability and cost score will have both more healthful options, and a more advantageous pricing scheme towards those options.

One important store attribute that the NEMS-S instrument does not collect or compute directly is a

Table 2: Grocery Store Attributes

		Utah (N=63)		Salt Lake (N=39)		San Juan (N=50)	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Registers (incl. self checkout)		12.5	11.7	9.9	8.9	6.1	8.8
NEMS-S availability score		18.7	8.4	16.2	8.1	13.2	7.6
NEMS-S cost score		1.9	2.3	2.3	2.2	1.9	1.9
Market basket cost		126.1	21.5	141.6	19.2	157.6	16.8
		N	Pct.	N	Pct.	N	Pct.
Type	Convenience Store	2	3.2	0	0.0	10	20.0
	Dollar Store	5	7.9	11	28.2	15	30.0
	Grocery Store	50	79.4	27	69.2	19	38.0
	Other	6	9.5	1	2.6	6	12.0
Pharmacy	FALSE	42	66.7	32	82.1	43	86.0
	TRUE	21	33.3	7	17.9	7	14.0
Ethnic market	FALSE	55	87.3	30	76.9	47	94.0
	TRUE	8	12.7	9	23.1	3	6.0
Other merchandise sold	FALSE	52	82.5	35	89.7	47	94.0
	TRUE	11	17.5	4	10.3	3	6.0

measure of the cost of common goods that can be compared across stores. We therefore used the data collected from the NEMS-S instrument to construct a market basket-based affordability measure that could be compared across stores, following the approach of Hedrick et al. (2022). This market basket score is based on the US Department of Agriculture (USDA) 2021 Thrifty Food Plan (FNS, 2021), which calculates a reference market basket for a family of four. Because this market basket contains more (and sometimes different) items than what the NEMS-S instrument requests, we chose relevant items from our NEMS-S data as replacements. For example, the USDA market basket contains a certain amount of poultry, but the NEMS-S score collects the per-pound cost of ground beef at various fat contents. For any stores that were missing any of the elements in the market basket, we first substituted with another ingredient that would fit the nutritional requirements. If no substitute was available, we included the average price of the missing good at other stores in that community multiplied by 1.5 as a penalty for not containing the product. The final market basket score is the total cost of all foods in the market basket. These costs can then be compared from store to store to understand general affordability comparisons between stores.

Table 2 presents the store attribute data collected for each community. Utah County generally has the largest average store size (as measured by the number of checkout registers) while having the lowest market basket cost, the highest availability of health food (the NEMS-S availability score) and the lowest difference between healthy and unhealthy food (the NEMS-S cost score). San Juan County has the smallest average stores, highest costs and the lowest availability of healthy options, and Salt Lake falls in between.

3.2.2. Imputation of Missing Store Data

We collected detailed store attributes for stores in Utah County, San Juan County, and a portion of Salt Lake County using the NEMS-S survey instrument. These attributes form the basis of the choice models used to determine access, but understanding access in other parts of Salt Lake City or the state of Utah requires us to impute the attributes onto the stores that we did not collect.

To do this, we used web-based mapping databases (including OpenStreetMap and Google Maps) to obtain a list of grocery stores, dollar stores, and appropriate convenience stores throughout the state. From this search, we were able to determine each store's location, brand name, and store type, which we also collected in the manual data assembly efforts. Using this information, we built a multiple imputation model using the `mice` package for R (van Buuren & Groothuis-Oudshoorn, 2011). The predictor variables in the imputation included the store brand and type, as well as the average income and housing density in the nine closest block groups to the store location (based on population-weighted centroids).

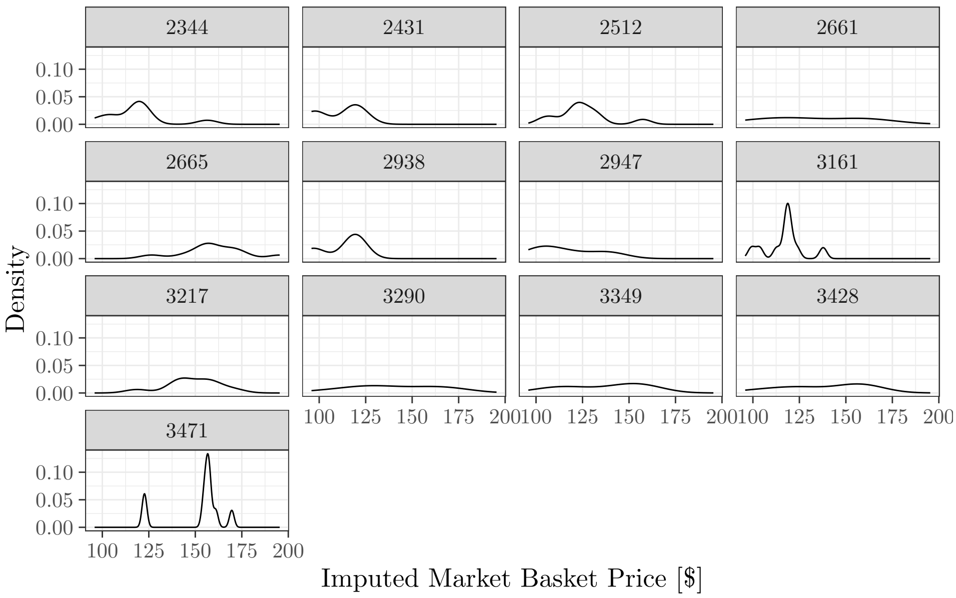


Figure 5: Imputed market price values for 15 random grocery stores.

Thirty iterations of the multiple imputation algorithm were run for each of ten independent imputations. Figure 5 shows the density of the ten imputed market basket prices for a randomly selected set of 15 stores. As the figure reveals, there is some general peaking in the predicted market price for most stores, but the imputation model still predicts a wide range of possible prices for most stores. When using the imputed data for analysis, we take the mean of the ten predictions for continuous values, and the mode for discrete values.

3.2.3. Travel Impedances

The second element of the utility equation in Equation 1 is the travel impedance between i and j. Many possibilities for representing this impedance exist, from basic euclidean distance to complex network paths. A primary purpose of the model we are developing in this research is to study comparative tradeoffs between infrastructure-focused and environment-focused improvements to the nutrition access of households. It is therefore essential that we use a travel impedance measure that can combine and compare the cost of traveling by multiple modes so that highway improvements and transit / active transport improvements can be compared in the same basic model.

