MOUNTAIN-PLAINS CONSORTIUM

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INVESTIGATING TRAVEL BEHAVIOR AND AIR QUALITY IN NORTHERN UTAH

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16. Abstract

U.S. residents across many regions continue to face episodes of poor air quality due in part to pollution and emissions from the transportation sector. Strategies to encourage travel behavior changes and reduced driving during such events may or may not be effective. To illuminate how area-wide air pollution affects traveler behaviors and to better understand the potential for travel behavior change strategies, we developed a multi-phase longitudinal (travel) survey data collection effort in Cache County, Utah, involving an initial survey about personal and household characteristics, a series of three two-day travel diary surveys during winter 2019, and a final survey about perceptions. We then analyzed the resulting data. First, we studied how measured (or perceived) poor air quality affected individuals' daily travel amounts, finding little change in trip frequencies or total travel times. We did find that respondents were mostly aware of when air pollution levels were elevated. Second, we studied the degree to which people attributed the responsibility for air pollution to themselves or others, finding three groups of people differentiated by various travel, perceptual, and personal characteristics. People assuming more responsibility reported more travel behavior changes. Third, we analyzed 20 different activity and travel outcomes (taken from the travel diary surveys) for associations with air quality, while controlling for personal/household characteristics and neighborhood type. We found some "altruistic" travel behavior changes in response to air pollution, as well as differences for urban vs. suburban/rural residents. More research on these topics is needed in different urban areas.

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Investigating Travel Behavior and Air Quality in Northern Utah

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ABSTRACT

U.S. residents across many regions continue to face episodes of poor air quality due in part to pollution and emissions from the transportation sector. Strategies to encourage travel behavior changes and reduced driving during such events may or may not be effective. To illuminate how area-wide air pollution affects traveler behaviors and to better understand the potential for travel behavior change strategies, we developed a multi-phase longitudinal (travel) survey data collection effort in Cache County, Utah, involving an initial survey about personal and household characteristics, a series of three two-day travel diary surveys during winter 2019, and a final survey about perceptions. We then analyzed the resulting data. First, we studied how measured (or perceived) poor air quality affected individuals' daily travel amounts, finding little change in trip frequencies or total travel times. We did find that respondents were mostly aware of when air pollution levels were elevated. Second, we studied the degree to which people attributed the responsibility for air pollution to themselves or others, finding three groups of people differentiated by various travel, perceptual, and personal characteristics. People assuming more responsibility reported more travel behavior changes. Third, we analyzed 20 different activity and travel outcomes (taken from the travel diary surveys) for associations with air quality, while controlling for personal/household characteristics and neighborhood type. We found some "altruistic" travel behavior changes in response to air pollution, as well as differences for urban vs. suburban/rural residents. More research on these topics is needed in different urban areas.

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EXECUTIVE SUMMARY

Many regions in the United States (including parts of Utah and the Intermountain West) experience episodes of poor air quality, whether due to temperature inversions in bowl-shaped urban valleys, the formation of ground-level ozone in sunny locations, or from wildfire smoke. The large and growing population residing in such areas suggests episodic area-wide air pollution is an important public health issue. Because the transportation sector—especially gas-powered automobile use—contributes a large portion of air pollutants and precursor emissions, current (mostly voluntary) programs encourage travel behavior change through reduced driving, shifting to public transit and active transportation modes, teleworking, and other strategies. Unfortunately, there is little evidence about how effective such strategies may be. Research in this area is challenged by a lack of person-level data on detailed travel behaviors and travel decisions during periods with good and with poor air quality, along with necessary information about people's attitudes, values, norms, perceptions, and opinions about transportation and air quality. Therefore, this study had four primary objectives:

1. Understand how measured (or perceived) poor air quality affects individuals' daily travel amounts.
2. Identify what factors (personal characteristics, travel behaviors, and measured air quality) affect perceptions of air quality.
3. Understand patterns of attribution of responsibility of air pollution, the relationship with stated travel behavior changes, and the impact of awareness of consequences, risk perception, self-efficacy, and socio-demographics.
4. Determine whether and how measured (or perceived) area-wide air pollution affects individuals' daily activities and travel behaviors, as well as how those associations differ by neighborhood type.

To illuminate how area-wide air pollution affects traveler behaviors and better understand the potential for travel behavior change strategies, we developed a multi-phase longitudinal (travel) survey data collection effort involving an initial survey about personal and household characteristics, a series of travel diary surveys during winter 2019, and a final survey about perceptions. First, we sampled U.S. Census block groups in Cache County, Utah, and recruited adults within households to participate. After completing an initial survey, participants completed a series of three two-day travel diary surveys, intended to capture a range of air pollution levels during January and February (months when the study area tends to be subject to temperature inversions that trap and concentrate air pollution in the cold mountain valley). The study was completed with a final survey asking for people's opinions about transportation and air pollution. After processing, cleaning, and geocoding the data, we obtained multi-day information for around 350 adults in roughly 200 households.

First, we studied how measured (or perceived) poor air quality affected individuals' daily travel amounts. Our panel data regression analyses found no changes in the number of trips or total travel time that participants reported on days with better or worse air quality, suggesting that individual-level travel behaviors in our study region may have been fairly stable regardless of air pollution levels. We also studied the factors (personal characteristics, travel behaviors, and measured air quality) affecting perceptions of air quality on each travel diary survey day. Perceived air quality was positively correlated with measured air pollution and seemed to be affected by awareness of air quality impacts. This means that people (in general) are aware of air pollution in this region.

Second, we sought to understand patterns of attribution of responsibility for air pollution, including relationships with stated travel behavior changes and the impacts of psychological variables and socio-demographics. Using latent class analysis, we found that there are three distinct classes of individuals based on their attribution of responsibility: (i) High internal–high external attributors, (ii) moderate internal–moderate external attributors, and (iii) low internal–low external attributors. These classes were differentiated on their views of increasing/decreasing automobile usage vs. other mode usage and how such choices impact air quality. Several socio-demographic factors (age, gender, education) and psychological constructs (self-efficacy, awareness of consequences) were found to be significant predictors of the class membership. People who attributed greater responsibility to themselves and others for reducing air pollution reported a greater likelihood of making travel behavior changes in response to poor air quality.

Third, we conducted more detailed modeling about whether and how measured (or perceived) area-wide air pollution affected a range of daily activity and travel behaviors, as well as how those associations differed by neighborhood type (urban vs. suburban/rural). Our models found some measurable changes in activity and travel patterns on days with poor air quality. In urban areas, people engaged in more mandatory (work/school) activities, whereas there was no discernible change in suburban/rural areas. The total travel time for urban residents increased, driven by increases in trip-making and travel time by public modes (bus) and increases in travel time by private modes (car). On the other hand, suburban/rural residents traveled shorter total distances (mostly through lower vehicle miles traveled), and there was a notable uptick in the probability of being an active mode user (walk/bike). The results were somewhat encouraging, finding more evidence of altruistic than risk-averse travel behavioral responses to episodes of area-wide air pollution; although, more research is needed.

Overall, we found some (albeit modest) evidence of travel behavior changes in response to elevated area-wide air pollution among residents of Cache County, Utah, in winter 2019. It appears that "soft" (voluntary) policies designed to spread awareness of the harms of air pollution from automobile emissions and encourage travel behavior changes to reduce driving may have small but beneficial effects. However, their impacts appear to be fairly small, and more rigorous (and semi-mandatory) policy strategies may be necessary in order to have a more substantial effect on reducing driving (and resulting air pollution) during such times. People do seem to be aware of elevated air pollution levels, and more than half of our respondents seemed willing to at least consider making more sustainable travel behavior changes. A major challenge appears to be reducing barriers and providing options for people to more easily change their travel patterns, including strategies that will increase public transit and active transportation options and build communities in such a way as to reduce automobile dependence.

1. INTRODUCTION

Many parts of Utah, particularly areas along the Wasatch Front and in Cache Valley, experience episodes of poor air quality and are classified as nonattainment areas for some criteria pollutants by the Environmental Protection Agency (EPA). In the wintertime, temperature inversions trap pollutants against mountain ranges or within mountain valleys, leading to buildups of fine particulate matter (PM2.5) that exceed the National Ambient Air Quality Standards (NAAQS). For instance, an episode in January 2004 resulted in PM2.5 concentrations among the highest ever recorded in the United States (Malek et al., 2006; Silva et al., 2007). In the summertime, warm temperatures and sunlight combine with other air pollutants to yield high concentrations of ground level ozone. Long-term exposure to particulate matter and ozone has adverse public health impacts, including increased morbidity and mortality from negative effects to respiratory and cardiovascular systems. The large and growing population residing in nonattainment areas of Utah suggests that these poor air quality episodes are a public health issue.

Transportation is a major mobile source of emissions like nitrogen oxides (NOx) and volatile organic compounds (VOC) that contribute to the formation of $PM_{2.5}$ and ground level ozone. Therefore, a potential technique for mitigating the adverse impact of poor air quality episodes is to reduce levels of driving before and during such events. Current travel behavior change strategies, such as the TravelWise program (UDOT, 2017) organized by the Utah Department of Transportation (UDOT), provides information about options for reduced driving—such as riding public transit, walking, or bicycling, and teleworking—and facilitates carpool matching. These voluntary programs encourage travelers to change their behavior but, based on two prior studies, the effectiveness of their strategies appears to be limited (Teague et al., 2015; Tribby et al., 2013). However, these two studies used aggregate data on traffic volumes and air pollution concentrations, which are unable to examine effects at a disaggregated personal level, where strategies are targeted. In order to design more effective interventions and techniques for improving air quality, more research focused on individual motivators, constraints, and behaviors is needed to examine the reasons behind the transportation impacts (or lack thereof) of such strategies.

Travel demand management (TDM) strategies, which focus on the demand side of transportation, may be a useful source of techniques for reducing driving (Meyer, 2016). Encouragement or "carrot" (soft) strategies that provide information about or tools to facilitate walking, bicycling, riding public transit, carpooling, flextime, and telecommuting may be particularly applicable to Utah's poor air quality events. Initiatives that provide a financial incentive or individualized marketing could also be appropriate. On the other hand, "stick-based" (hard) strategies, such as variable road pricing or prohibiting car use on certain days, appear to be most effective at reducing driving but are likely to be politically or practically infeasible (Gärling & Schuitema, 2007). Other longer-term TDM strategies that involve constructing non-auto infrastructure or managing land uses are not relevant for this study.

Health psychology offers alternative perspectives for designing travel behavior change strategies. For example, the normative decision-making model (Klöckner, & Matthies, 2004) and the transtheoretical model (Prochaska & Velicer, 1997) describe behavior change as a process, moving from consideration to preparation to action. Many aspects may be necessary to generate a behavior change—not simply information to create an awareness of the need and potential actions, but also perceived ability and control, social and institutional support, mitigation of behavioral constraints, and mental or monetary rewards. These and other frameworks may be useful guides when creating effective strategies for modifying travel behaviors during adverse air quality episodes in Northern Utah.

There are two major challenges to disaggregate-level research illuminating how area-wide air pollution affects traveler behaviors and better understanding the potential for TDM or other travel behavior change strategies to succeed. First, there is a relative lack of person-level data on detailed travel behaviors and travel decision-making over time (longitudinally), specifically during periods with good and periods with poor air quality. Most travel behavior studies are cross-sectional (studying multiple people at one time point), and even modern regional or statewide household travel surveys may only capture travel behaviors over a period of a few days to a week. Such durations are usually not long enough to observe how individuals' travel behaviors change during episodes of area-wide poor air quality, compared to days with low levels of air pollution. An analysis of data collected from different people recorded at different times (with differing air quality levels) risks confusing personal differences with air pollution effects. What is needed are panel datasets that track the same people's travel behaviors over time, capturing periods with differing levels of regional air quality, in order to be more confident that air pollution is causing measured behavior changes.

Second, there is a need for travel behavior data that are linked to rich information on attitudes, values, norms, perceptions, and opinions related to transportation and air quality. Knowing what people think about transportation and its connections with air pollution is critical for helping to understand how receptive people would be to various hard or soft travel behavior change strategies or policies. Even better, having this social-psychological data connected to actual travel behaviors (for the same people) can provide stronger linkages between perceptions and behavior, thus helping to understand who (what kinds of people) might be more or less willing to change their travel behavior to improve air quality. As an example, we expect people's perceptions of air pollution to impact their travel choices at least as much as any objective sensor measurement of air pollution levels.

1.1 Research Objectives

There are four primary objectives of this research:

1. Understand how measured (or perceived) poor air quality affect individuals' daily travel amounts.
2. Identify what factors (personal characteristics, travel behaviors, and measured air quality) affect perceptions of air quality.
3. Understand patterns of attribution of responsibility of air pollution, the relationship with stated travel behavior changes, and the impact of awareness of consequences, risk perception, self-efficacy, and socio-demographics.
4. Determine whether and how measured (or perceived) area-wide air pollution affects individuals' daily activity and travel behaviors, as well as how those associations differ by neighborhood type.

1.2 Research Approach and Overview

To achieve these objectives, we developed a multifaceted research approach involving a multi-phase longitudinal (travel) survey data collection effort, followed by data analysis of travel behaviors and perceptions. The study procedures and results are summarized in the following report overview and detailed in the subsequent chapters of this research report.

- **Chapter 2, "Data collection,"** describes the study area, data collection approach (including details about participant recruitment and the repeated surveying effort), data processing methods, descriptive statistics, and data availability.
- **Chapter 3, "Impacts of episodic poor air quality on trip-making behavior and air quality perceptions from a longitudinal travel diary study in northern Utah,"** considers the first two study objectives. It reports on a preliminary analysis of travel behavior, finding little change in trip frequencies or total travel times on days with worse air quality. It also studies factors affecting perceived air quality, finding that respondents were mostly aware when air pollution levels were elevated.

- **Chapter 4, "Segmentation analysis of attribution of responsibility over air pollution and its impacts on travel behavioral responses,"** tackles the third study objective. It studies the degree to which people attribute the responsibility for air pollution to themselves or others, finding three groups of people differentiated by various travel, perceptual, and personal characteristics. Also, it finds that different attributors report being more or less likely to change their travel behavior in response to air pollution.
- **Chapter 5, "Influences of area-wide air quality on the activity and travel behavior of urban, suburban, and rural residents of northern Utah,"** addresses the fourth study objective. It analyzes 20 different activity and travel outcomes (taken from travel diary surveys) for associations with air quality, while controlling for personal/household characteristics and neighborhood type. It finds some "altruistic" travel behavior changes in response to air pollution, as well as differences for urban vs. suburban/rural residents.
- **Chapter 6, "Conclusion,"** summarizes the key findings of this research study, and highlights recommendations and opportunities for future work.

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2. DATA COLLECTION

Recall our study's overarching objectives: to illuminate how area-wide air pollution affects traveler behaviors and better understand the potential for travel behavior change strategies. In order to achieve these objectives, we developed a multi-phase longitudinal (travel) survey data collection effort involving an initial survey about personal and household characteristics, a series of travel diary surveys during winter 2019, and a final survey about perceptions. In this chapter, we describe the design of the surveys, how participants were recruited, how the surveys were deployed, how the survey data were assembled and cleaned, and where others can access the data we collected.

This study was reviewed and approved by the Utah State University Institutional Review Board, protocol #9246.

2.1 Study Area

Our study area is Cache Valley, a region in northern Utah characterized by its distinctive geography, situated at a high elevation between two mountain ranges. This unique topography creates ideal circumstances for wintertime temperature inversions, leading to a significant accumulation of particulate matter and other air pollutants in the lower atmosphere. Also, at the time of the study, Cache Valley was designated as a non-attainment area for PM2.5 (this status was removed in 2021). The region regularly experiences air pollution in winter, and its air quality is sometimes the worst in the state of Utah and even in the entire nation (Wang et al., 2015). Residents of Cache Valley often expect wintertime air pollution, and air quality alerts (Utah DEQ, n.d.) and related travel demand management messages (UDOT, n.d.) are regularly distributed through local news media. Consequently, Cache Valley is an excellent location for studying the connections between travel behavior and air pollution because of how frequently elevated air pollution levels occur and the moderate awareness of this issue among the local population.

2.2 Data Collection

Our general approach to data collection involved conducting repeated online travel diary surveys of a panel of households recruited specifically for this study. As described in the sections below, we recruited participants through mailed letters and conducted an initial survey upon signup, three sessions of two-day online travel diaries, and a final survey.

Before rolling out the study during winter 2019, we conducted a small-scale pilot study during summer 2018 to test out the overall approach, survey questions, and recruitment methodology. We made several changes to streamline the process and reduce respondent burden.

2.2.1 Sampling and Respondent Recruitment

To ensure that we recruited people who lived in a variety of urban contexts, we classified U.S. Census block groups in Cache County into three strata: very urban, somewhat urban, and suburban/rural. Block groups were assigned to this neighborhood classification based on their scores on four variables (housing unit density, intersection density, job access by automobile, and transit frequency) from the EPA's Smart Location Database version 2.0 (U.S. EPA, 2018). We then conducted stratified random sampling to selected block groups that contained around 2,000 housing units in each of the very and somewhat urban groups, and 4,000 housing units in the suburban/rural group. We then obtained addresses for the roughly 8,000 households in these block groups. The selected block groups are depicted in Figure 2.1.