Just as the log-sum of a destination choice model is a measure that sums the utility of multiple destination attributes and costs in a rigorous manner, the log-sum of a mode choice model combines the utilities of all available travel modes. In this study we assert the following mode choice utility equations:

$$\begin{aligned} V_{\text{auto},ij} &= -0.028(t_{\text{auto},ij}) \\ V_{\text{bus},ij} &= -4 - 0.028(t_{\text{bus},ij}) - 0.056(t_{\text{wait},ij}) - 0.056(t_{\text{access},ij}) \\ V_{\text{walk,ij}} &= -5 - 0.028(t_{\text{walk},ij}) - 1.116(d_{ij<1.5}) - 5.58(d_{ij>1.5}) \end{aligned}$$

where t is the in-vehicle travel time in minutes for each mode between i and j. The transit utility function additionally includes the wait time for transit as well as the time necessary to access the transit mode on both ends by walking. The walk utility includes a per-mile distance disutility that increases for distances greater than 1.5 miles. These equations and coefficients are adapted from a statewide mode choice model developed for UDOT research (Barnes, 2021).

The log-sum, or total weighted impedance by all modes is therefore

$$k_{ij} = \ln(e^{V_{\text{auto},ij}} + e^{V_{\text{bus},ij}} + e^{V_{\text{walk},ij}}) \tag{4}$$

In this implementation, i is the population-weighted centroid of a 2020 Census block group, and j is an individual grocery store. We measure the travel times from each i to each j using the `r5r` implementation of the R5 routing engine (Conway et al., 2017, 2018; Conway & Stewart, 2019; Pereira et al., 2021). This algorithm uses common data elements — OpenStreetMap roadway and active transport networks alongside General Transit Feed Specification (GTFS) transit service files — to simulate multiple realistic route options by all requested modes. We obtained OpenStreetMap networks and the Utah Transit Authority GTFS file valid for May 2023 and requested the minimum total travel time by each mode of auto, transit, and walking for a departure between 8 AM and 9 AM on May 10, 2023. The total allowable trip time by any mode was set to 120 minutes, and the walk distance was capped at 10 kilometers; if a particular i, j pair exceeded these parameters then the mode was presumed to not be available and contributes no utility to the log-sum.

3.2.4. Mobile Device Data

The final element of destination utility presented in Equation 1 are the coefficients, which are often estimated from household travel surveys in a travel demand context. It is unlikely, however, that typical household diaries would include enough trips to grocery stores and similar destinations to create a representative sample.

Emerging mobile device data, however, could reveal the typical home locations for people who are observed in the space of a particular store. Macfarlane et al. (2022) present a method for estimating destination choice models from such data, which we repeat in this study. We provided a set of geometric polygons for the grocery stores of interest to StreetLight Data, Inc., a commercial location-based services aggregator and reseller. StreetLight Data in turn provided data on the number of mobile devices observed in each polygon grouped by the inferred residence block group of those devices during summer 2022. We then created a simulated destination choice estimation dataset for each community resource by sampling 10,000 block group - grocery store “trips” from the StreetLight dataset. This created a “chosen” alternative; we then sampled ten additional stores from the same community at random (each simulated trip was paired with a different sampled store) to serve as the non-chosen alternatives. Random sampling of alternatives is a common practice that results in unbiased estimates, though the standard errors of the estimates might be larger than could be obtained through a more carefully designed sampling scheme (Train, 2009).

4. Results

This section presents results on the nutrition environment in each of the three communities of Utah County, West Salt Lake County, and San Juan County, along with destination choice model estimates and their application to creating accessibility maps of each community and the entire state of Utah.

4.1. Nutrition Environment

Though some basic descriptive statistics of the grocery store attributes were presented in Table 2, some additional exploration of these attributes is valuable to understand the nutrition environment in these three communities.

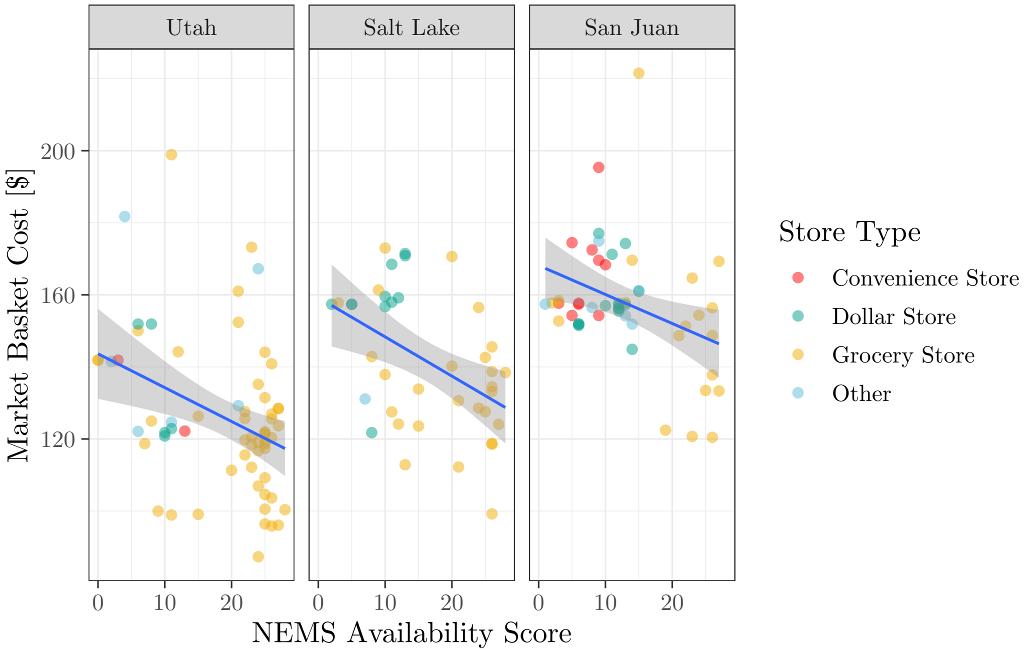


Figure 6: Relationship between NEMS availability score and market basket score in each study community. Utah county prices adjusted for 2021-2022 annual inflation.

Figure 6 presents the relationship between the recorded NEMS availability score and the USDA market basket cost at the stores by community and store type. In all three communities, the relationship is strongly negative, with stores that stock more varieties of goods also having overall lower prices for those goods. This is emphasized by the bottom-right quadrants of these plots (high availability, low-cost) being dominated by full-service grocery stores, which have more availability and lower prices than convenience stores or dollar stores, but require higher traffic and demand to make up for their lower profit margins. Average prices in Utah County are lower than prices in the other two communities across the availability spectrum; this is true even after adjusting for 9.4% annual inflation between March 2021 and March 2022 in food products (Bureau of Labor Statistics, 2023).

Figure 7 shows the relationship between the NEMS availability and cost scores. In this case the relationship is generally positive, with stores that stock more healthful options also placing these options at competitive prices. Conversely, stores with fewer options tend to place the options they do stock at a higher price point. This relationship between availability and cost of healthful goods is strongest in San Juan County, with convenience stores anchoring the low-availability, high-premium quadrant for healthy food. It should be noted that these convenience stores also exist in the Utah County community, but we explicitly included them in the San Juan data collection as they are the only food markets of any kind in multiple towns, with dozens of miles separating towns from each other.

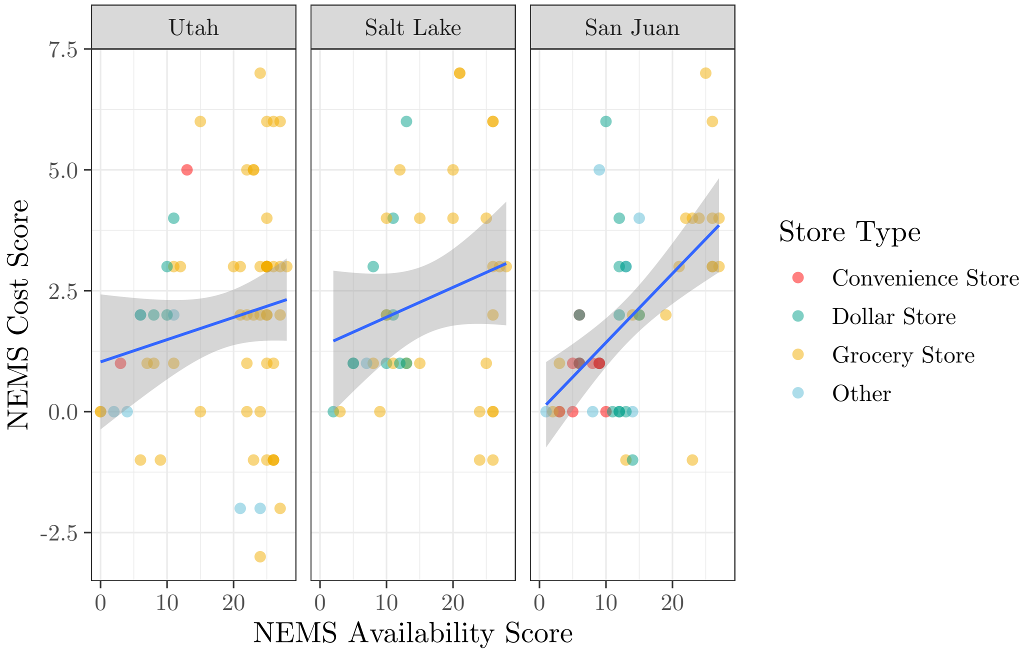


Figure 7: Relationship between NEMS availability score and cost score in each study community.

4.2. Destination Choice

Using the data collected and MNL destination choice model as described in Chapter 3, we estimate a series of model specifications in each community with the `mlogit` package for R (Croissant, 2020). To illustrate the role of different data elements on destination choice, we develop and estimate four different utility equations:

$$
\begin{aligned}
\text{Access} &= \beta_{MCLS}(k_{ij}) \\
\text{NEMS} &= \beta_{n-a}(\text{NEMS} - \text{Availability}) + \beta_{n-c}(NEMS - Cost) \\
\text{Attributes} &= \beta_{mkt}(\text{MarketBasket}) + {}_{type}(\text{Type}) \\
\text{All} &= \text{Access} + \text{NEMS} + \text{Attributes}
\end{aligned}
$$

The Access model includes only the mode choice logsum described in Equation 4. The NEMS model includes the NEMS cost and availability scores describing the goods the store offers, while the Attributes model contains information that might be more conventionally available to shoppers including the size, type, and average prices at the store. As the nutrition environment in each community contains different types of stores, the specific type coefficients differ by community. The All model contains all of the other three sets of estimated coefficients.

Table 3 presents the estimated coefficients in the Utah County community. In general, the utility coefficients

Table 3: Estimated Models of Utah County

	Access	NEMS	Attributes	All
Mode Choice Log-sum	8.090**			8.592**
	(95.354)			(87.875)
NEMS Availability Score		0.034**		-0.010**
		(23.136)		(-3.191)
NEMS Cost Score		0.029**		0.035**
		(6.344)		(5.075)
USDA Market Basket			-0.007**	-0.008**
			(-8.943)	(-8.756)
Registers			0.057**	0.062**
			(55.241)	(39.579)
Store Type: Dollar Store			1.955**	2.136**
			(57.226)	(41.639)
Store Type: Convenience Store			-1.637**	-1.769**
			(-7.256)	(-7.351)
Store Type: Other			-1.604**	-1.560**
			(-12.267)	(-11.076)
AIC	31,798.55	49,021.43	42,045.1	25,587.52
ρ_0^2	0.36	0.014	0.154	0.485

* $p < 0.05$, ** $p < 0.01$

t-statistics in parentheses

are statistically significant and in a direction that would be expected by informed hypothesis. The Access model has a positive coefficient on its mode choice log-sum term, which indicates that as the mode choice logsum between a block group and a store increases — indicating lower travel costs between Census block groups and the store, because travel times in Equation 4 have a negative relationship with utility — a higher proportion of mobile devices residing in that block group are observed to travel to that store. The NEMS model shows a positive relationship between both environment variables and utility, indicating that people are more likely to choose stores with higher availability of healthy goods and more advantagous prices for those goods, all else equal. The Attributes model suggests that
people are less willing to visit stores with higher prices, fewer registers, and convenience stores or other non-standard grocery stores with the exception of dollar stores, which they are *more* attracted to. Combining all of these variables in the All model retain the significance, direction, and basic scale of all previous estimates with the exception of the NEMS availability variable. In this case, it seems that the previous positive relationship may have been a result of correlation between NEMS availability and other variables such as cost or the number of registers. And when controlling for all other variables, the role of transportation access becomes somewhat more important than considering only distance alone, implying that people are willing to travel somewhat further for stores with attributes they value.

The overall fit of the four models in Table 3 is also revealing: the model with only NEMS variables against almost no predictive power over randomly selecting any store in the community (as revealed by the ρ_0^2 statistic). Though all sets of variables contribute to the overall fit, it is apparent that the bulk of model explanatory power is due to transportation proximity.

Table 4 presents the estimated coefficients in the west Salt Lake Valley community, and Table 5 presents the estimated coefficients in San Juan County. The same general story about coefficient direction and hypotheses applies in both of these communities, except in regards to the NEMS variables. In Salt Lake, the NEMS cost score appears negative when estimated alone but becomes positive when other variables are included. In San Juan, these variables are consistently positive. Additionally, the story of model fit is reversed: in both Salt Lake and San Juan, the attributes of the store explain more of the model fit than the transportation impedance term.