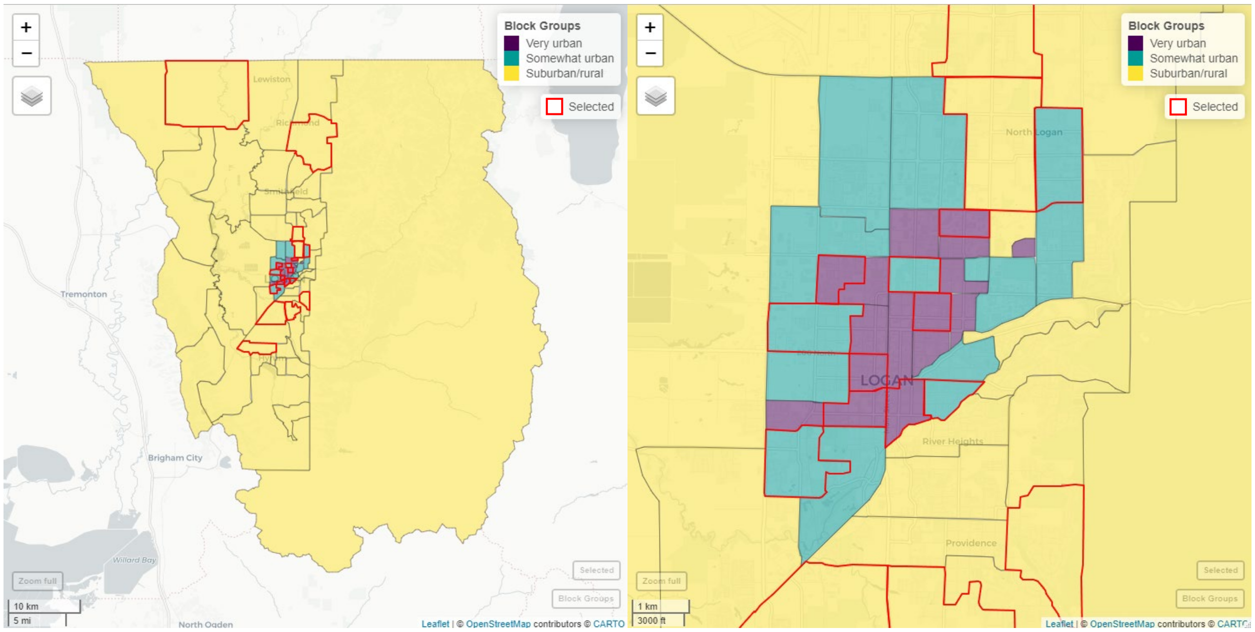

Figure 2.1 Map of selected U.S. Census block groups in Cache County, Utah
Left: overview of Cache County; Right: inset view of Logan city

In early January 2019, each address was mailed an envelope containing a letter that described the survey and included a link (and QR code) to the study's website. The letter described a "Winter Transportation Study" but did not mention air quality as the focus. Once on the website, potential respondents could fill out a brief survey to register their household for the study. Compared with the 8,376 letters mailed, 255 households (representing 479 adults) completed all aspects of the signup process for a low-end response rate of 3% (some addresses may have been vacant or non-residential). This was slightly lower than our target of 5%, but higher than the 1.7% rate we received for the pilot study that utilized postcards mailed through USPS Every Door Direct Mail (often viewed as "junk" mail).

2.2.2 Repeated Surveys

We structured our study in three phases. The first phase involved the sign-up survey, which (upon completion) was automatically re-directed to an **initial survey** that asked for basic demographic and transportation information about the household and all adult members. The second phase involved three periodic rounds of two consecutive days of **travel diary surveys**, completed by every adult in each household. The travel diary survey asked for information about every trip conducted on the survey day, including departure/arrival times, mode, locations, and purpose. At the end of phase two, each adult was instructed to complete a **final survey** that involved questions about attitudes, values, norms, and opinions related to air quality. Many questions in the final survey were borrowed from existing measurement scales to ensure comparability with existing research. Respondents received a unique household code to enter (along with their first name) to allow for matching records across surveys.

Decisions about when to deploy each two-day round of the travel diary survey during winter (January, February, and early March) 2019 were made strategically to try to target a variety of air quality conditions: "good" (AQI = 0–50), "moderate" (AQI = 51–100), and "unhealthy" (AQI > 100). Air quality tracking systems in Utah provide real-time data as well as a three-day forecast of air quality categories, based on pollution levels and weather conditions (UDEQ, n.d.). The evening before the desired start of a two-day session, participating households were sent an email informing them that we would be asking them to complete the diary survey(s) over the next two days. (We only surveyed on weekdays.) Each of those evenings, we also sent emails with links to the online travel diary survey along with instructions for each adult member to complete the survey once per day. We tracked responses and followed up with non-responding households with up to two reminder emails. Households (25) with no responses to the first two-day travel diary survey were dropped from the study.

Of the 255 households (479 adults) who completed the initial survey, 209 households (364 adults) completed both days of the first travel diary round, 191 households (343 adults) completed both days of the second round, 183 households (327 adults) completed both days of the third round, and 189 households (337 adults) completed the final survey. This represents around an overall 26%–30% attrition rate, which is fairly reasonable for a study of this duration. Table 2.1 summarizes the recruitment procedures for each survey, along with the response rate and overall attrition rates at each stage.

Table 2.1 Details of recruitment procedures, surveys, and response rates

Survey	*Date*	*# Sent*	*# Completed*	*Response rate*	*Attrition rates*
Sign-up, initial survey	2019-01-04	8,376 letters	255 households, 479 adults	3.0%	—
Travel diary surveys 1 & 2	2019-01-14 & 15	257 emails	209 households, 364 adults	81.3%	18%, 24%
Travel diary surveys 3 & 4	2019-01-29 & 30	232 emails	191 households, 343 adults	82.3%	25%, 28%
Travel diary surveys 5 & 6	2019-02-21 & 22	232 emails	183 households, 327 adults	78.9%	28%, 32%
Final survey	2019-03-04	232 emails	189 households, 337 adults	81.5%	26%, 30%

The method of strategically selecting the travel diary survey days in order to achieve a variation in air quality levels was partially successful. The forecast on the day before the first round was for two "unhealthy" days, but both days ended up being "moderate." The two-day forecast on the day before the second round was also "unhealthy," but the days ended up being "good" and "moderate." The two-day forecast on the day before the third round ended up being correct, with two "good" days. Overall, the winter quarter of 2019 experienced only six "unhealthy" days with AQI > 100, and four of those (unfortunately) happened to occur in early January prior to the start of our travel diary surveys. However, we were able to capture a low-to-moderate range of air quality conditions on our six target study days (AQI = 28, 31, 41, 52, 62, 79). Additionally, we actually captured a wider range of air quality levels (AQI = 3–128, with smaller samples) due to some respondents not answering on the requested days. Figure 2.2 shows the dates when people responded to each survey, along with a time plot of the daily AQI in Cache County.

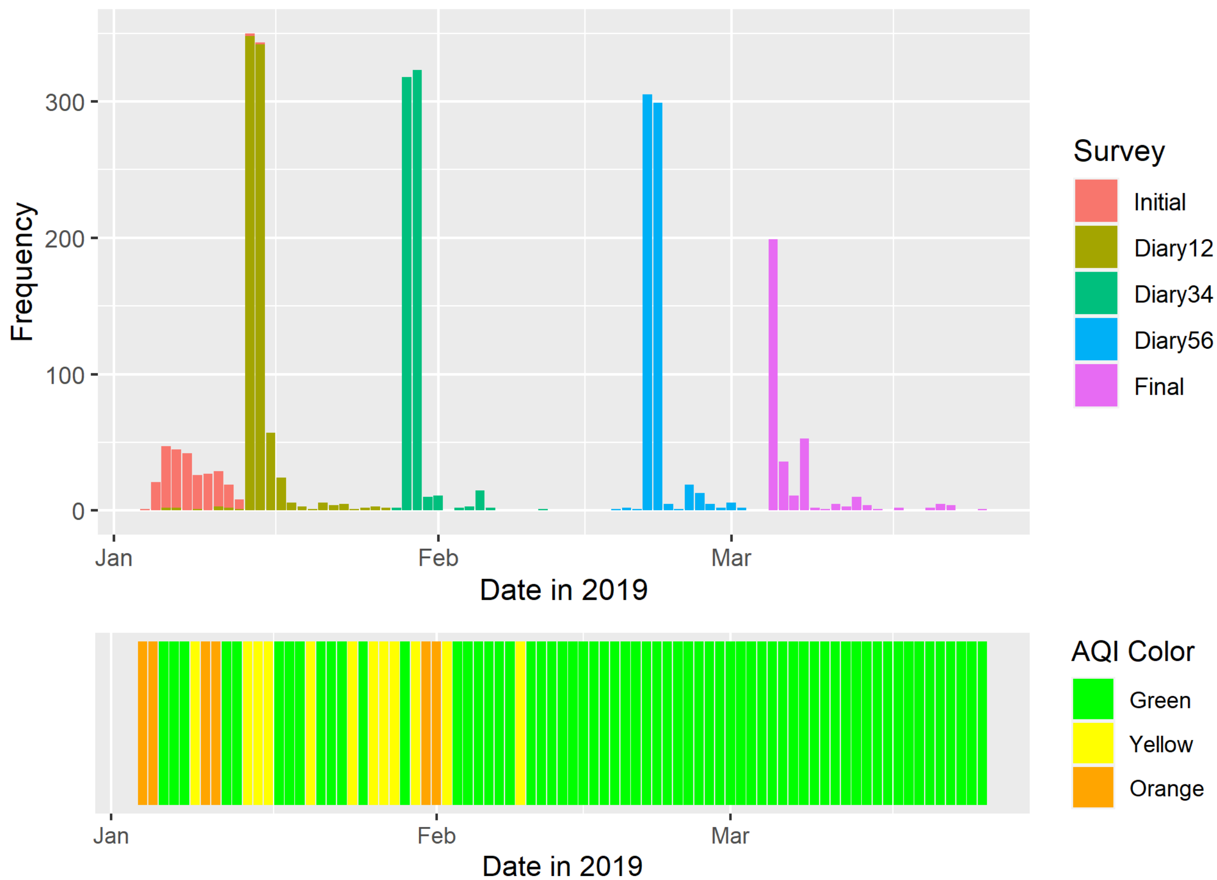

Figure 2.2 Frequency of responses to each survey (above), by date, compared to daily AQI (below)

At the completion of the study (late March 2019), households that completed all three phases of the research study were sent a $10 Visa gift card for their participation.

2.3 Data Processing

To ensure high quality and accurate data, we conducted extensive data cleaning and processing procedures. Some of this occurred during data collection. For example, as data were being collected for each travel diary survey, we checked responses for completeness and tracked who had completed each survey. Several reminder emails were sent to those contacts whose household members had not all completed a particular survey. After the data collection phase was complete, we conducted several more detailed rounds of data cleaning and formatting.

First, we downloaded CSV files for each survey from the Qualtrics online platform. Second, we formatted each set of survey responses to convert data types, construct unique identifiers (codes for each household, person, etc.), and create a series of linked datasets:

- HH: Information about households, taken from the initial survey.
- PER: Information about people (persons), taken from the initial survey.
- VEH: information about household vehicles, taken from the initial survey.
- DIARY: information about travel diaries, taken from the travel diary surveys.
- PLACE: information about places visited on travel diary survey days, processed from DIARY.

- TRIP: Information about trips made on travel diary survey days, processed from PLACE.
- PER_final: Information about personal attitudes and perceptions, taken from the final survey.
- meta_initial: Metadata about the initial survey.
- meta_diary: Metadata about the travel diary surveys.
- meta_final: Metadata about the final survey.

Third, we cleaned each dataset to ensure accurate and complete responses. This effort took the longest time and involved the biggest effort. Many survey responses had missing, incorrect, or inconsistent information: for example, mistyping household codes or person names, forgetting or putting the wrong date, or selecting an "other" category when an existing category was more appropriate. We identified and fixed these issues to the best of our ability, although some errors may remain.

It was most challenging to clean the travel diary surveys. Although we used a standard online form (that was based on existing paper-based household travel surveys), this required people to precisely fill out all information about the places they visited (location, activity, arrival/departure times) and the trips they made between places (mode, other travelers, vehicle). Naturally, some people made mistakes when recalling their day's travel (even when submitting at the end of that day), including errors and omissions. We checked for missing fields (i.e., did not fill out activity or mode) and filled in this information when we could be fairly confident about the likely answer: for example, based on the type of place (destination) or other modes used for trip chains. Despite clear instructions, some people did not fill out the name or description, address or cross-streets, and city/town of each place visited. Therefore, we made some informed guesses based on the household location or common destinations from other travel diary surveys for the same person. When we were unsure, we assumed the city hall for each town, except for Logan (population ~50,000), most towns in Cache County are small (population ~10,000 or less) and compact. We also checked for inconsistent and potentially incorrect responses, i.e., zero or negative activity or trip durations, long activities of certain types (change mode, drop-off/pick-up), or short activities of certain types (work, trips school). To fix missing or potentially erroneous responses, we inspected the travel patterns reported by the same people on different travel diary surveys or other adults in the same households. Overall, we inspected each travel diary survey entry and tried to ensure it was as complete and accurate as possible. We also identified and coded reasons to remove some travel diary survey entries because they were incomplete or a duplicate, the person or household withdrew from the study, or there was one or more unknown places, activities, modes, dates, or times.

Fourth, we georeferenced the datasets. Our first step involved geocoding every home, work, and school location listed in the initial survey and every place listed in the travel diary surveys. We used the "geocode" function from the "ggmap" package in R (Kahle et al., 2022) to do the geocoding, which uses the Google Maps Geocoding API. Although we asked for the place name or description, address or cross-streets, and city, initially some responses could not be geocoded (due to spelling or text formatting issues, or vague place names) or generated potentially inaccurate results (i.e., in a different county or state). After an initial geocode, we checked the results and edited the places to generate geocoded results or fix the issues identified, again checking against other information (i.e., trip duration) contained in the travel diary survey entries. We eventually saved the latitude, longitude, Google address, and unique Google Place ID for each geocoded home/work/school location or travel diary place.

Our next geocoding step involved obtaining travel distances and durations for each trip constructed from the travel diary surveys. For this, we used the "mapdist" function from the "ggmap" package in R (Kahle et al., 2022), which uses the Google Maps Distance Matrix API. In the query, we used the unique Google Place IDs (obtained from the first step of geocoding) for each trip's origin and destination, as well as the reported trip departure time. We did this for four different modes supported by the Distance Matrix API: driving, walking, bicycling, and transit (only bus in Cache County). We saved the results as distance (in miles) and duration (in minutes) for each trip, as if it were made by each of the four modes. We also identified Google Maps' reported distance and duration of each trip for the selected mode. Again, we did sanity checks of distances by mode and self-reported vs. Google-reported travel times and cleaned the data more when major errors were detected.

Fifth, and finally, we anonymized the data by creating versions of the datasets with all personally identifiable information removed. Of course, names and email addresses were removed, as were most open-text responses to various questions (because some contained personal information). We also removed all specific location and place information (e.g., names, addresses) and replaced them with U.S. Census Bureau geographic identifiers (GEOIDs) for the block groups containing the point locations. Therefore, we retained general location information for each place (block group level) while retaining point-location-based travel times and trip distances, thus accommodating confidentiality and the need for precision in transportation information.

2.4 Descriptive Statistics

The tables on the following pages show descriptive statistics for each dataset: Table 2.2 for households, Table 2.3 for persons, Table 2.4 for vehicles, Table 2.5 for diaries, Table 2.6 for places, and Table 2.7 for trips. Descriptive statistics for data from the final survey are in the open data resource described in the following section.

2.5 Data Availability

Full access to the complete (cleaned and anonymized) dataset and associated documentation is available on the project's open data repository (Singleton, 2024), hosted by Zenodo: https://zenodo.org/doi/10.5281/zenodo.11640318.

2.6 References

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Table 2.2 Descriptive statistics for households (N = 257)

Variable	*#*	*%*	*Mean*	*SD*
Housing type				
Mobile home or trailer	5	1.95		
Single-family house, detached from any other house	182	70.82		
Single-family house, attached to other houses (row house)	4	1.56		
Building with 2 apartments/condos (duplex)	14	5.45		
Building with 3 or 4 apartments/condos	45	17.51		
Building with 5 to 9 apartments/condos	6	2.33		
Building with 10 to 19 apartments/condos	0	0.00		
Building with 20 or more apartments/condos	1	0.39		
Other (please specify)	0	0.00		
Housing tenure				
Owned or mortgaged	169	66.02		
Rented	87	33.98		
Length lived in current home				
Less than 1 year	57	22.18		
1 to 2 years	55	21.40		
3 to 5 years	40	15.56		
6 to 10 years	30	11.67		
11 or more years	75	29.18		
Household income				
Less than $10,000	7	2.73		
$10,000 to $14,999	12	4.69		
$15,000 to $24,999	29	11.33		
$25,000 to $34,999	23	8.98		
$35,000 to $49,999	30	11.72		
$50,000 to $74,999	64	25.00		
$75,000 to $99,999	28	10.94		
$100,000 to $149,999	34	13.28		
$150,000 or more	12	4.69		
Do not know	3	1.17		
Prefer not to answer	14	5.47		
Number of children				
0 (none)	158	61.48		
1	30	11.67		
2	35	13.62		
3	21	8.17		
4	7	2.72		
5+	6	2.33		
Number of people (adults + children)			1.88	0.60
Number of bicycles available at home				
0	72	28.02		
1	59	22.96		
2	58	22.57		
3	16	6.23		
4	20	7.78		
5	12	4.67		
6+	20	7.78		
Motor vehicles available at home				
Yes	248	96.88		
No	8	3.13		
Number of vehicles			1.82	0.86
Home location is approximate	1	0.39		

Table 2.3 Descriptive statistics for persons (N = 483)

Variable	#	%	*Mean*	*SD*
Age				
18 to 19 years	14	2.90		
20 to 24 years	72	14.94		
25 to 34 years	143	29.67		
35 to 44 years	85	17.63		
45 to 54 years	67	13.90		
55 to 64 years	51	10.58		
65 to 74 years	35	7.26		
75 to 84 years	12	2.49		
85 years and over	1	0.21		
Prefer not to answer	2	0.41		
Race/ethnicity				
White	447	92.74		
Hispanic or Latino	17	3.53		
Asian	10	2.07		
Black or African American	5	1.04		
American Indian or Alaska Native	4	0.83		
Native Hawaiian or other Pacific Islander	4	0.83		
Other (please specify)	0	0.00		
Prefer not to answer	6	1.24		
Gender				
Female	246	50.93		
Male	233	48.24		
Other (please specify)	0	0.00		
Prefer not to answer	4	0.83		
Education				
Less than a high school diploma	9	1.87		
High school diploma or equivalent (e.g., GED)	39	8.09		
Some college, no degree	98	20.33		
Associate degree (e.g., AA, AS)	50	10.37		
Bachelor’s degree (e.g., BA, BS)	178	36.93		
Master’s degree (e.g., MA, MS, MEng, MEd, MSW, MBA)	68	14.11		
Professional degree beyond a bachelor's degree (e.g., MD, DDS, DVM, LLB, JD)	10	2.07		
Doctorate degree (e.g., PhD, EdD)	30	6.22		
Prefer not to answer	0	0.00		
Student status				
Yes, full-time	91	18.88		
Yes, part-time	21	4.36		
No	370	76.76		
Typical travel mode(s) to school				
Walk	15	3.11		
Bicycle	5	1.04		
Car/Van/Truck/SUV Driver	77	15.98		
Car/Van/Truck/SUV Passenger	18	3.73		
Motorcycle/Scooter/Moped	0	0.00		
Local Bus (CVTD or Aggie Shuttle)	31	6.43		
School Bus	1	0.21		
Other (please specify)	0	0.00		
Typically, no travel to/from school	11	2.28		
Typical travel mode to school				
Auto only	60	53.57		
Multimodal	22	19.64		
Walk/Bike/Bus	19	16.96		