To better visualize how the preferences in the three communities differ from each other, Figure 8 plots the coefficient estimates from the All model in each community. The mode choice log-sum is strongly significant in all three communities, but it has its smallest value in San Juan County where people often must travel long distances to reach any stores. The highest mode choice log-sum value is in Salt Lake, but this explains a smaller proportion of the model outcomes than the lower value in Utah County; a possible hypothesis for this observation may include the higher density of stores in Salt Lake — attributes are more important when so many stores are close together — paired with the somewhat lower vehicle ownership in that community

Table 4: Estimated Models of West Salt Lake Valley

	Access	NEMS	Attributes	All
Mode Choice Log-sum	9.767**			11.924**
	(73.003)			(73.366)
NEMS Availability Score		0.135**		0.010**
		(73.114)		(2.627)
NEMS Cost Score		-0.039**		0.049**
		(-8.534)		(8.223)
USDA Market Basket			-0.009**	-0.006**
			(-12.442)	(-6.686)
Registers			0.106**	0.128**
			(71.242)	(51.661)
Store Type: Dollar Store			0.301**	0.530**
			(6.618)	(9.354)
Store Type: Other			-0.024	0.320*
			(-0.184)	(2.323)
AIC	43,025.99	42,037.02	39,775.88	31,636.5
ρ_0^2	0.134	0.154	0.2	0.364

* $p < 0.05$, ** $p < 0.01$

t-statistics in parentheses

Table 5: Estimated Models of San Juan County

	Access	NEMS	Attributes	All
Mode Choice Log-sum	0.732**			1.233**
	(83.411)			(74.178)
NEMS Availability Score		0.134**		0.049**
		(61.893)		(10.191)
NEMS Cost Score		0.249**		0.072**
		(38.689)		(8.690)
USDA Market Basket			-0.010**	-0.031**
			(-13.568)	(-23.484)
Registers			0.022**	0.052**
			(20.793)	(27.317)
Store Type: Dollar Store			-2.126**	-1.443**
			(-47.105)	(-20.779)
Store Type: Convenience Store			-3.720**	-1.376**
			(-31.352)	(-9.810)
Store Type: Other			-1.567**	-1.574**
			(-29.544)	(-22.209)
AIC	40,351.12	35,021.59	37,361.16	23,143.56
ρ_0^2	0.188	0.295	0.248	0.535

* $p < 0.05$, ** $p < 0.01$

t-statistics in parentheses

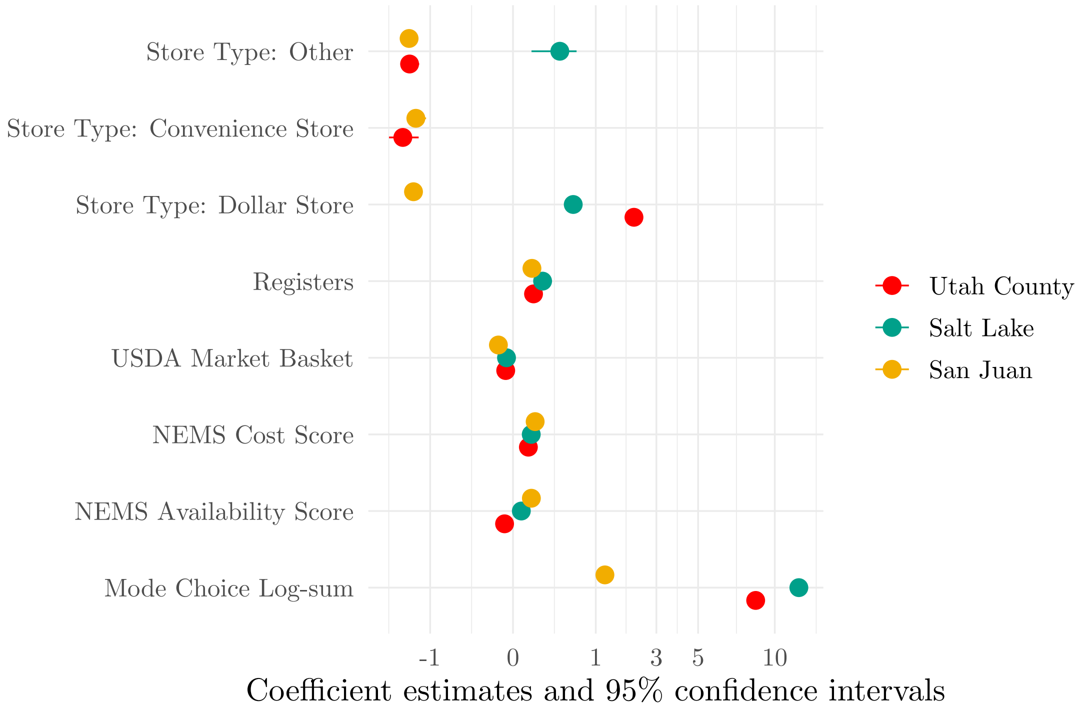


Figure 8: Comparison of county model coefficient estimates. Absolute square root transformation applied to improve visibility.

driving up the coefficient value. Most other estimates are somewhat consistent across counties, with the exception of the NEMS variables discussed previously and the role of dollar stores and other stores in each community.

4.3. Accessibility

With the models estimated in Section 4.2, we can evaluate the spatial access of each community. Figure 9 shows the value of the grocery store destination choice log-sum for block groups in Utah County. Unsurprisingly, the block groups in the core of the urban areas of the region have the highest access to grocery stores, because this is where the stores are located and also where the transportation access to multiple destinations is highest. This map also contains somewhat interesting implications for the equity of access. A perhaps unique feature of Utah County's demographic geography is that the wealthiest neighborhoods tend to be located on the mountain benches east of the main urban areas. This means that in Utah County, at least, the neighborhoods with the lowest access to grocery stores are actually some of the wealthiest neighborhoods with the lowest concentrations of ethnic minorities in the region.