No travel	11	9.82		
Worker status				
Yes	365	75.73		
No	117	24.27		
Days per week commute to work			4.25	1.45
Days per week work from home			1.12	1.70
Hours per week worked			34.54	14.56
Work schedule flexibility				
Very flexible	58	15.89		
Somewhat flexible	147	40.27		
Neither flexible nor inflexible	51	13.97		
Somewhat inflexible	60	16.44		
Very inflexible	49	13.42		
Typical travel mode(s) to work				
Walk	32	6.64		
Bicycle	19	3.94		
Car/Van/Truck/SUV Driver	291	60.37		
Car/Van/Truck/SUV Passenger	38	7.88		
Motorcycle/Scooter/Moped	0	0.00		
Local Bus (CVTD or Aggie Shuttle)	33	6.85		
Other (please specify)	0	0.00		
Typically, no travel to/from work	14	2.90		
Typical travel mode to work				
Auto only	294	80.55		
Multimodal	21	5.75		
Walk/Bike/Bus	36	9.86		
No travel	14	3.84		
Have a driver license				
Yes	467	98.11		
No	9	1.89		
Know how to ride a bicycle				
Yes	454	94.39		
Not well	25	5.20		
No	2	0.42		
Know how to drive an automobile				
Yes	475	98.55		
Not well	4	0.83		
No	3	0.62		
Know how to use public transit				
Yes	363	76.10		
Not well	89	18.66		
No	25	5.24		
Have a physical or mental condition that seriously limits or prevents				
Seeing	3	0.62		
Hearing	3	0.62		
Sitting	1	0.21		
Standing	4	0.83		
Climbing stairs	12	2.49		
Walking	15	3.11		
Riding a bicycle	13	2.70		
Driving an automobile	8	1.66		
Using public transit	3	0.62		
None of the above	444	92.12		
Work location is approximate	32	8.77		
School location is approximate	4	3.57		

Table 2.4 Descriptive statistics for vehicles (*N* = 468)

Variable	#	%	*Mean*	*SD*
Vehicle type				
Car/Van/Truck/SUV	456	97.44		
Motorcycle/Scooter/Moped	12	2.56		
Other (please describe)	0	0.00		
Vehicle use				
Primary household vehicle	281	60.04		
Secondary household vehicle	187	39.96		
Vehicle age (years before 2019)			11.42	7.50

Table 2.5 Descriptive statistics for diaries (*N* = 2,046)

Variable	#	%	*Mean*	*SD*
Travel diary survey				
Surveys 1 and 2	756	36.95		
Surveys 3 and 4	656	32.06		
Surveys 5 and 6	634	30.99		
Rating of the traffic on the survey day				
Great	428	23.46		
Good	868	47.59		
Fair	454	24.89		
Bad	71	3.89		
Terrible	3	0.16		
Rating of the weather on the survey day				
Great	474	23.28		
Good	931	45.73		
Fair	493	24.21		
Bad	121	5.94		
Terrible	17	0.83		
Rating of the air quality on the survey day				
Great	276	13.55		
Good	768	37.70		
Fair	712	34.95		
Bad	239	11.73		
Terrible	42	2.06		
Idled motor vehicle on the survey day				
Yes	343	22.06		
No	1212	77.94		
How long (minutes) spent idling (if yes)			7.41	9.18

Table 2.6 Descriptive statistics for places (N = 9,938)

Variable	*#*	*%*	*Mean*	*SD*
Place type				
Home	4961	49.92		
School	366	3.68		
Primary job	1299	13.07		
Secondary job	74	0.74		
Bus stop or parking location (not at your destination)	260	2.62		
Other place	2978	29.97		
Place location is approximate	772	7.77		
Primary activity at the place				
Home activities	4990	50.21		
Work activities	1373	13.82		
School activities	366	3.68		
Change mode	274	2.76		
Work- or school-related activities	100	1.01		
Eat meal at restaurant	231	2.32		
Service private vehicle (gas, oil, repairs, etc.)	46	0.46		
Shopping (groceries, clothing, convenience store, etc.)	705	7.09		
Drop off or pick up passenger(s)	735	7.40		
Civic or religious activities	199	2.00		
Other errands or appointments (bank, professional office, doctor/dentist, etc.)	359	3.61		
Outdoor or indoor exercise (sports, jogging, bicycling, walking dog, gym, etc.)	265	2.67		
Social or entertainment activities (friends/relatives, movie, etc.)	295	2.97		
Other (please specify):	0	0.00		
Activity duration (minutes)			284.2	292.7
Main reason for no travel				
Vacation or personal day	8	3.65		
Not scheduled to work	20	9.13		
Sick	28	12.79		
Child or other household member was sick	8	3.65		
Homebound, elderly, or disabled	5	2.28		
Worked at home (for pay)	14	6.39		
Worked around home (not for pay)	34	15.53		
No transportation available	1	0.46		
No reason to travel	87	39.73		
Weather	5	2.28		
Other (please specify)	9	4.11		

Table 2.7 Descriptive statistics for trips ($N = 7,892$)

Variable	*#*	*%*	*Mean*	*SD*
Travel mode				
Walk	570	7.22		
Bicycle	110	1.39		
Car/Van/Truck/SUV Driver	6142	77.83		
Car/Van/Truck/SUV Passenger	813	10.30		
Motorcycle/Scooter/Moped	0	0.00		
Local Bus (CVTD or Aggie Shuttle)	243	3.08		
School Bus	6	0.08		
Other (please specify)	8	0.10		
Number of other travelers				
0 (none)	4883	61.87		
1	1898	24.05		
2	636	8.06		
3	307	3.89		
4	89	1.13		
5+	79	1.00		
Vehicle used				
Primary household vehicle	5129	73.75		
Other household vehicle (please describe)	1520	21.85		
A non-household (someone else's) vehicle	306	4.40		
Trip time (minutes), survey			15.39	22.47
Trip distance (miles), Google routing				
By driving			6.57	38.50
By walking			6.24	37.84
By bicycling			6.80	42.07
By transit			8.45	34.53
By selected mode			5.86	18.86
Trip time (minutes), Google routing				
By driving			10.72	34.39
By walking			123.3	744.4
By bicycling			35.21	212.4
By transit			39.75	77.01
By selected mode			13.10	61.32

3. IMPACTS OF EPISODIC POOR AIR QUALITY ON TRIP-MAKING BEHAVIOR AND AIR QUALITY PERCEPTIONS FROM A LONGITUDINAL TRAVEL DIARY STUDY IN NORTHERN UTAH

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3.1 Abstract

Much research has shown how transportation sources contribute to air pollution, which negatively affects the environment and public health. In this paper, we investigate an understudied topic—how air quality or air quality perceptions impact travel behaviors or transportation choices—with a unique focus on individual-level (rather than aggregate-level) data. This allows us to incorporate perceptual aspects that can inform the design of effective behavior-based strategies. Specifically, we utilize a multi-day travel diary dataset, collected during winter 2019 from over 300 residents of Cache Valley in northern Utah, a small urban area that is in non-attainment for small particulate matter due to wintertime inversions. Our panel data regression analyses find no changes in the number of trips or total travel time that participants reported on days with better or worse air quality, suggesting that individual-level travel behavior is fairly stable regardless of air quality levels. Perceived air quality was positively correlated with measured air quality and seemed to be affected by awareness of air quality impacts. Overall, our results suggest that residents are somewhat aware of air quality issues (but perhaps not air quality programs), but do not make measurable travel behavior changes in response to episodes of poor air quality (likely due to various constraints). "Hard" policies that involve restrictions and disincentives may be more effective than "soft" informational and encouragement strategies, but they receive less public support, which challenges efforts to improve air quality through travel behavior change.

3.2 Introduction

Transportation is a major mobile source of emissions like nitrogen oxides (NOx) and volatile organic compounds (VOC) that contribute to the formation of $PM_{2.5}$ and ground level ozone. According to the U.S. EPA (2018a), the transportation sector contributes the largest share of greenhouse gas emissions (28.2%) of any industry. Within the transportation sector, automobile (involving passenger cars, light duty cars, pickup trucks, and minivans) sources are responsible for about 50% of the total emissions by transportation. Higher air pollution levels adversely impact public health, with increased risks of cardiovascular and respiratory diseases along with neurological and reproductive disorders (EPA, 2018a). Similarly, air pollution impacts may be felt in the transportation sector as smog or other particulates can decrease visibility and thus reaction time while driving (Sager, 2019).

Although research about the effects of transportation on air quality is plentiful (Caiasso et al., 2013), research emphasizing the reverse link—i.e., how air quality or air quality perceptions impact individuals' travel behaviors or transportation choices—is minimal (as will be detailed in the Background section below). Scant research in this area suggests that knowledge about the transportation-related negative consequences of air quality is the first step in attempts to encourage travel behavior changes such as choosing advanced technology (or electric vehicles) or non-automobile transportation options (Bamberg et al., 2011; Stern et al., 1999; Ghazali et al., 2019). Currently, communities around the world are applying various air quality improvement policy measures through reducing/shifting automobile demand, which can essentially be categorized into hard and soft policy measures (Bamberg et al., 2011). Hard policy measures include infrastructure interventions—such as the improvement of transit services or the addition of bicycle facilities—and mandatory government policies implemented to increase the cost of automobile use through taxes, tolls, registration fees, or rationing. On the other hand, soft policy measures attempt to achieve voluntary behavioral change via methods like information dissemination, financial incentives, social pressure, and encouragement. Hard measures often face political and social backlash, which has helped turn considerable attention to the implementation of soft measures.

Whether they are hard or soft, most policies are assumed to operate on and influence *individuals* and their travel choices (rather than organizations or larger economic structures). As a result, knowledge of an individual's attitudes, values, and perceptions of air quality (and subsequent effects on individual-level travel behaviors) is pivotal in formulating (as well as evaluating) policies, strategies, and interventions designed to improve air quality through transportation behavior changes. Yet (as we will show in the Background section below), there is limited existing research on individual-level perceptions and behaviors.

In this study, we attempt to fill this gap by examining air quality associations with two critical travel behavior outcomes—daily trip frequency and travel time—along with air quality perceptions, using individual-level data from a longitudinal travel diary. Our study population included residents of Cache Valley in northern Utah, surveyed during the winter months of 2019. Due to its narrow geography between two mountain ranges and high-elevation floor that is often covered in snow, Cache Valley provides optimal conditions for temperature inversions during wintertime, which cause an accumulation of air pollutants, specifically of particulate matter ≤ 2.5µm ($PM_{2.5}$). $PM_{2.5}$ concentrations during winter often rise to more than 35µgm^{-3}, the threshold value for the 24-hour National Ambient Air Quality Standard (NAAQS) for $PM_{2.5}$; hence this region is designated as a non-attainment area for $PM_{2.5}$. Wintertime air quality levels in Cache Valley can be the worst in the state and even the worst in the nation (Wang et al., 2015). Inversions and air pollution concentrations often build up over the period of a few days, but rarely last longer than a week before being swept away by a low-pressure weather system. These specific conditions—periodic but somewhat predictable episodes of adverse air quality caused in part by transportation emissions—make Cache Valley a good candidate location for studying the impacts of air quality on travel behaviors.

The paper is organized as follows: First, we provide a brief background about existing research on air quality perceptions, impacts of air quality on travel behavior, and air quality policies. Next, we describe the data collection approach and analysis methodology and present the results. Finally, we close with a discussion of key findings, policy implications, limitations, and recommendations for future work.

3.3 Background

Few studies have focused on understanding perceptions toward air quality and the behavioral responses of travelers during periods of poor air quality. In this section, we provide a brief overview of investigations into air quality perceptions and a detailed description of research studying the impacts of air quality on travel behavior.

3.3.1 Perceptions of Air Quality

Studies investigating perceptions of air quality across different geographical settings have found socio-demographic factors, health status, neighborhood characteristics, and measures of the built environment to be strong determinants (Schmitz et al., 2018). Socio-demographic factors such as age, education, gender, and health status are associated with varying perceptions regarding air quality: (a) people aged

40+ years and those living in urban areas are more likely to perceive air quality as poor than younger people and rural residents (Guo et al., 2016); (b) females are more likely to rate air quality as poor compared with men (Elliott et al., 1999; Jacquemin et al., 2007); and (c) people with respiratory symptoms and poor health status expressed higher frustration regarding air quality (Jacquemin et al., 2007; Howel et al., 2002). Similarly, air quality perceptions are found to vary spatially, with those living near industrial areas and in urban neighborhoods being more likely to rate the air quality poorer than those living across rural areas and other places more distant from industries (Howel et al., 2002; Brody et al., 2004; Mally, 2016). Additionally, Schmitz et al. (2018) found that concern over air quality was the strongest determinant of air quality rating, whereas perceived information about air quality had no significant relationship with air quality ratings.

3.3.2 Air Quality Impacts on Travel Behavior

Findings about the relationship of air quality levels on travel behavior are somewhat inconsistent. Most literature finds that there is no reduction in the amount of travel during days of poorer air quality. But some research also hints at small reductions in car trips and travel, due to various soft-policy measures, mostly focused on information dissemination to the public about current air quality and travel planning. These studies are detailed below.

Cummins and Walker (2000) developed a model, using hourly counts at 22 locations in Georgia, to forecast aggregate traffic volumes in order to examine the influence of voluntary mobile source emission programs (VMEPs). Results indicated that the effectiveness of VMEPs in reducing traffic volumes was limited, and that the small reductions observed could be attributed to noise (error in the model). Similarly, Welch et al. (2005) analyzed the impact of ozone action days (OADs) (providing information to the public when a high ozone level is expected for the following day) on public transit ridership in Chicago. Using a fixed effects regression model, the authors found that there were no statistically significant changes in transit ridership during OADs from 2002 to 2003. However, the authors suggested that there were substantial changes in hourly ridership patterns, which they attributed to: (a) substitution effects (commuters choosing transit over other modes, or telecommuting), or (b) scheduling effects (individuals shifting their commute time earlier or later).

Henry and Gordon (2003) inspected travel behavior changes (number of trips and miles driven) during ozone alert days by conducting tracking surveys of over 119 Atlanta residents. Overall miles driven was significantly lower on alert days compared with non-alert days, but no significant difference was found for the overall number of trips. Another study by Noonan (2011), using travel diaries from Atlanta households (collected for a regional transportation plan) and ozone data, found that Atlanta's smog alert programs did not significantly affect household vehicle miles traveled. However, based on park usage patterns during the summer of 2005, Noonan (2011) suggested that air quality information was successful in influencing the behavior of certain sensitive groups, i.e., a lower proportion of older adults and children visited a park during alert days.

In the context of Utah, two previous research efforts have attempted to examine the travel impacts of air quality reduction measures, including the "Clear the Air Challenge (CAC)" (a program focused on encouraging non- and low-automobile transportation choices to improve air quality during the summer ozone season) (Teague et al., 2015), and an air quality alert system (Tribby et al., 2013).

Teague et al. (2015) assembled daily information on ground level ozone, color-coded daily air quality designations, and meteorological data to estimate the effectiveness of the CAC program. Using time series models and control groups (days covered by CAC vs. not), the authors reported that only one model showed a statistically significant association between the CAC program and ground level ozone.

However, they pointed out that this small reduction (~3.6%) did not reflect any considerable impact when viewed from a public health perspective.

Tribby et al. (2013) analyzed traffic data from 28 automated traffic counters in two urban counties, cross-referenced with approximately 10 years of air quality data, to investigate the effectiveness of air quality alert programs. Utah used a three-category system to characterize air quality levels based at the time on (a now older version of) the U.S. Air Quality Index (AQI): green (AQI = 0–50), yellow (AQI = 51–73), and red (AQI > 73). Using green days as a control, authors analyzed average daily traffic counts and differences in patterns on yellow and red days for both summer and winter seasons. Yellow alert days showed an increase in daily traffic while red alert days were associated with decreased traffic in summer and increased traffic in winter. Traffic tended to decrease on alert days in the central city where public transit is well-serviced, but traffic increased toward the edge of metropolitan areas and at the mouths of canyons (routes to skiing and areas above the pollution layer). Researchers recommended the implementation of hard policies (such as mandatory restrictions on driving and free public transit) for travel behavior changes in the areas.

3.3.3 Summary

Studies examining the influence of air quality levels on travel behaviors mostly use secondary sources (traffic counts) and perform aggregate analyses on such data. However, policies formulated to induce behavioral change (such as information about adverse air quality levels, trip chaining, and carpooling strategies) are not effective unless individuals form positive perceptions (and feel conscious about the effect of their transportation choices on air quality) and alter their travel behaviors. As such, the use of aggregate data and analysis can only suggest (but not explain) why and how travel behaviors are affected (if at all) and thus whether or not a particular policy is effective. Hence, focusing on individual-level perceptions and travel behaviors could yield more insights into the effectiveness of policies while also being able to investigate individuals' thought processes (including awareness, preferences, attitudes, values, and beliefs related to air quality). Finally, previous studies have often focused on summer ozone levels (rather than wintertime particulate matter) and data for large cities.

3.3.4 Study Objectives

In this study, we use data from multi-day travel diary surveys to examine individual-level travel behaviors (trip frequencies and travel times) and perceptions on winter days of varying air quality, in Cache Valley, Utah, a small, urbanized area troubled by periodic high concentrations of $PM_{2.5}$. The primary goal of this study is to answer the following research questions:

- How does measured (or perceived) poor air quality affect individuals' daily travel amounts?
- What factors (personal characteristics, travel behaviors, and measured air quality) affect perceptions of air quality?

3.4 Data

3.4.1 Overall Approach

Our general approach to data collection involved conducting repeated online travel diary surveys of a panel of households recruited specifically for this study. As described in the sections below, we recruited participants through mailed letters and conducted an initial survey upon signup, three sessions of two-day online travel diaries, and a final survey.

Before rolling out the study during winter 2019, we conducted a small-scale pilot study during summer 2018 to test the overall approach, survey questions, and recruitment methodology. We made several changes to streamline the process and reduce respondent burden.

3.4.2 Sampling and Respondent Recruitment

To ensure that we recruited people who lived in a variety of urban contexts, we classified U.S. Census block groups in Cache County into three strata: very urban, somewhat urban, and suburban/rural. Block groups were assigned to this neighborhood classification based on their scores on four variables (housing unit density, intersection density, job access by automobile, and transit frequency) from the EPA's Smart Location Database (EPA, 2018b). We then conducted stratified random sampling to selected block groups that contained around 2,000 housing units in each of the very and somewhat urban groups, and 4,000 housing units in the suburban/rural group. We then obtained addresses for the roughly 8,000 households in these block groups.

Each address was mailed an envelope containing an anonymous letter that described the survey and included a link (and QR code) to the study's website. The letter described a "Winter Transportation Study" but did not mention air quality as the focus. Once on the website, potential respondents could fill out a brief survey to register their household for the study. Compared with the 8,376 letters mailed, 255 households (representing 479 adults) completed all aspects of the signup process, for a low-end response rate of 3% (some addresses may have been vacant or non-residential). This was slightly lower than our target of 5%, but higher than the 1.7% rate we received for the pilot study that utilized postcards mailed through USPS Every Door Direct Mail (often viewed as "junk" mail).

3.4.3 Repeated Surveys

We structured our study in three phases. The first phase involved the sign-up survey, which was automatically re-directed to an initial survey that asked for basic demographic and transportation information about the household and adult members. The second phase involved three periodic rounds of two consecutive days of travel diary surveys, completed by every adult in each household. The travel diary survey asked for information about every trip conducted on the survey day, including departure/arrival times, mode, locations, and purpose. At the end of phase two, each adult was instructed to complete a final survey that involved questions about attitudes, values, norms, and opinions related to air quality. Respondents received a unique household code to enter (along with their first name) to allow for matching records across surveys.

Decisions about deploying each two-day round of the travel diary survey were made strategically to try to target a variety of air quality conditions: "good" (AQI = 0–50), "moderate" (AQI = 51–100), and "unhealthy" (AQI > 100). Air quality tracking systems in Utah provide real-time data as well as a three-day forecast of air quality categories based on pollution levels and weather conditions (UDEQ, n.d.). The evening before the desired start of a two-day session, participating households were sent an email informing them that we would be asking them to complete the diary survey(s) over the next two days. (We only surveyed on weekdays.) Each of those evenings, we also sent emails with links to the online travel diary survey along with instructions for each adult member to complete the survey once per day. We tracked responses and followed up with non-responding households with up to two reminder emails. Households (25) with no responses to the first two-day travel diary survey were dropped from the study.

Of the 255 households (479 adults) who completed the initial survey, 209 households (364 adults) completed both days of the first travel diary round, 191 households (343 adults) completed both days of the second round, 183 households (327 adults) completed both days of the third round, and 189 households (337 adults) completed the final survey. This represents around an overall 25%–30% attrition rate.

The method of strategically selecting the travel diary survey days in order to achieve a variation in air quality levels was partially successful. The forecast on the day before the first round was for two "unhealthy" days, but both days ended up being "moderate." The two-day forecast on the day before the second round was also "unhealthy," but the days ended up being "good" and "moderate." The two-day forecast on the day before the third round ended up being correct, with two "good" days. Overall, the winter quarter of 2019 experienced only three "unhealthy" days with AQI > 100, and three of those (unfortunately) happened to occur in early January prior to the start of our study. However, we were able to capture a moderate range of air quality conditions on our six target study days (AQI = 28, 31, 41, 52, 62, 79). Additionally, we actually captured a wider range of air quality levels (AQI = 3–128, with smaller samples) due to some respondents not answering on the requested days.

3.4.4 Final Dataset

Table 3.1 includes descriptive statistics of socio-demographic characteristics of the participating adults. Table 3.2 presents descriptive statistics of the study's outcomes of interest: daily trip frequency and travel time, as well as perceptions of air quality. On average, respondents made between four and five trips (for all purposes) and spent around 70 minutes traveling per day. This is more than the national average of 3.37 daily person-trips but about the same amount of total time (74.6 minutes) (NHTS, 2017). Additionally, guided by the literature review, perceptual variables were used in our analysis, including perceptions of air quality as well as weather and traffic conditions. Awareness of consequences measures an individual's belief in the adverse consequences of air pollution and transportation's cause. Awareness of impact measures an individual's belief and perceived quantification of the adverse impacts of air pollution on various dimensions. Finally, attitudes toward health were adapted from health consciousness sections of the HealthStyles survey (Dutta-Bergman, 2004). Overall, awareness of consequences, awareness of impacts, and health attitudes showed high internal consistency (Cronbach's alpha > 0.7). Scores for each domain were calculated as the mean of the individual scores on the relevant items.

Table 3.1 Socio-demographic profile of respondents (*N* = 311)

Variable		*Categorical* #	*Categorical* %	*Continuous* *Mean*	*Continuous* *SD*
Age					
	18-24	51	16		
	25-34	97	31		
	35-44	53	17		
	45-54	43	14		
	55-64	32	10		
	65+	31	10		
	NA	4	1		
Gender					
	Female	164	53		
	Male	143	46		
	Prefer not to answer	4	1		
Education					
	Less than undergraduate degree	120	39		
	Undergraduate degree	117	38		
	Graduate degree	72	23		
	NA	2	1		
Income					
	$0-10,000	9	3		
	$10,000-49,999	105	34		
	$50,000-75,000	79	25		
	$75,000-100,000	39	13		
	$100,000	59	19		
	NA	20	6		
Student					
	Yes	73	23		
	No	236	76		
	NA	2	1		
# of children				1.945	1.350
# of adults				2.032	0.670
# of motor vehicles				2.000	0.930
# of bicycles				3.081	1.900
Housing type					
	Single-family	234	75		
	Multi-family	77	25		
Primary mode choice					
	Walk & bicycle	33	11		
	Auto, driver	241	77		
	Auto, passenger	25	8		
	Others	12	4		

Table 3.2 Descriptive statistics of other variables

Variables (Items)	*Scale*	*Mean*	*SD*
AQI		48.66	21.13
Trip characteristics			
Number of trips (per day)		4.28	2.42
Total travel time (per day)		70.8	73.08
Perception of…			
Air quality	-2 to +2 (Terrible – Good)	0.50	0.95
Weather		0.85	0.86
Traffic		0.89	0.80
Awareness of consequences (α = 0.70) • Air pollution is a big problem • Transportation is a major cause of air pollution	-2 to +2 (Strongly disagree – Strongly agree)	1.24	0.82
Awareness of impacts (α = 0.89) Air pollution contributes to: • Human health • Animal health • Plant health • Water quality • Local economy	1 to 4 (Not at all – A lot)	2.82	0.78
Health attitudes (α = 0.75) • I do everything I can to stay healthy • Living life in best possible health is very important to me • I actively try to prevent disease and illness • Eating right, exercising, and taking preventative measures will keep me healthy for life • My health depends on how well I take care of myself	-2 to +2 (Strongly disagree – Strongly agree)	1.22	0.54

3.5 Analysis and Results

3.5.1 Longitudinal Data Analysis

Survey responses from 311 respondents (*N* = 311) were acquired for 39 different days; although most people answered for six specific days, some survey participants provided responses on other days or more/fewer numbers of days. Since all the *N* members did not respond on each day, the resulting dataset was an unbalanced panel. A basic panel data model, including individual heterogeneity, can be described by the following general model:

$$y_{it} = \alpha_{it} + \beta x_{it} + \mu_i + \epsilon_{it} \tag{1}$$

where: $i = 1,\ldots\ldots n$ is the index for each respondent, $t = 1,\ldots\ldots..T$ is the time index, μ_i is the individual error component, and ϵ_{it} is the idiosyncratic error. Analysis was conducted using the *plm* package in R (Croissant & Millo, 2008), which allows for fixed or random effects and unbalanced panel data.

3.5.2 Number of Trips and Total Travel Time

For our first set of models, the total number of trips (*tn*) and total time spent traveling (*tt*) were aggregated for each individual for each day. In order to examine variations in individuals' trip-making behavior as explained by air quality as well as other determinants, *tt* and *tn* entered into Equation 1 as dependent variables (y_{it}), with other variables (socio-demographics, mode choice, air quality measurements, and traffic, weather, and air quality ratings) as independent variables (x_{it}). Daily travel time was log-transformed to reduce variability in travel time.

These particular models involve both time *invariant* variables—such as age, gender, and income—which remain constant over time, and time *variant* variables—such as the AQI—which differ for each day. To explain cross-sectional as well as time-varying heterogeneity, a fixed effect model with two-way effects was used for the analysis of trip characteristics.

Table 3.3 provides coefficient estimates, standard errors, and p-values for significant variables in the two models.

Table 3.3 Model results for number of trips and total travel time

Variables		*Number of trips (tn)*			*ln(Total travel time (tt))*		
		β	*SE*	*p*	*β*	*SE*	*p*
Age (ref = 25-34)							
	18-24	-0.700	0.548	0.201	0.118	0.168	0.483
	35-44	0.584	0.477	0.221	*-0.279*	*0.143*	*0.051*
	45-54	-0.344	0.563	0.541	**0.521**	**0.179**	**0.004**
	55-64	*1.162*	*0.622*	*0.062*	**0.587**	**0.189**	**0.002**
	65+	0.966	0.592	0.103	0.100	0.178	0.576
Income (ref = $10,000-50,000)							
	$0-10,000	-4.138	2.744	0.132	**2.922**	**0.808**	**0.000**
	$50,000-75,000	*-0.833*	*0.424*	*0.050*	*0.240*	*0.137*	*0.080*
	$75,000-100,000	**-1.348**	**0.604**	**0.026**	**0.684**	**0.188**	**0.000**
	$100,000+	0.307	0.491	0.532	**0.325**	**0.153**	**0.033**
	No answer	0.126	0.633	0.842	0.209	0.196	0.286
Student: Yes		NS	NS	NS	**0.374**	**0.152**	**0.014**
# of children		*0.276*	*0.141*	*0.051*	*0.071*	*0.042*	*0.091*
# of adults		NS	NS	NS	*0.154*	*0.086*	*0.074*
Primary mode choice (ref = Auto, driver)							
	Walk & bicycle	*-0.496*	*0.285*	*0.082*	0.039	0.084	0.647
	Auto, passenger	**-0.768**	**0.215**	**0.000**	**0.157**	**0.063**	**0.014**
AQI		0.003	0.003	0.214	-0.039	0.084	0.634
Perception of air quality		-0.014	0.081	0.862	-0.011	0.024	0.653
Perception of traffic		NS	NS	NS	**-0.132**	**0.026**	**0.000**
Total travel time (tt)		**0.008**	**0.001**	**0.000**	—	—	—
Number of trips (tn)		—	—	—	**0.160**	**0.008**	**0.000**
N				1,561			1,549
R^2				0.11			0.14

Notes: Statistical significance: **bold** = $p \leq 0.05$, *italic* = $p \leq 0.10$. — = variable not included, NS = not significant.

Results indicate that individuals' trip frequency and travel time is independent of both measured AQI and perceived air quality conditions, as no significant effects were found in the model.

Instead, personal and household characteristics as well as mode choice were found to influence the reported number of trips and total time spent traveling during those trips. People aged 55–65 made more trips, and people aged 45–64 spent longer time traveling, than people aged 25–34 years. Although $50,000–$100,000 earners made fewer trips than people with an income of $10,000–$50,000, they spent significantly more time traveling, as did those with very high (>$100,000) and very low (<$10,000) incomes. Students and people in larger households (with more children and adults) had longer travel times, and trip frequency was positively associated with the number of children. Active mode users (pedestrians & bicyclists) and auto passengers undertook fewer trips than auto drivers, but auto passengers spent more time on travel, compared with auto drivers. Additionally, better traffic ratings by an individual were associated with having lower travel time on those days. As expected, the model results revealed a positive and bi-directional link between the number of trips and total travel time. Other variables not shown in the model (including health attitudes and measures of awareness of air quality consequences and impacts) were not significantly associated with daily travel amounts.

3.5.3 Perceptions of Air Quality, Weather, and Traffic

In order to find linkages between individual perceptions of air quality (also, weather and traffic) and actual AQI—plus the effects of socio-demographics, mode choice, and other trip-making characteristics—a similar panel data analysis was performed. Like the previous models, the dataset was an unbalanced panel, so a fixed effect model was estimated (using the "within" method), with perception ratings as the dependent variables. Note that these perceptions were recorded on a continuous scale (-2 = *Terrible*, +2 = *Good*). Table 3.4 provides coefficient estimates, standard errors, and p-values for significant variables in the three models.

Table 3.4 Model results for perceptions of air quality, weather, and traffic

Variables	*Air quality*			*Weather*			*Traffic*		
	β	*SE*	*p*	*β*	*SE*	*p*	*β*	*SE*	*p*
Age (ref = 25-34)									
18-24	**-0.493**	**0.231**	**0.033**	0.223	0.200	0.265	NS	NS	NS
35-44	**0.334**	**0.165**	**0.044**	0.022	0.164	0.895	NS	NS	NS
45-54	-0.014	0.209	0.948	**-0.513**	**0.198**	**0.010**	NS	NS	NS
55-64	0.148	0.224	0.509	**-0.613**	**0.214**	**0.004**	NS	NS	NS
65+	0.122	0.238	0.608	**-0.402**	**0.205**	**0.050**	NS	NS	NS
Gender: Male	NS	NS	NS	NS	NS	NS	**-0.776**	**0.305**	**0.011**
Education (ref = Less than undergraduate degree)									
Undergraduate degree	NS	NS	NS	0.113	0.136	0.408	NS	NS	NS
Graduate degree	NS	NS	NS	**-0.483**	**0.154**	**0.002**	NS	NS	NS
Income (ref = $10,000-$50,000)									
$0-$10,000	0.030	0.949	0.975	NS	NS	NS	-0.664	0.853	0.437
$50,000-$75,000	**0.464**	**0.182**	**0.011**	NS	NS	NS	-0.107	0.118	0.366
$75,000-$100,000	**0.856**	**0.229**	**0.000**	NS	NS	NS	0.266	0.177	0.134
$100,000+	**0.454**	**0.188**	**0.016**	NS	NS	NS	**0.576**	**0.147**	**0.000**
No answer	0.310	0.276	0.262	NS	NS	NS	-0.056	0.197	0.774
Student: Yes	**0.699**	**0.186**	**0.000**	**-0.579**	**0.162**	**0.000**	NS	NS	NS
# of bicycles	**-0.071**	**0.033**	**0.031**	**0.076**	**0.030**	**0.012**	**-0.071**	**0.027**	**0.010**
Primary mode choice (ref = Auto, driver)									
Walk & bicycle	NS	NS	NS	NS	NS	NS	**-0.776**	**0.305**	**0.011**
Auto, passenger	NS	NS	NS	NS	NS	NS	*-0.776*	*0.305*	*0.100*
AQI	**-0.014**	**0.001**	**0.000**	NS	NS	NS	**0.002**	**0.001**	**0.019**
Perception of air quality	—	—	—	**0.296**	**0.024**	**0.000**	**0.111**	**0.026**	**0.000**
Perception of weather	**0.287**	**0.029**	**0.000**	—	—	—	**0.224**	**0.025**	**0.000**
Perception of traffic	**0.139**	**0.033**	**0.000**	**0.244**	**0.030**	**0.000**	—	—	—
Total travel time (tt)	NS	NS	NS	NS	NS	NS	**-0.001**	**0.000**	**0.037**
Number of trips (tn)	NS	NS	NS	NS	NS	NS	**-0.019**	**0.009**	**0.038**
Awareness of impact	**-0.195**	**0.082**	**0.017**	—	—	—	—	—	—
N			1,361			1,551			1,557
R^2			0.32			0.21			0.15

Notes: Statistical significance: **bold** = $p \leq 0.05$, *italic* = $p \leq 0.10$. — = variable not included, NS = not significant.

On days with poorer air quality (higher AQI), people reported more negative perceptions of air quality. People had better ratings of traffic conditions on these days, but there was no impact of AQI on weather perceptions. People who traveled longer and had more trips also reported worse ratings for traffic during that day, but there was no impact of travel amounts on air quality perceptions. The positive associations between ratings of air quality, weather, and traffic in all three models symbolize that people may rate these factors in a similar way.

Some socio-demographic variables had a significant association with air quality perceptions. Compared with adults aged 24–34, younger adults had more negative ratings of air quality, while those of adults aged 35–44 were more positive. People with incomes greater than $50,000 had significantly more positive assessments of air quality than those with $10,000–$50,000 incomes. Students perceived air quality to be better than non-students, and air quality perceptions were negatively related to bicycle ownership. Those with greater awareness of the negative impacts of air quality also had more negative ratings. There were no significant associations of air quality perceptions with gender, education, household size, vehicle ownership, primary mode choice, health attitudes, or awareness of air quality consequences.

3.6 Discussion

3.6.1 Number of Trips and Total Travel Time

Our analysis (see Table 3.3) indicates that there was no substantial change in people's travel amounts due to variations in air quality, whether measured or perceived. There was no significant difference in the number of trips people carried out on days with good versus poor measured air quality (4.26 trips when AQI $\leq$ 50; 4.30 trips when AQI > 50). Similarly, there was no significant difference in total time spent traveling (69 minutes when AQI $\leq$ 50; 72 minutes when AQI > 50). Furthermore, there was no significant association of travel amounts with perceived air quality (perceptions were correlated with AQI). This lack of a relationship is also corroborated by results from a non-individual-level study conducted in similar settings (wintertime in Utah) by Tribby et al. (2013), where motor vehicle traffic counts were found to actually increase on days with bad air quality.