Of course, much of this high access in the urban core of Utah County is achieved by cheap and available automobile transportation. We can consider what access looks like for those without cars by re-computing

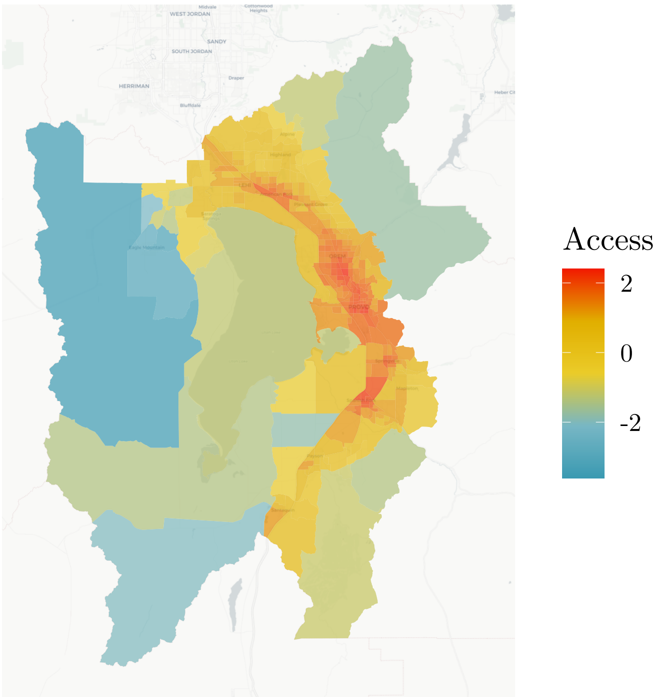
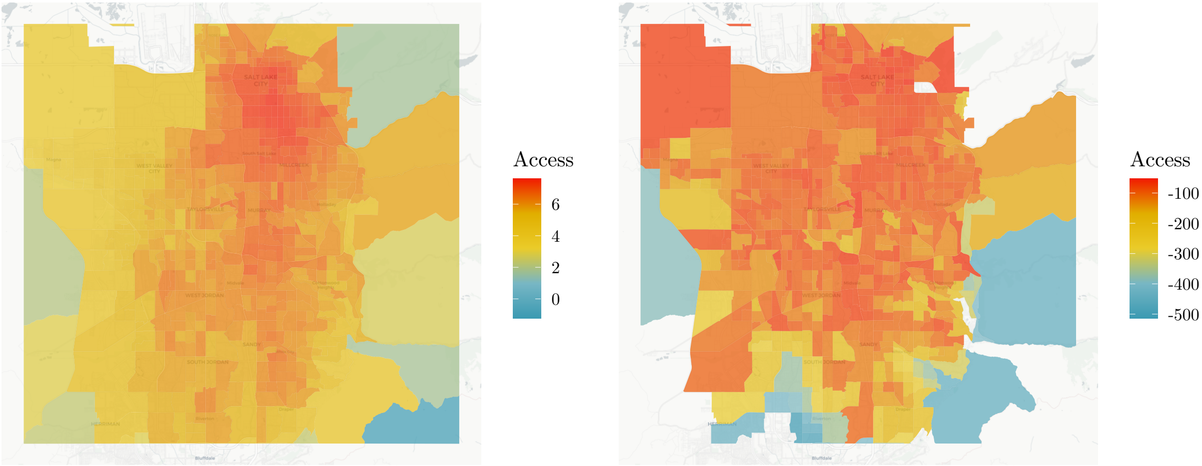


Figure 9: Modeled access to grocery stores in Utah County

the mode choice log-sum described in Section 3.2.3 between all block group / store pairs but eliding the automobile mode, and examining the resulting impact to destination choice utility. Figure 10 shows the results of this analysis: whereas the total access (with car included) is a smooth gradient across the valley, the access for individuals without vehicles is blocky and discontinuous, with neighborhoods of relatively good access immediately next to neighborhoods with bad or non-existent access. This may reflect the discontinuous nature of active transport and public transit facilities in the region, as well as the auto-dominated locations of many grocery stores. Note also that even for neighborhoods of relatively good non-vehicle access, the destination choice log-sum value is substantially lower than the logsum with vehicle access; the minimum value on with vehicles is just below 0, whereas the *maximum* log-sum without vehicles is around -100. Because the log-sum occurs on the same scale in both cases, this represents a serious additional cost for non-vehicle users.

5. Application

In this section, we develop a series of scenarios to which we apply the models estimated in Chapter 4. These scenarios are constructed to ascertain what may be the best strategy to improve nutrition access in a community. We first describe how each scenario was constructed, and then discuss the results together.



(a) With vehicles

(b) Without vehicles

Figure 10: Access to groceries in Salt Lake County with and without a vehicle.

The accessibility of each scenario was to be determined using the approximated utility coefficients of the All model estimated in Chapter 4,

$$U_{ij} = \beta_{MCLS}(k_{ij}) + \beta_{n-a}(\text{NEMS} - \text{Availability}) + \beta_{n-c}(NEMS - Cost) + \beta_{mkt}(\text{MarketBasket}) + \boldsymbol{\beta}_{type}(\text{Type}) \tag{5}$$

and the total access benefit is defined as the consumer surplus given in Equation 3. Note that this benefit is denominated in units of utility (Ben-Akiva & Lerman, 1985), and the coefficients in Equation 5 serve to convert between the units of the variable and utility. Specifically, the β_{mkt} coefficient represents how many dollars of grocery cost a person is willing to spend to increase their utility by one unit.

In actuality, the utility formula in Equation 5 is a relative utility added by an unknown constant, $U_{ij} = f(, X_{ij}) + C$, but this C term is included in all the alternatives and therefore cancels out (Train, 2009) in estimation. This means we cannot asses the *absolute* value of utility, but we can assess the *relative* monetary benefit of the difference between two scenarios as

$$\text{Benefit} = \sum_i \left(-\frac{\omega_i}{\beta_{mkt}} (CS_i^1 - CS_i^1) \right)$$

where a weight ω accounts for the population in each origin zone i and the β_{mkt} converts the difference in utility into a dollar amount.

5.1. Scenario Descriptions

There are three general strategies we develop scenarios around:

1. Erect a new grocery store in the community, in a place where one does not already exist.

2. Improve an existing convenience store or dollar store so that it has the attributes of a full-service grocery store.
3. Improve the transit and non-motorized access to stores in a region.

We implement all three strategies in scenarios on the west Salt Lake valley community. We also implement strategy 1 (a new store) in the San Juan and Utah County communities for comparison.

5.1.1. Erect a new store

This strategy assumes that the nutrition environment would benefit from a new store located in a place that presently has low grocery store access. To examine the potential for this strategy to improve access to nutrition in each community, we calculate the change in destination choice log-sum when a new store is added to the region in a location where access is currently poor. The new store is a full-service grocery store with a number of registers equal to the mean of other grocery stores in the community, and NEMS availability score, NEMS cost score, and market basket cost equivalent to the 75^{th} percentile for the community. Thus the store is expected to be better-than-average quality as perceived by the residents of the community. The location for this new store is at 4100 S and 2700 W in West Valley City.

5.1.2. Improve an existing store

This strategy assumes that existing stores are in locations that the community values and can access, but that those stores may not have high availability of quality goods. To examine the potential for this strategy to improve access to nutrition, we improve the attributes of an existing dollar store in the community so that it has the size, prices, and availability of goods as a full-service grocery store. As above, we create a full-service grocery store with a number of registers equal to the mean of other grocery stores in the community, and NEMS availability score, NEMS cost score, and market basket cost equivalent to the 75^{th} percentile for the community. Thus the store is expected to be better-than-average quality as perceived by the residents of the community; the difference from the previous scenario is that the improved store takes the place of an existing convenience store or dollar store.