Why do people seem to not be affected by poor air quality, at least not enough to make detectable travel behavior changes? This could be due to much travel being mandatory trips to work, school, or for life-sustaining activities (e.g., grocery shopping) that cannot be easily rescheduled for another day or conducted remotely. It also could be that air quality does impact travel amounts, but only at levels of adverse air quality beyond what we were able to observe during the winter of 2019. Finally, the effect size of air quality influences on travel behavior may be small, and we may not have had a sufficient sample size to detect a significant effect.

Although theories of pro-environmental behaviors (e.g., Stern et al., 1999; Ghazali et al., 2019) suggest psychological variables (knowledge, awareness and consequences of air quality) are strong determinants of behavioral change, our study shows that knowledge and perceptions about the consequences (or impacts) of air quality (or positive health attitudes) might not be enough to necessarily induce travel behavior changes (such as traveling less during days with poor air quality).

3.6.2 Perceptions of Air Quality, Weather, and Traffic

Overall, air quality was perceived to be slightly better than fair (average rating of +0.5). However, our analysis (see Table 3.4) found that perceptions of air quality varied across a few segments of population. Associations with age (negative for < 25, positive for 35-44) were somewhat consistent with other findings that older groups perceive air quality to be better. The fact that higher-income respondents reported more positive ratings for air quality is notable. Perhaps high-income people, who may drive more due to preferences for larger and more suburban residential locations, may feel more indifferent toward air quality. On the other hand, perhaps they can better afford green vehicles (or alternative technologies), which produce less harm to environment, furthering the disconnect with air quality conditions. Lower income populations may have limited non-driving options due to their job type, schedule, and location.

Interestingly, people's perceptions of air quality were positively associated with the AQI. In other words, people were at least somewhat aware of actual air quality conditions. The result is in contrast with past studies, which indicates no relationship between perceived and objective measures of air quality (Schmitz et al., 2018; Brody et al., 2004; Mally, 2016). Winter inversions in Cache Valley are characterized by higher concentrations of $PM_{2.5}$ and other pollutants being settled in low layers over the valley. Hence, days with poorer air quality can sometimes be visually apparent to residents in the form of haze or low visibility (as demonstrated in Figure 3.1). Furthermore, initiatives to make people aware of air quality through advertising and news alerts in this area could be aiding people in the knowledge of air quality levels. This conclusion is supported by our finding that people with a greater awareness of negative impacts had more negative ratings of daily air quality.

Figure 3.1 Midday views of Cache Valley on (top) 15 January 2019 with AQI = 79 and (bottom) 21 February 2019 with AQI = 28

3.6.3 Policy Implications

There are several air quality programs in Utah—such as Utah TravelWise (UDOT, 2017) and others mentioned below—that use informational and marketing strategies to raise awareness of air quality issues and encourage travel behavior changes through carpooling, trip-chaining, shifting to public transit or active transportation, utilizing alternative work schedules, and teleworking. This study suggests that these soft policies and programs alone are not affecting the travel behaviors of Cache Valley residents. Furthermore, Figure 3.2 shows that over half of respondents have never heard of any of the air quality organizations and activities in Utah, and less than 20% of people were familiar with even the most well-known program. If such policies are to take shape, public knowledge of such programs must be increased, which suggests the need for more efficient, robust, and sustained advertising strategies. One way of increasing awareness about such strategies and about air quality levels is to apply a multi-media, multi-channel approach (Henry & Gordon, 2003). Innovative advertising strategies such as electronic highway signs, radio advertising during rush hours, and information distribution through university/schools or transit could be some of the measures likely to reach the target audience.

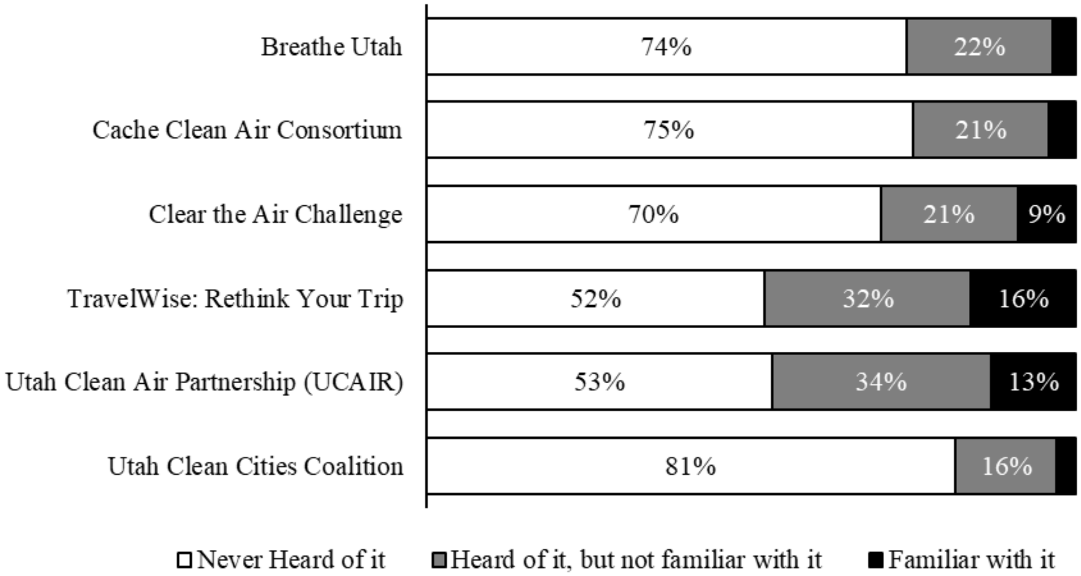

Figure 3.2 Knowledge of and familiarity with Utah air quality organizations ($N = 344$)

In contrast to other literature, we found that air quality perceptions are affected by actual AQI. Since residents are aware of poor air quality days, it could be relatively easier to advise them of travel behavior modification strategies on such days. This supports the implementation of programs (such as TravelWise) to encourage individuals to refrain from increased car use during adverse air quality episodes. Furthermore, it provides ideas for policymakers to consider increasing the reliability and accessibility of public transit, providing flexible door-to door-service, and other ways of practicing mobility-as-a-service (MaaS) schemes.

It could be that travel behavior changes in response to poor air quality would be stronger if more rigorous and mandatory policies were implemented. Public support/disagreement with policies is strongly related to their successful implementation and ability to produce desired results. As found in numerous other studies (e.g., Bamberg et al., 2011) and general expectations about public perceptions, we found that respondents were generally supportive of “softer” policy measures (providing information about air quality) and financial incentives to purchase alternative transport modes (electric or hybrid vehicles) or dispose of older vehicles (see Figure 3.3). However, they were less supportive of “harder” policies such as increasing taxes or fees and imposing stricter emission standards. Public inclination toward soft and benefit-framed policy measures (as opposed to hard or punitive/restrictive policies) suggests that the public may be more willing to make these types of changes if they are voluntary; however, these sorts of policies may be less effective at actually solving the air quality problem through behavior change (Gärling & Schuitema, 2007).

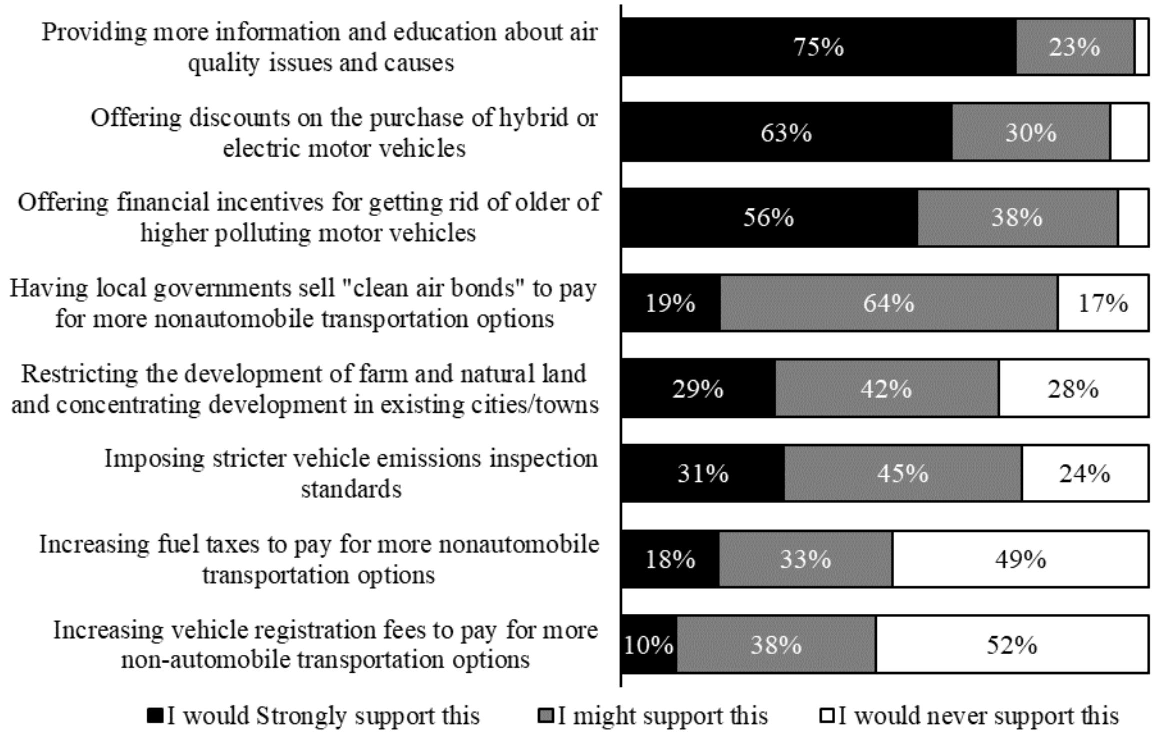

Figure 3.3 Support for air quality related policies (*N* = 278)

3.7 Conclusion and Future Recommendations

This paper analyzed individuals' trip-making behaviors and perceptions of air quality on winter days with variable air quality in one part of Utah (Cache Valley) that sees periodic unhealthy concentrations of $PM_{2.5}$. Our study is one of the first efforts to examine travel behavioral and perceptual impacts of poor air quality at an individual (rather than aggregate) level—and in a small urban area (rather than a large city) and during periods with high concentrations of particulate matter (rather than ozone)—which is essential since policies encouraging travel behavior changes in response to poor air quality are often targeted to individuals. To summarize, travel amounts (trip frequencies and travel times) did not change on days with poorer air quality, but perceptions of air quality were related to the AQI. Overall, our findings suggest that existing policies and advertising strategies in Utah intended to achieve voluntary reductions in total trips and automobile use have not translated into detectable changes in travel behavior; however, they may have helped to develop awareness surrounding air quality levels and consequences. Even if these programs could not directly result in short-term behavioral change (as measured in our study), long-term changes could potentially occur. More work could be done to increase awareness of air quality programs and foster public support of harder and potentially more effective policies to facilitate behavioral change.

In order to improve upon our efforts, future work quantifying individual-level travel behavior changes to episodes of poor air quality should attempt to use larger cross-sectional samples, collect travel behavior data over more days, capture wider variations in air quality levels, and potentially test the effectiveness of one or more interventions or treatments. Additional work to better understand the psychology surrounding air quality and travel behavior change would be beneficial to creating effective strategies for modifying travel behaviors during adverse air quality episodes. Some theories (e.g., Klöckner & Matthies, 2004) describe behavior change as a sequential process, moving from consideration to preparation to action. Information and awareness (of the need and potential actions) is necessary but not sufficient; perceived ability and control, social and institutional support, mitigation of behavioral constraints, and mental or monetary rewards also play a role. Similarly, theories on pro-environmental behaviors suggest an influence of values, attitudes toward health and environment, ascription of responsibility, and person and social norms, in addition to awareness of consequences and impacts (e.g., Stern et al., 1999; Ghazali et al., 2019). Future research should include these factors and examine the nature of relationships between psychology and stated/measured travel behaviors in order to explicitly inform strategies to reduce the negative impacts of transportation on air quality and health.

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4. SEGMENTATION ANALYSIS OF ATTRIBUTION OF RESPONSIBILITY OVER AIR POLLUTION AND ITS IMPACTS ON TRAVEL BEHAVIORAL RESPONSES

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4.1 Abstract

This study focuses on the linkages between attribution of responsibility, awareness of consequences, risk perception, self-efficacy, travel behavior modifications, and socio-demographics in the context of transportation and air quality. Specifically, we aim to empirically understand heterogeneous patterns of attribution of responsibility of air pollution, the relationship with stated travel behavior changes, and the impact of awareness of consequences, risk perception, self-efficacy, and socio-demographics. We utilize a multi-day travel diary dataset, collected during winter 2019 from over 300 respondents of Cache Valley in northern Utah, a small urban area troubled by air pollution due to wintertime inversions. Using latent class analysis, we found there are three distinct classes of individuals based on their attribution of responsibility: (i) High internal–high external attributors, (ii) moderate internal–moderate external attributors, and (iii) low internal–low external attributors. These classes were differentiated on their views of increasing/decreasing automobile usage vs. other mode usage and how such choices impact air quality. Several socio-demographic factors (age, gender, education) and psychological constructs (self-efficacy, awareness of consequences) were found to be significant predictors of the class membership. Finally, there were significant differences in travel behavioral response scores corresponding to different classes of attributors.

4.2 Introduction

The use of petroleum-fueled automobiles produces harmful gases (such as nitrogen oxides and volatile organic compounds) in the atmosphere, resulting in air pollution. In the U.S., the transportation sector contributes the largest share of greenhouse gas emissions, and automobile driving is associated with about 50% of total transportation emissions (US EPA, 2018). As the direct links between auto driving and air quality are evident, policymaking has turned to improving air quality conditions via reducing automobile usage along with encouraging more sustainable and active transportation modes such as walking, bicycling, and public transit. Air pollution reduction policies often involve increasing awareness and promoting behaviors that reduce air pollution via strategies (such as targeted advertising and information dissemination) that seek to increase a sense of responsibility for the consequences of one's actions.

Past research has already made significant progress in understanding individual behavioral responses to air pollution and has explored a number of influential factors such as risk perception, attribution of responsibility, awareness of consequences, and socio-demographic factors (Tan & Xu, 2019; Bamberg & Moser, 2007; Bickerstaff & Walker, 2002). There is, however, a need to further investigate and validate relationships between these factors empirically and to explore individuals' perceived causation of air pollution from theirs and others' transportation choices. In the following sections, we first explain in detail the relevant psychological constructs—risk, attribution of responsibility, risk perception, awareness of consequences, and self-efficacy. Next, we apply the existing findings and past theories to explore connections between these concepts. Finally, we develop our study objectives by identifying gaps in the literature and extending the previous findings in context of a transportation-air quality link.

4.2.1 Risk and Attribution of Responsibility

There are many definitions of risk, varying across disciplines, research areas, and usage contexts. In this study, we borrow from Rohermann & Renn (2000) in defining risk as "the possibility of physical or social or financial harm/detriment/loss due to a hazard within a particular time frame." Within this framework, air pollution can be referred to as a risk (or a risk event) pertaining to its adverse effects on humans (e.g., cardiovascular diseases), animals (e.g., loss of habitat), and the environment (ecosystem imbalance). When faced with a risk event, humans make judgments about causes and responsibilities of events and outcomes through direct observation, availability and processing of information, past experiences, and situational context (Cheng et al., 2017; Heider, 1958; Kelly, 1973; Weiner, 1986). The connection of causation with outcomes is often referred to as *causal attribution*, and understanding the psychological processes behind how individuals ascribe the cause of one or more behavioral outcomes is the scope of *attribution theory* (Kelley, 1973; Weiner, 1986).

When presented with a risk event, individuals judge the causal attributors of the risk and assign the risk responsibility. First, attribution research has found that how individuals perceive causality is dichotomized into internal and external attribution (Kelly & Michela, 1980; Weiner, 1986; Tan & Xu, 2019). *Internal attribution* symbolizes an individual's belief that they are the cause of a risk event, whereas *external attribution* refers to the ascription of a risk event to situational factors (e.g., policies) or other people (Tan & Xu, 2019; Weiner, 1986). Behavioral responses depend on whether people attribute the responsibility of an outcome internally or externally (Schmitt & Branscombe, 2002). Internal attribution for unfavorable outcomes heightens feelings of guilt (Weiner, 2000), which in turn stimulates adaptive/mitigating behaviors toward the risk (Bamberg & Moser, 2007). A positive association between internal attribution and individuals' mitigating behaviors has been found in studies of various risk events such as climate change (Jang, 2013; Chang et al., 2017), air quality (Tan & Xu, 2019), and health research. Alternatively, external attribution is found to be a negative predictor of positive behavioral response; i.e., attributing cause to external factors might inhibit one's motive to take protective actions (Tan & Xu, 2019; Lyden et al., 2002). Overall, most of the research differentiates individuals based on their attribution of responsibility (internal vs. external)—assuming that these are distinct segments—and there are behavioral discrepancies (concerned with risk management actions) across these segments.

Although attribution of risk to self is found to be an important predictor of risk management behaviors (Kahlor, 2002), it is valuable to acknowledge that relationships with behavioral responses could be insignificant in some cases. For example, Bickerstaff and Walker (2002) found that although people took a share of responsibility and expressed high levels of concerns for air quality, they were reluctant to act.

Another line of research provides evidence for attributional biases, especially when concerned with a negative outcome (such as environmental risks). Much research supports the notion that good outcomes are often attributed to personal causes, whereas negative outcomes are attributed to external ones (Kahlor, 2002; Bickerstaff & Walker, 2002). Specifically, for risk associated with individuals' collective actions (e.g., climate change, air pollution), individuals are less inclined to take personal accountability and therefore shift the responsibility onto other individuals; this is referred to as *diffusion of responsibility* (Mynatt & Sherman, 1975; Bickerstaff & Walker, 2002). For example, a person on a routine commute to work might not be concerned about the impacts of his/her auto-driving on air quality, instead placing the responsibility onto other commuters.

4.2.2 Risk Perception, Awareness of Consequences and Self-efficacy

Risk perception is another key factor motivating behavioral response (Dawson, 2020). As defined by Slovic (2000), *risk perception* is "the intuitive judgement of individuals and groups, of risks in the context of limited and uncertain information." There is ample evidence that indicates positive correlations between risk perception and risk management behaviors for different types of risk events, such as earthquakes (e.g., Huang et al., 2014), climate change (Yu et al., 2013), volcanos, and tsunamis (Cui et al., 2016). That is, a high level of concern regarding a particular risk drives people toward protective actions for risk reduction in order to reduce psychological discomfort arising from fear, anger, and sympathy (or other similar emotional states). For example, Cheng et al. (2017) reported that individuals who were highly concerned with the negative effects of city smog were more inclined to reduce personal car use in favor of public transport.

A related construct to risk perception is *awareness of consequences* (awareness of the potential consequences of one's actions in the creation of risk), which has been found to be a crucial determinant of risk management behaviors. For pro-environmental behaviors (e.g., Ghazali et al., 2019), awareness can act either directly or indirectly through the creation of personal norms (feelings of accountability to take protective actions in mitigating risks) and social norms (social obligation to engage in actions alleviating the risk). Specifically, awareness of consequences is often found to be a primary antecedent of other predictors (such as norms or attitudes) in models such as the value-belief-norms (VBN) framework or the theory of planned behavior (Bamberg & Moser, 2007), implying a direct or indirect effect (through the predictors) on intentions and behaviors.

Even if people internally attribute the responsibility of a risk such as air pollution and are aware of the consequences of (in)action, they may not act in part because they do not believe that they can act. Perceived *self-efficacy* refers to "people's beliefs about their capabilities to produce designated levels of performance that exercise influence over events that affect their lives" (Bandura, 1994). The literature suggests that individuals' perceived ability to perform actions (i.e., self-efficacy) is associated with risk management behaviors as well as pro-environmental behaviors (Bamberg & Moser, 2007).

4.2.3 Associations between Attribution of Responsibility and Other Factors

Since both causal attribution of responsibility and risk perception influence behavioral response, it is plausible that there exists an association between these two factors. Dawson (2020) found that the relationship between self-attribution for risk creation and risk management behaviors was moderated by risk perception. Another study by Chang et al. (2016) established an empirical relationship between attribution of responsibility to others and risk perception, i.e., attributing responsibility of climate change to the government was found to increase perceptions of risk to self, others, and the next generation. However, self-attribution did not have any significant association with risk perception. Other research by Rickard (2014) analyzing risk perceptions of accidents found a positive correlation between risk controllability and internal causal attribution (and alternately a negative correlation with external attribution), suggesting a significant relationship between risk perception and attribution of responsibility.

Empirical evidence tends to support the notion that individuals high in self-efficacy are more likely to attribute the responsibility of causes and consequences of a risk event to themselves, as they believe in their ability to successfully adhere to actions that mitigate the risk (e.g., Stajkovic & Sommer, 2000; Tan & Xu, 2019). Some studies also indicate that self-efficacy acts as a mediator linking attribution of responsibility to risk management behaviors (Bamberg & Moser, 2007; Lindell & Whitney, 2000).

Socio-demographic attributes have also been associated with perceived causality and risk response. For example, Tan and Xu (2014) found that women (compared with men) and high-income populations tended to perceive the risks of air pollution with a greater degree of urgency and were also more liable to take adaptive measures in response. Other influential socio-demographic attributes are age, income, and race (Zeidner & Shecter, 1988; Tan & Xu, 2019).

4.2.4 Study Objectives

This study investigates the linkages between attribution of responsibility, awareness of consequences, risk perception, self-efficacy, travel behavior modifications, and socio-demographics in the context of transportation and air quality. Although previous studies have offered valuable insights, there is a need to expand on empirical findings connecting transportation mode choices, air pollution, and the aforementioned psychological factors. Specifically, we aim to empirically understand heterogeneous patterns of attribution of responsibility of air pollution, the relationship with stated travel behavior changes, and the impact of awareness of consequences, risk perception, self-efficacy, and socio-demographics. Overall, our goal is to gain deeper insights into how individuals make these connections, and this knowledge would allow behavior change policies and programs to be more effective in achieving their intended outcomes.

To accomplish this overall goal, this study uses data from multi-day travel diary surveys in a small, urbanized area of Cache Valley, Utah, troubled by high concentrations of PM2.5. The primary research objectives of this study are to:

- Identify heterogeneous classes of individuals based on their attribution of responsibility of transportation mode usage and its impact on air quality.
- Determine socio-demographic characteristics and psychological variables (risk perception, awareness of consequences, self-efficacy) associated with different classes.
- Ascertain differences in travel behavior responses of different classes.

4.3 Data and Methods

4.3.1 Study Area

Due to its unique geography (at high elevation between two mountain ranges), Cache Valley in northern Utah has optimal conditions for winter inversions, resulting in high atmospheric concentration of particulate matter and other air pollutants in the winter. Similarly, the area is designated as a non-attainment area for PM2.5. Wintertime air quality conditions in Cache Valley can reach to lowest air quality levels in the state and even the whole nation (Wang et al., 2015). Thus, these specific conditions make Cache Valley a good candidate location for studying relationships between travel behavior and area-wide poor air quality.

4.3.2 Data Collection

We conducted an online panel travel diary survey of households in Cache Valley during the winter of 2019. Stratified random sampling of U.S. Census block groups was performed in order to recruit participants from varied urban contexts (very urban, somewhat urban, and suburban/rural); see Humagain and Singleton (2021) for more details. For the housing units in the selected locations, each address was mailed an anonymous letter that included a link to the study's website along with the description of the survey. The data collection method was structured into three phases:

1. **Initial survey**: After signing up for the study, respondents answered questions about basic household composition, demographic, and transportation information.

2. **Travel diary surveys**: This second phase involved three rounds of two consecutive days of travel dairy surveys (targeted by the researchers to capture a variety of air quality conditions), where each adult provided information about every trip conducted on the survey day, including departure/arrival times, mode, location, and purpose.
3. **Final survey**: Each adult completed a final survey that involved questions about psycho-social factors such as attitudes, values, norms, mitigation, and adaptive behaviors related to mode choice and air quality.

Overall, out of 8,376 letters mailed, 255 households (representing 479 adults) completed the initial survey (a 3% response rate), while 189 households (337 adults) completed the final survey (a 25%–30% attrition rate). The final dataset used in the study includes 321 adults after cleaning and removing incomplete responses. Descriptive statistics of respondents are presented in Table 4.1.

Table 4.1 Socio-demographic profile of respondents ($N = 321$)

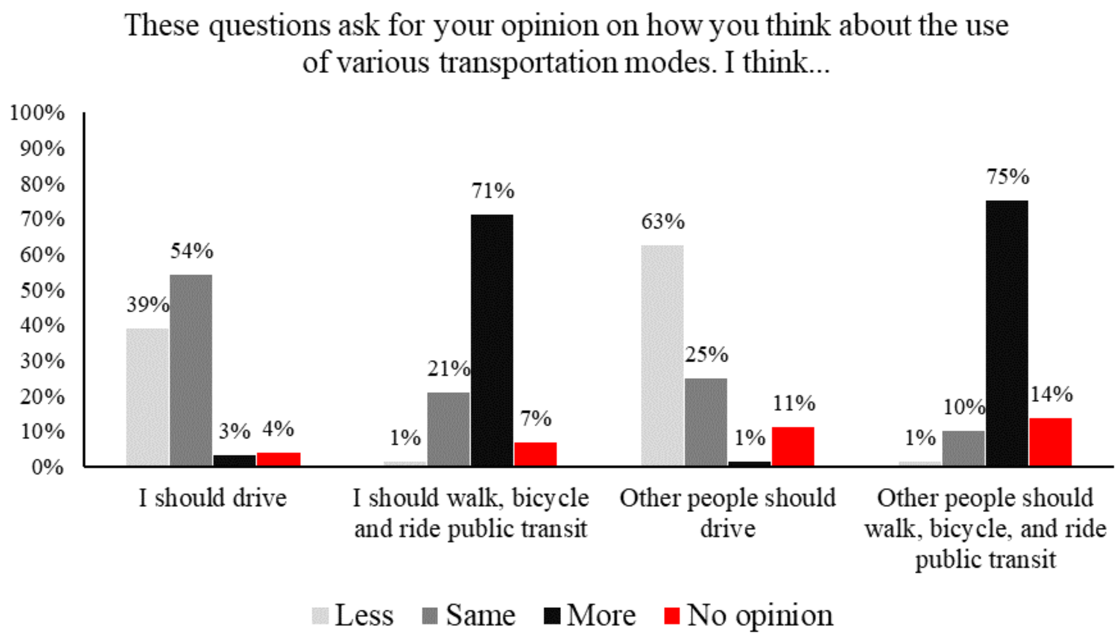
	Categorical		*Continuous*	
Variable	*#*	*%*	*Mean*	*SD*
Age				
18-24	45	14.02		
25-34	93	28.97		
35-44	69	21.50		
45-54	52	16.20		
55+	62	19.31		
Gender				
Female	171	53.27		
Male	150	46.73		
Race				
White-alone	303	94.39		
Non-white/multiple	18	5.61		
Household Income				
$10,000–$50,000	107	33.33		
$50,000–$75,000	96	29.91		
$75,000+	100	31.15		
Prefer not to say	18	5.61		
Education				
Below Undergrad	117	36.45		
Undergrad	127	39.56		
Graduate	77	23.99		
Student				
Yes	65	20.25		
No	256	79.75		
# adults per household			2.03	0.65
# bikes per household			3.21	1.96

4.3.3 Variables

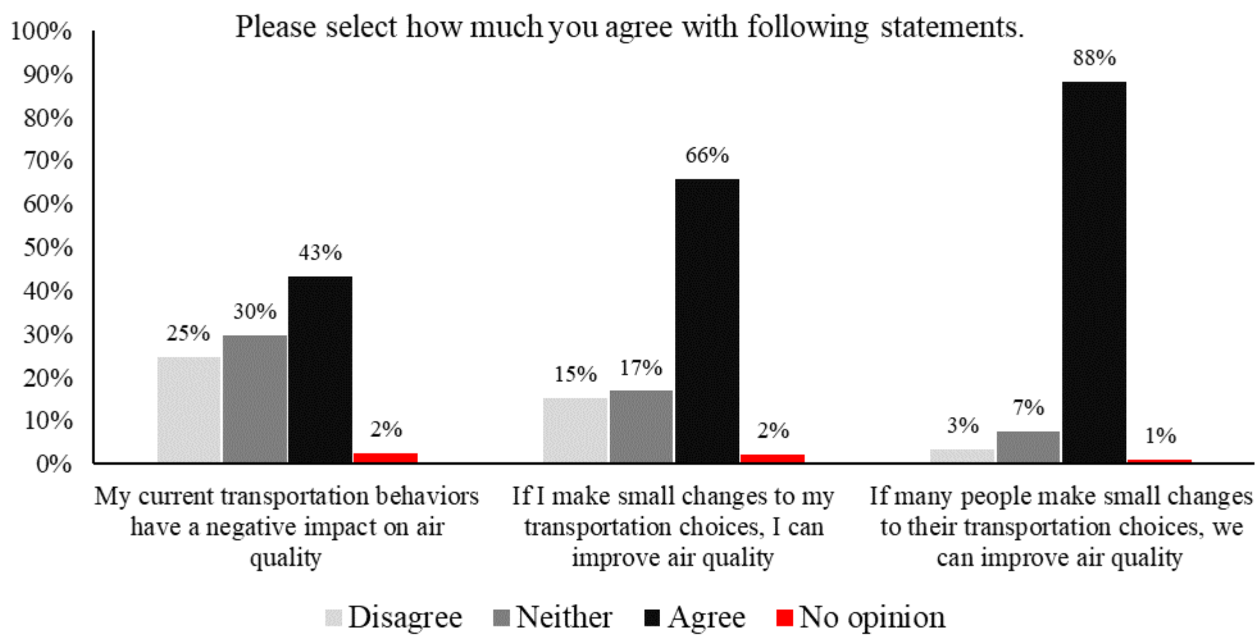
4.3.3.1 Attribution of Responsibility

The variables assigned to measure attribution of responsibility were divided into two sets on the final survey. The first set of questions asked about respondents' personal views on the use of different modes, primarily differentiating between driving (automobile) vs. other sustainable modes (walk, bicycle, and transit) as well as between their use vs. others' use. Responses were on a five-point scale {Much less, Somewhat less, About the same, Somewhat more, Much more}, with an additional "No opinion" option. The second set of questions asked respondents about their perceptions on the impacts of transportation choices on air quality. Respondents reported agreement/disagreement on a five-point scale {Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree}, again with a "No opinion" option with three statements (see Figure 4.1).

Together, these sets of questions measure an individual's perceptions of their use and others' use of various transport modes as well as the impacts of those choices on air quality. In other words, these questions cover both the aspects of internal and external attribution related to causation of air pollution. For each set of questions, the five ordinal response categories were collapsed into three categories (less, same, more; disagree, neither, agree) for simplification, as three categories are enough to provide the direction of responses (i.e., positive, neutral, and negative) for our analysis. The "No opinion" responses are conceptually different from the other response categories, in line with the philosophical stances espoused by Iannario et al. (2018). Therefore, we did not remove any of these no opinion responses to avoid reduction in sample size as well as to conduct further analysis of these responses. Figure 4.1 shows the percentages of responses for each of the attribution of responsibility questions. Most of the "No opinion" responses (>10%) were observed for questions concerned with other people's mode usage, whereas the frequencies of "No opinion" responses were very low (<2%) for questions relevant to impacts of transportation on air quality.



(a) Transport mode usage



(b) Impacts of transportation choices on air quality

Figure 4.1 Frequency of responses for items measuring attribution of responsibility

4.3.3.2 Psychological Variables

Other psychological variables—related to awareness of consequences, risk perception, and self-efficacy—were also measured in the final survey. Descriptive statistics for these variables are shown in Table 4.2.

Awareness of consequences—i.e., an individual's perception of how transportation impacts air quality—was captured by asking respondents to report agreement/disagreement with the following statement, "I think… Transportation is a major cause of air pollution" on a five-point scale {Strongly disagree, …, Strongly agree}, with a "No opinion" option.

Second, risk perception was measured by asking respondents, "In your opinion, how much does air pollution in Cache Valley negatively impact…" each of four items, measured on a 4-point scale {Not at all, A little, Moderately, A lot}, with a "No opinion" option. An exploratory factor analysis found that all items loaded on single factor and displayed high reliability (Cronbach's alpha = 0.87). For further analyses, this risk perception factor was then calculated as the average score of all four items.

For measuring self-efficacy, respondents reported their agreement/disagreement—on a five-point scale {Strongly disagree, …, Strongly agree}, with a "Not applicable" option—with six statements about their ability to use non-automobile transportation modes during different situations. The exact question was: "Please state how much you agree with following statements. I can use transportation methods other than my own car (such as walking, bicycling, or public transit)…" All six items loaded on single factor when conducting exploratory factor analysis and showed high internal consistency (Cronbach's alpha = 0.90). Like risk perception, the self-efficacy factor was calculated using mean scores of all the items.

4.3.3.3 Travel Behavior Responses

According to existing research findings, air quality conditions could influence individuals' travel behaviors (Doubleday et al., 2021; Li & Kamargianni, 2017). Hence, we measured stated willingness of individuals to engage in different travel behavior strategies during days with poor air quality conditions by asking "When the air quality in Cache Valley is bad, do you do any of the following?" and allowing respondents to select any/all from among seven options, one "Other" open-text option (that we re-coded), or "None of the above." Seven specific behaviors considered in this study are detailed in Table 4.2. For each of these three categories, the behavioral change score was the sum of the number of activities the respondents selected in each category.

Table 4.2 Properties of variables

Variables	*Items*	*Factor loadings*	*Mean*	*SD*
Awareness of consequences	I think… Transportation is a major cause of air pollution.		1.27	0.94
Risk perception	In your opinion, how much does air pollution in Cache Valley negatively impact…		3.21	0.80
	• Human health	0.71		
	• Animal health	0.87		
	• Plant health	0.83		
	• Water quality	0.74		
Self-efficacy	I can use transportation modes other than my own car (such as walking, bicycling, or public transit)…		2.99	1.03
	• Even when it is inconvenient.	0.76		
	• Even if it takes longer.	0.81		
	• Even when I am running late.	0.71		
	• Even when I am tired.	0.82		
	• Even when the weather is bad.	0.76		
	• Even when my regular schedule changes.	0.77		
Behavior change perceptions	When the air quality in Cache Valley is bad, do you do any of the following?			
Mode	• I carpool with others to work or school		0.43	0.74
	• I use public transit for some/all of my trips			
	• I walk or bicycle for some/all of my trips			
Trip	• I try to trip chain, grouping my errands into one trip instead of returning home after each one		1.02	0.90
	• I telecommute, working or studying at home			
	• I skip or postpone making some trips until the air quality is better			
Idling	• I make sure not to idle or keep my motor vehicle running when parked		0.57	0.50

4.3.4 Methods

We employed latent class analysis (LCA) (using the poLCA package in R), a probabilistic classification model, for our data analysis. The primary step of this method involves the creation of an unobserved classifier—or latent class(es)—based on responses to seven items (manifest variable) measuring attribution of responsibility. Here, we assumed that all seven items describe a single unobserved latent variable that is discrete in nature. This latent class step achieves our first objective: to identify segments of respondents based on their perceptions of mode choice usage and its impact on air quality. The regression step deals with identifying associations of latent classes and covariates or predictors, which include demographic and psychological variables (Harel et al., 2013), thus achieving our second objective.

4.4 Results

The first step in latent class regression analysis involves selecting the number of classes that provides the best model fit. The Bayesian information criterion (BIC) is the most common statistical tool used for choosing the number of latent classes. When testing various numbers of latent classes (i.e., from 2 to 10), the BIC value was minimized at three.

Examining this optimal solution, we see that most samples belonged to Class 1 (62%), with Class II (28%) and Class III (10%) comprising smaller groups. The clustering portion of the model also yields the response patterns of "attribution of responsibility" variables within each class, which can be observed by either the shares of question responses within each class (see Table 4.3) or by the conditional class membership probabilities (not shown here because it provides similar information as the frequency table). For example, for question ATT_4 ("Other people should walk, bicycle, and ride public transit…"), almost everyone in Class I reported "More," half of people belonging to Class II reported "More" while the other half reported "No opinion," and most Class III respondents responded with "About the same."