The improved stores are at the following locations in each community:

- An ethnic store near 2700 W 3500 S in West Valley City (Salt Lake)
- A small grocery store in Santaquin (Utah County)
- A dollar store in Blanding (San Juan County)

5.1.3. *Improve transit and non-motorized transport*

This strategy assumes that people cannot easily travel to existing stores because they cannot or do not drive for a variety of reasons, and that the public and and active transport networks provide an insufficient level of service. To examine the potential for this strategy to improve access to nutrition, we improve the travel time costs in the Salt Lake community for non-motorized and public transportation in the region and calculate the change in destination choice log-sum.

For active transportation, the lack of pedestrian facilities across and alongside roads both in reality and in the OpenStreetMap dataset may substantially increase measured walk distances and times. In this scenario, we replace the times measured from OpenStreetMap using R5 with an idealized Euclidean distance function,

$$t_{\text{walk}} = \frac{\sqrt{2} * d'_{ij}}{v_{\text{walk}}} \tag{6}$$

where d'_{ij} is the Euclidean (straight-line) distance between i and j and v_{ij} is an average walking speed equivalent to 3.5 feet per second (Fitzpatrick et al., 2006). The distance is multiplied by the square root of 2 to reflect the Manhattan distance (along a gridded street system). We retain the cap on walking distance at 10 kilometers. Though this distance may radically understate the real walking distance, we are trying to create an idealized scenario of effectively frictionless active transport. For public transit, we assume that the frequency of service is such that all transfer and initial wait times are at most 5 minutes, and that no person must walk more than 10 minutes to access their first public transport service.

Travel times are improved in this way for all block group — store pairs in the west Salt Lake Valley community.

5.2. *Scenario Results*

Using the methodology described above, we recalculated the destination choice log-sum value for each block group under each scenario, and compared the change in accessibility resulting from the improvement.

Figure 11 shows the geographic distribution of benefits associated with locating a new store at a site in the Salt Lake community. The benefits are largest immediately next to the new store, where they exceed 1 for each household each time the household makes a trip to a grocery store.

Figure 12 shows the results of the scenario improving an existing store in the Salt Lake community. Compared to the results of the new store scenario, the scale of the benefits are not as substantial (a maximum per-household-trip benefit of less than \$1), and seem to not cover quite as large a geographic region. Figure 13 shows the results of improving a store in Utah and San Juan Counties. As in Salt Lake, the benefits are most strongly concentrated in the immediate vicinity of the improved store. One interesting observation

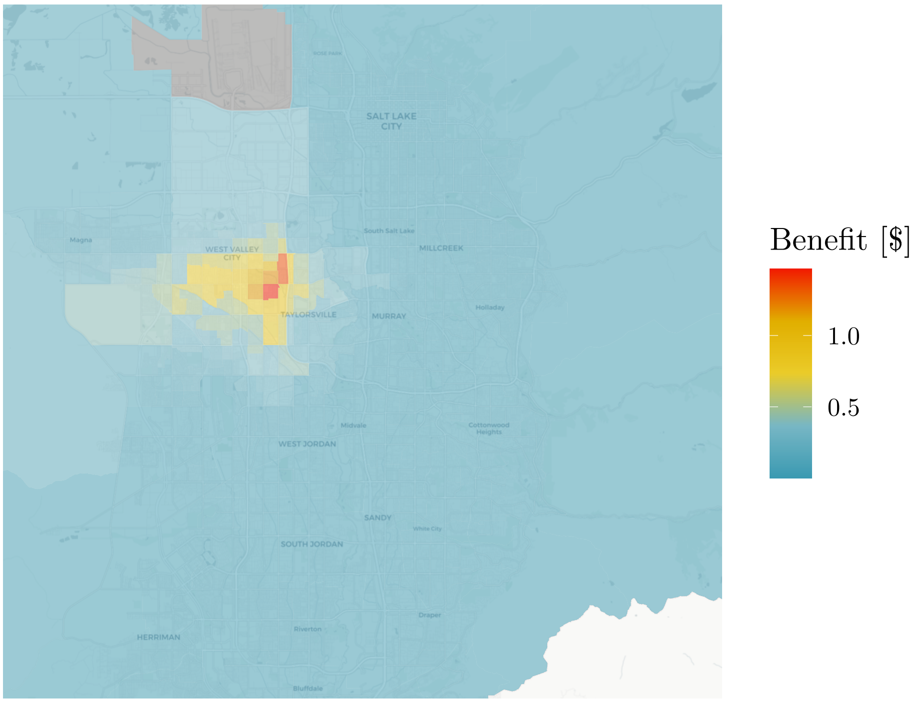


Figure 11: Estimated per-household benefits of adding new full-service store in west Salt Lake Valley