Table 4.3 Percentages of responses within each class

		Share of responses (%)		
Variables	*Response*	*Class I*	*Class II*	*Class III*
I should drive…	Less	**57.43**	10.34	0.00
	About the same	39.60	**75.86**	**87.50**
	More	2.97	2.30	6.25
	No opinion	0.00	11.49	6.25
I should walk, bicycle, and ride public transit…	Less	0.99	0.00	6.25
	About the same	15.35	10.34	**84.38**
	More	**83.17**	**66.67**	6.25
	No opinion	0.50	22.99	3.13
Other people should drive…	Less	**89.11**	18.39	15.63
	About the same	10.40	37.93	**81.25**
	More	0.00	3.45	3.13
	No opinion	0.50	**40.23**	0.00
Other people should walk, bicycle, and ride public transit…	Less	0.99	0.00	6.25
	About the same	0.99	0.00	**93.75**
	More	**98.02**	49.43	0.00
	No opinion	0.00	**50.57**	0.00
My current transportation behaviors have a negative impact on air quality.	Disagree	28.22	18.39	18.75
	Neither disagree/agree	21.78	**43.68**	**40.63**
	Agree	**50.00**	31.03	34.38
	No opinion	0.00	6.90	6.25
If I make small changes to my transportation choices, I can improve air quality.	Disagree	9.41	27.59	18.75
	Neither disagree/agree	6.44	29.89	**46.88**
	Agree	**83.66**	**35.63**	34.38
	No opinion	0.50	6.90	0.00
If many people make small changes to their transportation choices, we can improve air quality.	Disagree	0.50	8.05	9.38
	Neither disagree/agree	0.50	16.09	28.13
	Agree	**99.01**	**72.41**	**62.50**
	No opinion	0.00	3.45	0.00

Bold ~ Predominant response for each class

Based on response frequencies of attributional variables within each class (see Table 4.3), the three latent classes can be characterized as follows:

Class 1: High internal–high external attributors (62%): This group of individuals perceive that both themselves and others should curb the use of automobiles ("Less") in favor of non-polluting (walking/cycling) or more sustainable travel modes (public transit) ("More"). Furthermore, these people seem to acknowledge the role of their (and others') transportation choices on air quality, as shown by the high frequency of "Agree" responses on questions relating to impact of transportation choices on air quality. Relevant to this study, this group symbolizes high internal–high external attributors.

Class II: Moderate internal–moderate external attributors (28%): Individuals belonging to this class are more disinterested in reporting an opinion about other people's use of transportation modes, as observed by more frequent "No opinion" responses on all questions, especially those about other people's transport choices. This group also reports some preferences for use of active modes and public transit (although less strong than Class I) but thinks they should drive "About the same" as they are currently. Although they are split as to whether their own transportation choices/behaviors affect air quality, they do "Agree" that if they and other people improve transport choices, it would affect the air quality (although less so than Class I). In terms of attribution, this group represents moderate internal–moderate external attributors.

Class III: Low internal–low external attributors (10%): Individuals belonging to this class shoulder no responsibility toward increased/decreased usage of automobiles vs. more sustainable modes, as observed by "About the same" responses for first four set of questions on mode usage. Additionally, most people belonging to this class attribute the air quality problem to the transportation choices of others ("Neither agree/disagree"), rather than being accountable of their own transportation choices. In terms of attribution of responsibility, they can be thought of as low internal–low external attributors.

Meanwhile, the regression portion of the model yields information on the magnitude and direction of relationships between class membership and predictor variables: awareness of consequences, risk perception, self-efficacy, and socio-demographics. This is a polytomous logistic regression that identifies associations between predictors and class membership. The coefficients can therefore be interpreted as the log-odds of membership in a particular class with respect to a reference class for each variable, and the odds ratio can be calculated by exponentiating these coefficients. Class I was selected as the reference class and Table 4.4 reports only significant and marginally significant ($p < 0.10$) associations.

Table 4.4 Latent class regression results

Variables	*Class II (ref: Class I)*			*Class III (ref Class I)*		
	β	*SE*	*p*	β	*SE*	*p*
(Intercept)	**7.896**	**2.051**	**0.000**			
Education: Undergrad (ref: Below undergrad)	**-1.722**	**0.668**	**0.011**			
Gender: Male (ref: Female)	*0.788*	*0.438*	*0.073*			
Race: Non-white/multiple (ref: White)	*1.584*	*0.861*	*0.067*			
Awareness of consequences	**-1.106**	**0.280**	**0.000**	**-0.778**	**0.375**	**0.039**
Self-efficacy	**-0.674**	**0.239**	**0.005**			
Number of bicycles				*-0.556*	*0.291*	*0.058*

Note: **Bold** ~ p<0.05*, Italics* ~ p<0.1

To expound, only a few demographics were significant predictors in the model. Individuals with an undergraduate degree were more likely to be in Class I than those who were without an undergraduate degree. Similarly, males (compared with females) were more likely to be moderate internal–moderate external attributes than high internal–high external attributors. Compared with white individuals, non-white individuals and those reporting multiple races were more likely to be in Class II.

Switching gears, awareness of consequences, and self-efficacy were found to be significant predictors of class membership. Those who reported being highly aware of the impacts of transportation on air quality were more likely to belong to Class I than others. Similarly, those reporting higher self-efficacy to use active modes were more likely to be in Class I than Class II. Individuals with a greater number of bicycles in their household were also more likely to be high internal–high external attributors. Risk perceptions were not significantly associated with classes of attribution of responsibility.

Finally, to ascertain differences in the responses to questions about stated travel behavior modification strategies (during days of poor air quality) across the three classes, mean behavior change scores were first calculated, and the Kruskal-Wallis test was employed to reveal if the differences were significant or not. As seen in Table 4.5, behavior change scores were significantly higher for high internal–external attributors pertaining to all three behavior change strategies (mode, trip, and idling), moderate for moderate internal–moderate external attributors, and significantly lower for low internal–low external attributors.

Table 4.5 Mean behavior change scores across three classes

Variables	*Class I*	*Class II*	*Class III*	*Kruskal Wallis Chi-squared value*
Behavior change (Mode)	0.522	0.326	0.094	13.832*
Behavior change (Trip)	1.250	0.674	0.594	34.629*
Behavior change (Idling)	0.662	0.470	0.282	21.578*

Note: * ~ $p<0.05$

4.5 Discussion and Conclusion

Our study achieved the first objective—to identify heterogeneous classes of individuals based on how they view their (and other people's) transportation mode usages and the impact of those choices on air quality—by conducting latent class analysis on responses to seven questions that measure those perceived attributions of responsibility. We identified three classes of individuals: (i) Class I: high internal–high external attributors; (ii) Class II: moderate internal–moderate external attributors; and (iii) Class III: low internal–low external attributors. Individuals in Class I showed high preferences for their and other people's reduction in auto-driving and increase in use of walking/cycling and public transit, followed by moderate preferences of the same for Class II; whereas Class III individuals reported neither an increase or decrease in their or other people's usage of transport modes. We also observed that most of the "No opinion" responses were reported on questions that asked about other people's transport mode usages, which indicates a lack of interest in or unwillingness to judge others' behaviors. Similarly, although past research assumes that internal and external attributors are different in their perceptions and behaviors (Chang et al., 2016; Rickard, 2014; Tan & Xu, 2019), our study reveals that one can be a high internal attributor and a high external attributor at the same time. However, individuals in all classes seemed to agree that air quality could be improved by collective action and the individual transportation choices of many people. This is a common theme found in previous research as well, where causes and consequences of environmental threats are particularly diffused to groups of individuals (Bickerstaff & Walker, 2002).

From the latent class regression results, we identified significant factors that influenced class membership, thereby fulfilling our second research objective. First, only a few socio-demographic factors were influential, particularly education, gender, and race. Individuals with higher levels of education were likely to be high internal–high external attributors; past research has suggested that educated people are likely to place more value on conserving the environment (e.g., De Silva & Pownall, 2014). Male respondents were more relaxed about their transportation choices and their impacts on air quality, which is also in line with the existing findings that females are more likely to have pro-environmental feelings (e.g., Tan & Xu, 2019; De Silva & Pownall, 2014) and express higher levels of concern for risks caused by air pollution (Johnson, 2002). Similarly, there were racial differences in attribution of responsibility that could relate to the education effect mentioned earlier. Or this finding could be driven by differences in rates of active or public transportation usage—e.g., "I'm already driving less and using public transit more than others"—related to accessibility or air pollution burdens experienced by many communities of color (Heyer et al., 2020).

More importantly, the latent class regression also revealed associations between attribution of responsibility and psychological variables of interest. Those with increased awareness of transportation's consequences for air quality were more likely to be high internal–high external attributors, which supports existing findings that higher levels of awareness initiate personal and social accountability for risk creation (Bamberg & Moser, 2007; Ghazali et al., 2019). Interestingly, our analysis found no relationship between risk perception and class membership pertaining to attribution of responsibility. Although this finding is in contrast to some existing literature, other research has suggested no relationship between these variables (Bickerstaff & Walker, 2002). Perhaps there are some mediation effects of risk perception through self-efficacy, which rendered the variable insignificant in our model. First, due to regular exposure to poor air quality during winter (and the roles of geography and terrain), Cache Valley residents may develop a long-term perception that their transportation choices would not improve air quality conditions in any way. Another possible explanation is that risk perception questions discussed air quality in general, and the attribution of responsibility questions measured the transportation–air quality link. Since high self-efficacy was associated with being high internal–high external attributors, individuals who are more confident in using non-auto modes may perceive strong personal convictions that they (as well as others) can increase non-auto mode usage, curb auto usage, and consequently be able to make trip making decisions that can help improve air quality.

Finally, there were significant differences across the latent classes when asked about travel modification strategies individuals would adopt during days of poor air quality. Since the geography of Cache Valley aids the accumulation of particulate matters and other gases, it is difficult to control for the effects of geography, but policy actions could be taken to reduce driving during those times. Table 4.5 reveals that Class I individuals (high internal–high external attributors) would perform more beneficial travel behaviors than Class II and Class III. This implies that those who recognize they and others should select more non-auto travel behaviors are more interested in adopting travel modification strategies. Furthermore, across all classes, people were more likely to report trip-making changes (trip-chaining, rescheduling) than mode shifts (see Table 4.5). Perhaps, people would not revert to changes in travel modes (i.e., from auto driving to walking/cycling) to prevent themselves from air pollution exposure (i.e., feeling safer in encapsulated modes such as a car).

There are many policy implications that could be formulated based on the findings of our study. Our findings illustrate that almost 60% of people understand the impact of their transportation choices on air quality and are willing to shift to more sustainable modes (enthusiasts). This indicates benefits of policy measures providing adequate infrastructure for active modes like bike networks, adequate foot paths, and a more robust and reliable public transit service. Classifying Cache Valley residents according to their attribution of responsibility aids in finding target populations for specific advertising and communication strategies. As Class I individuals are more inclined to adopt travel behavior modification strategies, they should be targeted first, then the other classes. However, other advertising and marketing strategies regarding awareness and responsibility creation should target Class III people in an attempt to shift their attitudes toward environment sustainability. Awareness that transportation is a major cause of air pollution is another impacting factor, so tailored messages could be disseminated using different channels (e.g., TV, radio ads, messages at transit stops or on highway screens and billboards). Similarly, self-efficacy was found to influence causal attribution, so highlighting individual self-efficacy in response to air pollution might be beneficial. Similarly, our findings provide support to programs such as TravelWise (UDOT, 2017), which provides information regarding carpooling and trip chaining.

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5. INFLUENCES OF AREA-WIDE AIR QUALITY ON THE ACTIVITY AND TRAVEL BEHAVIOR OF URBAN, SUBURBAN, AND RURAL RESIDENTS OF NORTHERN UTAH

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5.1 Abstract

In this study, we explored whether and how area-wide air pollution affected individuals' activity participation and travel behaviors, and how these effects differed by neighborhood context. Using multi-day travel survey data provided by 403 adults from 230 households in a small urban area in northern Utah, U.S., we analyzed a series of 20 activity and travel outcomes. We investigated the associations of three different metrics of (measured and perceived) air quality with these outcomes, separately for residents of urban and suburban/rural neighborhoods and controlled for personal and household characteristics. Our models found some measurable changes in activity and travel patterns on days with poor air quality. In urban areas, people engaged in more mandatory (work/school) activities, whereas there was no discernible change in suburban/rural areas. The total travel time for urban residents increased, driven by increases in trip-making and travel time by public modes (bus) and increases in travel time by private modes (car). On the other hand, suburban/rural residents traveled shorter total distances (mostly through lower vehicle miles traveled), and there was a notable uptick in the probability of being an active mode user (walk/bike). Air quality perceptions also seemed to play a role, at least for urban residents who walked/biked longer distances, rode the bus for longer distances/times, and drove fewer miles on days with worse perceived air pollution. Overall, the results are somewhat encouraging, finding more evidence of altruistic than risk-averse travel behavioral responses to episodes of area-wide air pollution, although more research is needed.

5.2 Introduction

Despite plentiful knowledge about the effects of transportation on air quality (Caiazzo et al., 2013), research has rarely investigated the reverse link: How does air pollution or air quality perceptions affect individuals' travel behaviors? Such insights would be useful for evaluating and designing air quality improvement policy measures, including those that attempt to reduce polluting automobile use—and promote the use of active and sustainable modes (walking, bicycling, and public transit)—through "hard" and "soft" policies (Bamberg et al., 2011). Many policies are assumed to operate on and influence individuals and their transportation choices. Thus, knowledge of the effects of air pollution (and perceptions thereof) on individual-level travel behaviors is important. Furthermore, there are complex behavioral motivations at play during episodes of poor air quality: altruism (driving less and riding transit more to avoid contributing to air pollution) versus risk-aversion (walking and riding transit less to avoid exposure to air pollution) (Noonan, 2014). Studying travel behavioral sensitivities to air pollution advances understanding of decision-making under risk.

A limited but growing literature studies the effects of regional air quality levels on travel behaviors. Focusing just on U.S. research, findings are somewhat inconsistent and location-specific. While some studies find no significant change (or a modest decline) in motor vehicle traffic volumes on days with air quality alerts or elevated levels of air pollution, other research suggests that driving may increase on such days (Cummings & Walker, 2000; Cutter & Neidell, 2009; Tiwari et al., 2023). Ozone pollution alerts increased public transit usage in San Francisco (Cutter & Neidell, 2009) but not in Chicago (Welch et al., 2005). One fairly consistent finding (across four studies) is that high levels of air pollution tend to decrease active transportation, as measured by bicycle, pedestrian, and non-motorized trail counts (Tiwari et al., 2023; Doubleday et al., 2021; Holmes et al., 2009; Acharya & Singleton, 2022). However, all of the above-mentioned studies used secondary sources (traffic counts) and aggregate analyses of traffic volumes. These methods can only suggest (but not explain) why and how travel behaviors are affected by area-wide air pollution (if at all).

Instead, measuring individual-level travel behaviors could be more informative. Some limited travel survey-based research has been done in the U.S. Of two such studies in Atlanta, one found decreases in miles driven but not trips taken on ozone alert days (Henry & Gordon, 2003), while the other found that smog alerts did not significantly decrease household vehicle miles traveled (Noonan, 2014). Overall, most prior research has focused on summer ozone levels (rather than wintertime particulate matter) in a few large cities. Studying individual responses can also help control for some other personal and locational factors that contribute to heterogenous travel and activity behaviors. In particular, we anticipate that the influence of air quality on activity participation and travel behavior may differ across built environment contexts (e.g., urban and suburban/rural neighborhood types), as such areas have different transportation options and accessibilities to destinations that may facilitate or constrain behavioral responses to air pollution.

Our study's primary objective is to determine whether and how measured (or perceived) area-wide air pollution affects individuals' daily travel behaviors. A secondary objective is to assess how these associations differ by neighborhood type (urban vs. suburban/rural). To achieve these goals, we analyzed a series of activity participation and travel behavior outcomes taken from a multi-day travel diary survey (on winter days of varying air quality) in a small, urbanized area in northern Utah troubled by periodic high concentrations of PM2.5. In the following sections, we summarize our data and methods, and then discuss our results and interpret key findings.

5.3 Data and Methods

5.3.1 Study Area

Our study area is Cache Valley, a region in northern Utah characterized by its distinctive geography, situated at a high elevation between two mountain ranges. This unique topography creates ideal circumstances for wintertime temperature inversions, leading to a significant accumulation of particulate matter and other air pollutants in the lower atmosphere. Also, at the time of the study, Cache Valley was designated as a non-attainment area for PM2.5 (this status was removed in 2021). The region regularly experiences air pollution in winter, and its air quality is sometimes the worst in the state of Utah and even in the entire nation (Wang et al., 2015). Residents of Cache Valley often expect wintertime air pollution and air quality alerts (Utah DEQ, n.d.), and related travel demand management messages (UDOT, n.d.) are regularly distributed through local news media. Consequently, Cache Valley is an excellent location for studying the connections between travel behavior and air pollution because of how frequently elevated air pollution levels occur and the moderate awareness of this issue among the local population.

5.3.2 Data Collection

During the winter of 2019 (January–March), we conducted an online panel travel diary survey targeting households in Cache Valley. To ensure participants were recruited from a diverse range of built environment contexts, we first classified U.S. Census block groups into three strata—very urban, somewhat urban, and suburban/rural—based on their scores on four variables (housing unit density, intersection density, job access by automobile, and transit frequency) taken from the Smart Location Database version 2.0 (US EPA, 2018). Next, we used stratified random sampling to select block groups to fulfill our quotas of 2,000 households in each of the very and somewhat urban groups, and 4,000 households in the suburban/rural group. Finally, we obtained residential addresses for the selected block groups, and mailed each housing unit a paper letter containing a description of the study and a website link to register every adult member of the household.

The data collection process was organized into three distinct phases.