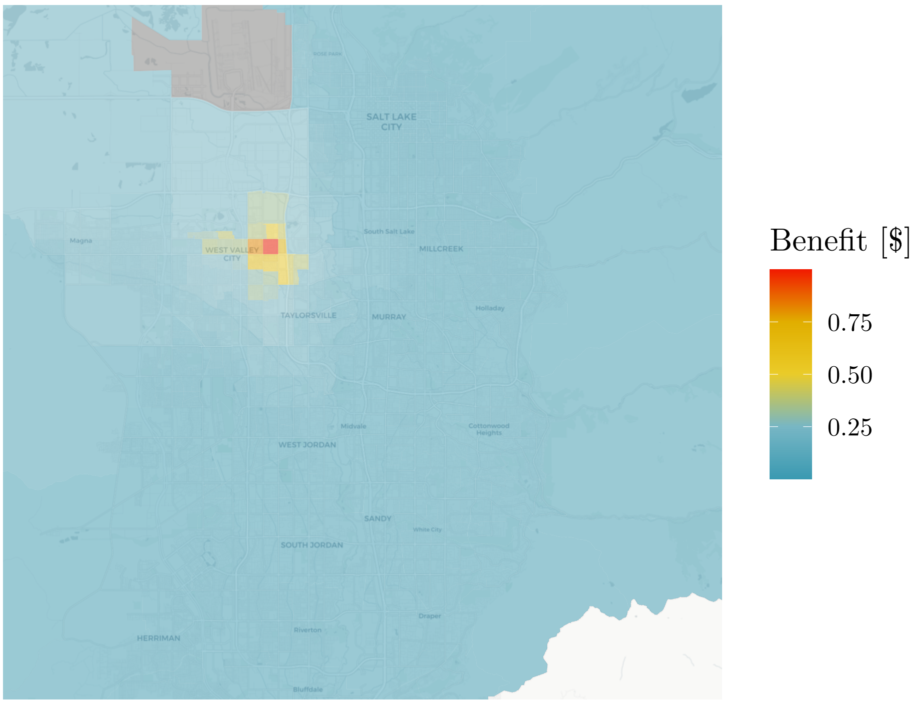
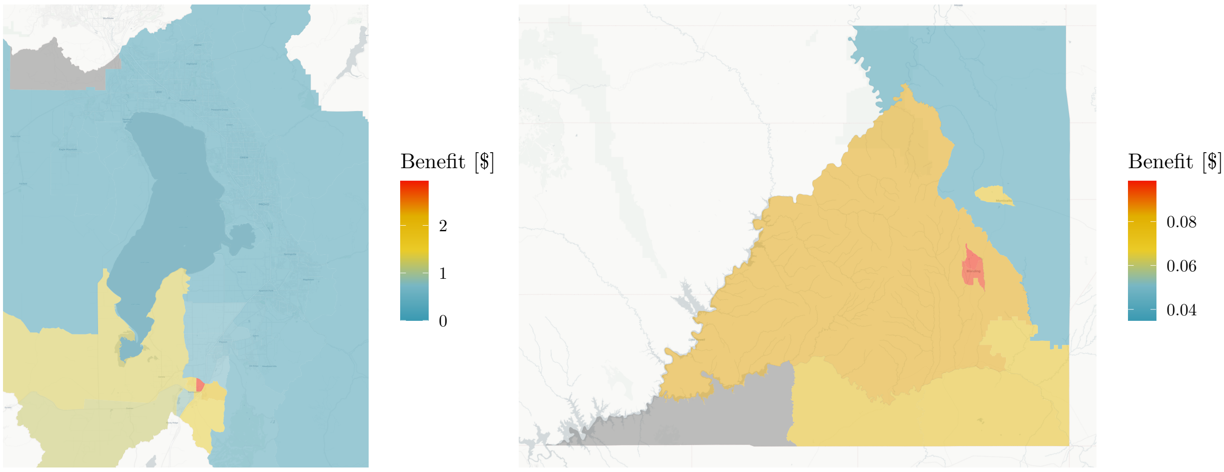


Figure 12: Estimated per-household benefits of improving an existing store in west Salt Lake Valley

— especially in Utah County — is that the improvements are felt more strongly in the block groups near the improved store that have lower availability of other options. The block group in Utah County directly containing the improvement sees a per-household-trip benefit well over $2, considerably more than the maximum benefit in Salt Lake. This is intuitive, as the improvement of a store matters less if the stores close to you are already sufficient.



(a) Utah County (in Santaquin)

(b) San Juan County (in Blanding)

Figure 13: Estimated per-household benefits of improving an existing store in Utah and San Juan Counties.

The results of the third scenario, improving the access of non-motorized and public transit access to stores, are shown in Figure 14. This benefit is spread over a larger area, and is concentrated on the 35 MAX bus rapid transit corridor where the improvement in walk access time to transit couples with high frequency transit service to large grocery stores on the corridor. The per-household-trip benefit is very small however, with a maximum benefit on the order of $0.25.

Although comparing the geographic distribution of benefits is helpful, the aggregate benefit is more likely to guide policy. Additionally, the aggregate benefits can be weighted in different ways to understand the effects of the various policies on different populations. Table 6 presents the aggregate benefit from each of the three scenarios (and the result of the second scenario in all three communities). The Households column multiplies the difference in destination choice log-sum at each block group by the number of households in that block group, while the non-white and low-income columns weight the difference by the share of non-white individuals and low-income households respectively. All demographic data comes from the American Community Survey 5-year aggregations.

These alternate weighting schemes help to illustrate the potential equity of the benefit distribution should each scenario be pursued. The new store scenario in the Salt Lake community, for example, has a total

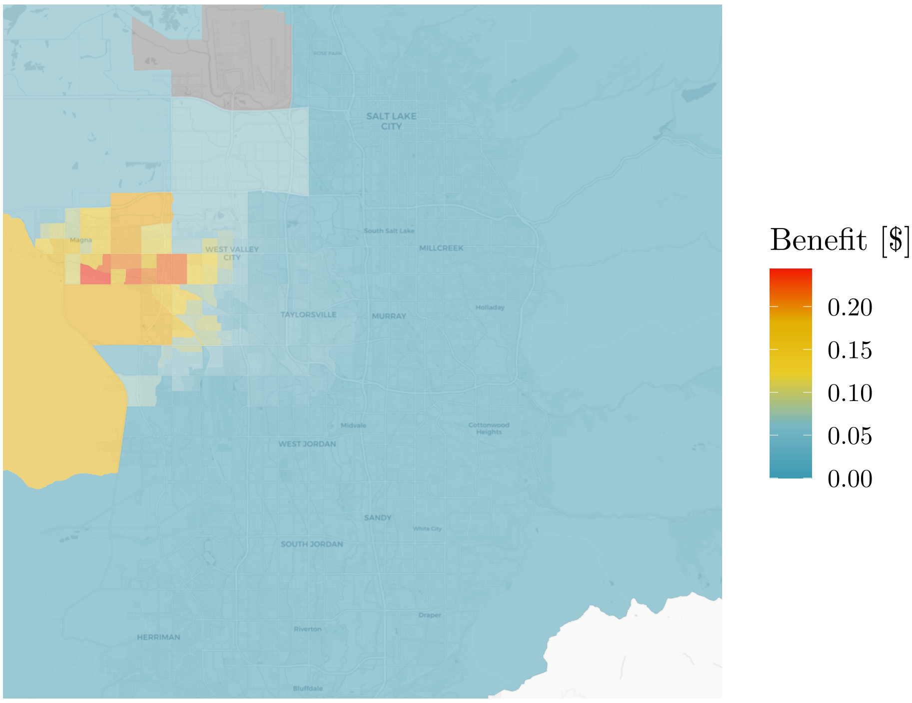


Figure 14: Estimated per-household benefits of improving non-motorized and public transport access to groceries in Salt Lake Valley.

Table 6: Scenario Benefits

	Weighted by		
Scenario	Households	Non-white	Low-Income
New Store	$5,538,988	$2,449,404	$961,684
Improved Store			
Salt Lake Valley	$2,849,176	$1,364,404	$569,364
Utah County	$1,516,458	$245,638	$233,778
San Juan County	$52,152.69	$26,914.35	$18,280.71
Improved Transport	$872,015	$393,554	$120,078

benefit of approximately $5.5 million. Of this amount, somewhat less than half the benefits go to non-white individuals and less than one-fifth to low-income households. These ratios are more or less the same for the store improvement scenario and the improved transport scenario in the Salt Lake Valley. The Utah County store improvement, on the other hand, has a somewhat higher proportion of benefits going to low-income households relative to non-white households. This is a reflection of the lower minority population in southern Utah County vis a vis west Salt Lake valley, but is nonetheless a metric that program evaluators might pay attention to.

Overall, the improved store brings more than twice the benefits of improving non-automobile transportation, and the new store more than five times the benefits. Understanding the costs of these various alternatives is outside the scope of this research, but the level of infrastructure investment required to increase transportation level of service to that constructed in the simulation is likely an order of magnitude higher than the cost of a single new grocery store. It should also be acknowledged that improving non-automobile infrastructure and services would have benefits beyond just grocery store trips that we do not attempt to enumerate here. It is also not clear whether the level of improvement simulated in the second scenario could be accomplished within the envelope of the existing store; it may be that such improvements would meet or exceed the cost of building a new store on a new site, along with stocking, staffing, and operating the store.

6. Conclusions and Recommendations

As outlined in Chapter 2, transportation agencies seeking to improve the health and quality of life for residents must consider not simply their mobility needs, but the safety of the transportation system, the effects of the system on disadvantaged populations, and the ability of residents to access quality community resources. Access to nutrition is a critical topic that has been a frequent focus of academic literature in public health, community planning, and engineering, but the varying and incomplete quantitative definitions of access have perhaps limited efforts at developing solutions.

In this research, we explored an emerging technique to measure access to nutrition in multiple communities in Utah that combines transport access with the quality of markets, weighted against each other. We then used this model to examine an array of targeted policies that would potentially improve access to nutrition to a specific community.

This concluding section presents both a series of limitations to this research with associated opportunities for future efforts, followed by specific recommendations to the Utah Department of Transportation as it seeks to pursue its mission to "Enhance the Quality of Life through Transportation."

6.1. Limitations

A number of assumptions made in Chapter 3 lead to limitations that other reasonable researchers might pursue differently, and thereby obtain marginally different outcomes.

In selecting a survey instrument with which to collect the store attribute data, we selected an existing and validated instrument from the nutrition environment literature. The NEMS-S focus on low-calorie and low-fat alternatives may be somewhat outdated in view of modern nutritional guidelines. For example, the NEMS-S does not track the availability and price of poultry, as "lean" poultry is not a goods category in the way that ground beef comes with multiple fat contents. Thus a major source of protein in typical American diets (FNS, 2021) was not traced across stores in each community. On a more basic level, the NEMS-S attempts to measure a store's stocking of goods that researchers believe are beneficial, and does not measure either what people wish to buy, or what they are actually buying at a store. Future research might attempt to survey shoppers on what they actually purchased at each store — or collect receipts of their purchases — though this would substantially raise the difficulty of collecting data.

Most households do not obtain all their groceries at a single store, though this research of necessity assumed that a simulated person chose exactly one store from stores available to them. Similarly, the location-based services data provided by StreetLight and used to identify which stores people traveled to only reveal whether a device was identified inside a geographic polygon, and not what they were actually doing in that polygon. This research had no way of distinguishing, for example, whether an individual device observed at a dollar store or a super market (e.g. Wal-Mart) was there to purchase groceries or some other household goods that might not be offered at more traditional food markets.

A number of simplifying assumptions concern the socioeconomic and spatio-temporal detail supplied to the choice models and accessibility calculators. The StreetLight data do not contain any demographic information on the individuals making trips, beyond the inferences made possible by the residence block group. This makes it difficult to estimate whether lower income households are more or less sensitive to travel distances or prices. Additionally, the research assumed that every trip was from the population-weighted block group centroid, which may vary substantially from the actual distance traveled, especially in large block groups. The methodology also used travel times calculated in the AM peak hour; though this time maximizes the availability of transit options, it is not a typical peak time for grocery shopping. All of these limitations could potentially be relaxed by using a synthetic population with detailed socioeconomic data and parcel-level locations determined by an activity-based model, as proposed by (Dong et al., 2006). In this exercise, which we leave to future research, the grocery maintenance trips could be explicitly modeled, with synthetic individuals of unique characteristics choosing destinations that are available on the course of their other daily activities, using their chosen travel modes.

Finally, the scenarios presented in Chapter 5 are designed to illustrate potential applications of this accessibility methodology, with a comparative analysis of strategies to improve access to nutrition. Selecting different sites, attribute levels, or transport policies might substantially change the scale or rank-ordering of the estimated benefits. A comprehensive search for the location that would maximize benefits would be an interesting exercise, which we also leave to future research.

6.2. Recommendations

This research results in two recommendations to the Utah Department of Transportation and its partner agencies.

First, the research has underlined that communities in Utah have large differences in their ability to access quality nutrition, and that many communities — especially in rural Utah — travel long distances to obtain quality goods. At some level, this is evidence that UDOT has succeeded in its mobility-focused goals of connecting communities with fluid and reliable transportation infrastructure. On a less encouraging note, this observation also underscores the disparity in access defined by the availability of automobiles with which to use this infrastructure. For Utah households with limited vehicle availability, access to nutrition is considerably constricted. The research also revealed, however, that simply improving transit access and active transportation paths might not be as beneficial as either improving the quality of goods available in existing stores, or encouraging new store locations. The role of UDOT in pursuing such policies needs to be investigated. One potential strategy might be to alter access management, highway prioritization, and other policies in a way that encourages more stores with high-quality offerings in more communities. This would alter the present pattern of locating large-scale stores near arterial roadways, which maximizes the area over which a single store can attract customers at the expense of neighborhood-level access.

At a methodological level, understanding the reasons why people participate in activities, and their priorities in doing so, is a necessary prerequisite to developing policies that improve the quality of life. This is a transition from goals that simply seek to minimize travel delay. To better facilitate and equip staff and researchers considering these kinds of questions, UDOT should encourage and develop activity-based approaches to travel forecasting. These approaches will enable the more realistic analysis described in Section 6.1, and provide better information for a host of policies aimed at improving Utah's communities and their quality of life.

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Graphics in the document are produced with multiple R packages (Arel-Bundock, 2022; Dunnington, 2023; Ram & Wickham, 2018; Wickham, 2016).

Author Contribution Statement

Gregory S. Macfarlane: Conceptualization, Methodology, Software, Resources, Writing - original draft, Visualization, Supervision **Emma Stucki:** Software, Investigation, Data curation, Writing - original draft **Myrranda Salmon:** Investigation, Data curation **Alisha H. Redelfs:** Methodology, Resources, Writing - review & editing **Lori Spruance:** Methodology, Resources, Writing - review & editing

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