1. **The initial survey:** Once participants enrolled in the study, they were asked to answer a set of questions regarding household composition, demographics, and transportation-related information.
2. **Travel diary surveys:** In the second phase, participants were required to complete three rounds of two-day travel diary surveys. We strategically scheduled these rounds over the course of several weeks to attempt to encompass a range of (good, moderate, and unhealthy) air quality conditions using day-ahead air quality forecasts. (In this way, we tried to take advantage of a natural experiment.) During this phase, each participant recorded detailed information about every trip undertaken on the survey day, including departure and arrival times, modes of transportation, locations, and trip purposes.
3. **Final survey:** Following the completion of the travel diary surveys, each participant was asked to participate in a final survey. This survey asked questions about various psycho-social factors, such as attitudes, values, and norms related to transportation choice and air quality. We did not use the responses from the final survey in this paper's analyses.

Invitations were sent to 8,376 households. From this, 255 households (consisting of 479 adults) completed the initial survey, a response rate of 3%. In the end, 189 households (337 adults) completed the final survey, for a 25%–30% attrition rate. The analyses presented here contain responses by 403 adults from 230 households, including anyone who completed at least one travel diary survey. For more details on the data collection effort see Humagain and Singleton (2021).

5.3.2.1 Dependent Variables

The dependent variables (DVs) in this study were measures of activity participation and travel behavior derived from the self-reported online travel diaries. We performed a significant amount of data cleaning on the survey responses, removing duplicate and incomplete entries, geocoding places, and calculating travel times and distances traveled using several Google Maps APIs. From the cleaned travel diary data, we constructed daily totals of each individual's activity participation—the number of out-of-home activities by activity category (mandatory, discretionary, or semi-mandatory/discretionary)—and travel behaviors: the number of trips made, distance traveled, and travel time, all segmented by mode category (active, public, private). These categories are defined in Table 5.1.

At the end of this process, we realized that many of our DVs had a preponderance of zeros due to either not traveling on the survey day or not using certain modes. Therefore, we constructed a series of sequential DVs, where earlier activity/travel decisions split the data, and models of later outcomes only used a subset of the data. The first binary DV was whether or not the respondent stayed at home (did not travel). Next, if false (did travel), a series of DVs represented daily activity participation and all-mode travel outcomes. Three binary DVs then assessed whether or not the respondent used each mode category. Finally, if true, the three remaining travel outcome DVs (trips, distance traveled, travel time) were calculated for people who did use each mode. Table 5.1 presents sample sizes and descriptive statistics for each of the study's 20 DVs.

Table 5.1 Descriptive statistics of the dependent variables

		Categorical		*Continuous*	
Dependent variable	*N*	*Freq*	*Perc*	*Mean*	*SD*
Stayed at home (did not travel)	2,044				
True		220	10.76		
False		1,824	89.24		
Activity participation (#)	1,824				
Total out-of-home				2.56	1.74
Mandatory[a]				1.01	0.90
Semi-mandatory/discretionary[b]				0.74	1.20
Discretionary[c]				0.82	1.14
Travel outcomes, all modes	1,824				
Number of trips (#)				4.32	2.43
Distance traveled (miles)				25.23	47.94
Travel time (minutes)				65.73	56.84
Used mode on travel day	1,824				
Active modes: True		295	16.17		
False		1,529	83.83		
Public modes: True		151	8.28		
False		1,673	91.72		
Private modes: True		1,703	93.37		
False		121	6.63		
Active mode[d] users	295				
Number of trips (#)				2.31	1.32
Distance traveled (miles)				4.66	20.33
Travel time (minutes)				34.83	28.89
Public mode[e] users	151				
Number of trips (#)				1.65	0.69
Distance traveled (miles)				5.70	11.56
Travel time (minutes)				23.64	21.82
Private mode[f] users	1,703				
Number of trips (#)				4.08	2.39
Distance traveled (miles)				25.71	48.48
Travel time (minutes)				62.27	57.78

[a] Mandatory activities include: work, school, work- or school-related
[b] Semi-activities include: civic or religious, drop off or pick up passenger, other errands or appointments, service private vehicle
[c] Discretionary activities include: eat meal at restaurant, social or entertainment, outdoor or indoor exercise, shopping
[d] Active modes include: walk, bicycle
[e] Public modes include: school bus, local bus
[f] Private modes include: car/van/truck/SUV driver or passenger, motorcycle/scooter/moped

5.3.2.2 Independent Variables

Given this study's focus on air pollution, we used several different air quality metrics as independent variables (IVs). Measured air quality was assessed using the Air Quality Index (AQI), a 0–500 measure of air pollution concentrations (AirNow, n.d.). To examine potential non-linear effects, we also categorized

AQI based on the well-publicized colors: green ("good" AQI = 0–50), yellow ("moderate" AQI = 51–100), and orange ("unhealthy" AQI = 101+). Despite our best attempts to capture a range of air quality conditions, most observations occurred on days with green or yellow air. Perceived air quality was measured by a response at the end of each travel diary survey, where respondents rated the air quality on a 1–5 scale (1 = great, good, fair, bad, 5 = terrible). AQI and perceived air quality were positively but not perfectly correlated (0.30). Together, these three air quality IVs (AQI number, AQI category, perceived air quality) were used to investigate variations in the relationships with the activity and travel behavior DVs.

Although not the primary focus of this study, we also considered as IVs other control variables pertaining to respondents' personal and household characteristics. Personal characteristics included self-reported age, race/ethnicity, gender, educational attainment, and student and worker statuses. Household characteristics included housing type, household income, household composition (children, adults), and mobility tools (bicycles, motor vehicles). Table 5.2 shows descriptive statistics for the IVs.

Additionally, we included home neighborhood type as a binary measure of the built environment; this was based on our block group sampling strategy (very/somewhat urban vs. suburban/rural) discussed earlier. Figure 5.1 maps the neighborhood type of the Census block groups that contained the home locations of study participants.

Table 5.2 Descriptive statistics of the independent variables

	Categorical		Continuous	
Independent variable	*Freq*	*Perc*	*Mean*	*SD*
Household characteristics				
Housing type: Single-family	304	75.62		
Multi-family	98	24.38		
Household income: < $35,000	96	24.00		
$35,000 to $74,999	158	39.50		
≥ $75,000	122	30.50		
Unknown	24	6.00		
Number of children			0.98	1.36
Number of adults			2.02	0.64
Number of bicycles			2.08	1.91
Number of motor vehicles			1.96	0.90
Neighborhood type[a]: Urban	237	58.81		
Suburban or rural	166	41.19		
Personal characteristics				
Age: 18 to 34 years	182	45.61		
35 to 54 years	132	33.08		
≥ 55 years	85	21.30		
Race/ethnicity: White-alone	368	92.93		
Non-white or multiple	28	7.07		
Gender: Male	190	47.50		
Female	210	52.50		
Education: Less than bachelor's	157	39.15		
Bachelor's degree or higher	244	60.85		
Student: No	313	78.05		
Yes	88	21.95		
Worker: Yes	304	75.81		
No	97	24.19		
Air quality measures				
Air Quality Index (AQI)			47.77	21.14
Green (0 – 50)	1,008	49.32		
Yellow (51 – 100)	1,013	49.56		
Orange (101 – 150)	23	1.13		
Perceived air quality[b]			2.51	0.94

[a] Classification of block groups based on housing unit density, intersection density, job access by automobile, transit frequency
[b] Rating of air quality, 1 = great, 5 = terrible

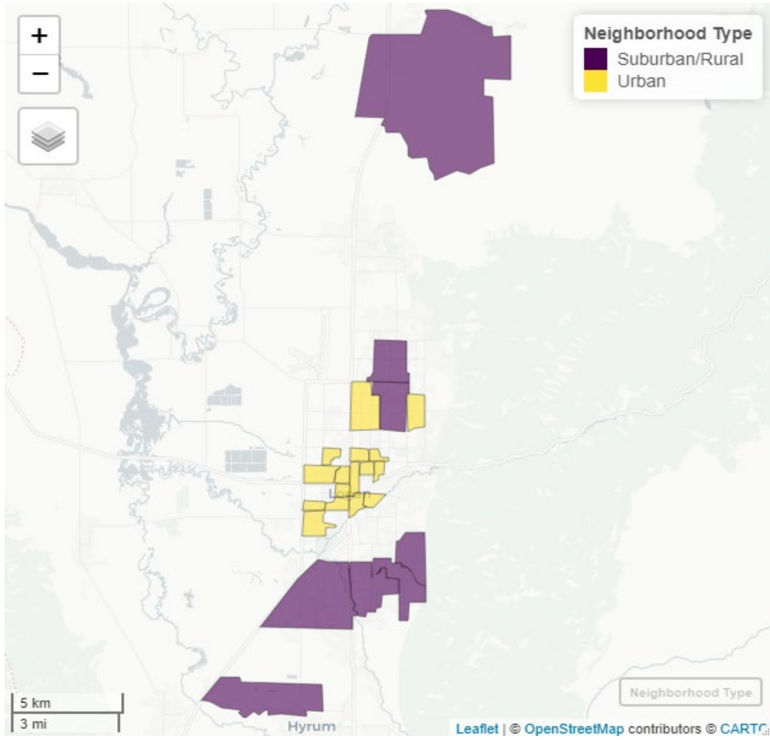

Figure 5.1 Map of sampled Census block groups by neighborhood type

5.3.3 Analysis Methods

As described earlier, we used 20 different DVs representing different activity and travel outcomes. Three different types of statistical models were applied depending on the type of DV.

- For each of the continuous DVs (distance traveled, travel time), we used a log-linear regression model. In this model, the original DV is transformed using the natural log, which we found to better fit our data and yield a more normal distribution. We also added 1 to the travel outcomes before taking the natural log, to avoid issues where ln 0 is undefined, and to avoid negative outputs.
- For each of the binary DVs (stayed at home, used each mode), we applied logistic regression, also known as the binary logit model.
- For each of the count DVs (number of activities, number of trips), we started by considering the Poisson regression model, a common choice for modeling non-negative integer values. However, the Poisson model assumes that the variance is equal to the mean, which is not always realistic. Instead, one can allow for over-dispersion (variance > mean) by adding an extra parameter to the variance equation that is either a linear or quadratic function of the mean, resulting in the quasi-Poisson or negative binomial models, respectively. We tried all three options and found that the quasi-Poisson models had better fits to the data, so we used quasi-Poisson regression for all count DVs.

Finally, we must mention that we actually estimated three sets of models, one set for each of the ways of representing air quality (AQI number, AQI category, perceived air quality). Also, to clarify, we interacted the air quality variables with our neighborhood type variable. Doing this allowed us to investigate how different types of neighborhoods (urban vs. suburban/rural) influence the manner in which air quality affects travel behavior changes.

5.4 Results and Discussion

5.4.1 Overall Results

Table 5.3 presents abbreviated model results—only the signs of statistically significant coefficients—for the 20 models (one for each of the activity participation and travel behavior DVs) containing the AQI representation of air quality. We also inspected model results for those using AQI category and perceived air quality; the abbreviated results are virtually identical for non-air quality IVs. More detailed results for the various air quality measures are contained in the next section. Here, we briefly report some key findings for the other household and personal characteristic IVs since they are not core to the study's objective. (Full model results are available from the authors upon request.)

Compared with people living in single-family detached houses, people living in multi-family housing participated in fewer mandatory activities but more semi-mandatory/discretionary and discretionary activities (and more total activities). They also tend to make more private mode (and total all) trips and have higher distance traveled for public modes. On the other hand, the number of trips by active modes and the odds of using public modes were lower for residents of multi-family housing.

Income level also played a significant role in travel behaviors (but not activity participation). Respondents in lower-income (< \$35,000) households were more likely to stay at home. If they did travel, they were more likely to use private modes (automobile driver or passenger) as their transportation means. They also made a higher number of trips with public modes. Meanwhile, members of lower-income households tended to travel less in both time and distance (overall, and for private modes). Lower-income active mode users made fewer trips and traveled shorter distances and for less time, while lower-income public mode users actually made more trips. In comparison, there were fewer associations for people in high-income households (≥ \$75,000). These individuals had higher total distance traveled by all modes. Also, members of high-income households took fewer trips by active and public modes if they were users of these modal categories.

Household composition also affected activity participation and travel behaviors. People in households with more children participated in more total activities—especially semi-mandatory/discretionary—but fewer mandatory activities. Compared with people with fewer children, these individuals made more trips and had higher distance traveled and travel time across all modes. Also, they tended to use private mode more and active and public modes less. However, among respective mode users, people in households with more children had higher distance traveled by active modes, higher travel distance and time by public modes, and more trips/distance/time using private modes. In contrast, having more adult members of the household was associated with a greater chance of staying home. The total number of activities (including mandatory and discretionary activities) tended to be less for this group. Besides, total distance traveled and travel time was also less for them. Regarding private modes, the number of trips, distance traveled, and travel time tended to be less for people in households with more adults. Interestingly, the odds of using public modes increased with the number of adults.

Table 5.3 Abbreviated model results for models with AQI

		Activities				*All modes*			*Active modes*				*Public modes*				*Private modes*			
Variable	*SH*	*T*	*M*	*S*	*D*	*NT*	*DT*	*TT*	*U*	*NT*	*DT*	*TT*	*U*	*NT*	*DT*	*TT*	*U*	*NT*	*DT*	*TT*
Housing type: Multi-family		+	−	+	+	+				−			−		+			+		
Household income: < \$35,000	+						−	−		−	−	−		+			+		−	−
≥ \$75,000							+			−				−						
Unknown		+				+	+					−						+	+	
Number of children		+	−	+		+	+	+	−		+		−		+	+	+	+	+	+
Number of adults	+	−	−		−		−	−					+					−	−	−
Number of bicycles	−					+		+	+		+		+				−			
Number of motor vehicles	−		+				+		−		−		−				+		+	+
Age: 35 to 54 years		+	−	+		+				−	−	−	−		−		+	+		
≥ 55 years		+	−	+	+	+				−			−	−	−			+		+
Race/ethnicity: Non-white or multiple			−	+				−	−	−			−			+				
Gender: Female		+	−	+	+	+	−		+				−		−	−		+	−	−
Education: Less than bachelor's	+	−		−		−	−	−	−	+					−			−	−	
Student: Yes	−	+	+	−	−	+		+	+	−	+		+				−			
Worker: No	+	+	−	+	+	+			−	−	−	−	−					+		
Neighborhood type: Suburban or rural							+	+	−		−	−	−				+		+	+
AQI: Urban			+					+						+		+			+	+
AQI: Suburban or rural							−		+			+							−	

Statistical significance: + $p < 0.10$ and $B > 0$, − if $p < 0.10$ and $B < 0$; blank if $p > 0.10$.
SH = stay at home; T = total, M = mandatory, S = semi-mandatory/discretionary, D = discretionary
U = user, NT = number of trips (#), DT = distance traveled (miles), TT = travel time (minutes)

The holding of more mobility tools like bicycles or motor vehicles was linked to some activity and travel outcomes. People with access to more bicycles and more motor vehicles were less likely to stay at home. Individuals with access to bicycles had a higher total number of trips and total travel time, and individuals with access to motor vehicles had a higher total distance traveled. Those in households with more bicycles were more likely to use active and public modes and less likely to use private modes. They also traveled longer distances using active modes. In contrast, individuals with access to more motor vehicles traveled longer distances overall, were less likely to use active or private modes, and were more likely to use private modes. Also, the distance traveled and travel time via private modes were higher. Regarding activities, individuals with access to motor vehicles participated in more mandatory activities.

Regarding age effects on activity participation and travel behaviors, compared with younger adults (below 35), middle-aged and older adults participated more in total activities, especially more semi-mandatory/discretionary, and fewer mandatory activities. Additionally, individuals older than 55 years participated in more discretionary activities. Both groups had a higher total number of trips. Increased age seemed to be correlated with reduced trip-making by active modes, a decrease in the odds of using public modes, and shorter distance traveled by public modes. Additional age-related results include fewer trips by public modes and longer travel time by private mode for adults older than 55 years, as well as shorter distances traveled and travel times by active mode.

Differences were observed in activity/travel behaviors based on self-identified race/ethnicity. People selecting one or more non-white racial/ethnic categories tended to participate in fewer mandatory and more semi-mandatory/discretionary activities, spent less time traveling in total, and used active and public modes less. Also, the number of trips by active mode decreased for these individuals, and they spent more time traveling using public modes.

Gender also had an impact on activity participation and travel behavior. People identifying as female did fewer mandatory activities and more semi-mandatory (discretionary) and discretionary activities (and total activities overall). While women made more total trips, those trips tended to be shorter (shorter total distance traveled); the same trend was true for women automobile users with shorter travel distances and times. Women were more likely to use active modes and less likely to use public modes. The distance traveled and time by public mode were also less for women than for men.

Some effects were found for educational attainment. Respondents without a bachelor’s degree were more likely to stay at home, and those who traveled made fewer total and semi-mandatory/discretionary trips. They also spent less time traveling, traveled shorter distances, and made fewer trips overall. Meanwhile, they were less likely to use active transportation modes, but if they used it, they made more trips by active modes. These individuals traveled shorter distances with public modes and had fewer trips and shorter distance traveled with private modes.

Student and worker status indicators were also connected to activity and travel outcomes. Students were less likely to stay at home and tended to do more mandatory and total activities but fewer semi-mandatory/discretionary or discretionary activities. They had more trips and longer travel time overall. Students were also more likely to use active and public modes and less likely to use private modes. Regarding active modes, the number of trips for students was less but they traveled longer distances. Non-workers were more likely to stay at home, and those who did travel tended to have a higher participation in activities overall; specifically, they participated in more semi-mandatory/discretionary and discretionary activities but fewer mandatory activities. While non-workers made more total trips than workers, they used active and public modes less. They made fewer trips, traveled shorter distances, and had shorter travel times by active modes. The only travel behavior that seemed to be elevated for this group was the number of trips by private modes.

Lastly, the neighborhood type of people's homes resulted in some significant differences in travel behaviors. Compared with urban residents, people living in more suburban or rural neighborhoods traveled longer distances and spent more time traveling overall. They used active and public modes less and private modes more. While they traveled longer distances and spent more time traveling by private mode, these trends were the opposite for active modes.

The following section describes and discusses results for air quality in more detail.

5.4.2 Air Quality Results

Table 5.4, Table 5.5, and Table 5.6 present more complete results (coefficient estimates B and p-values) for the air quality measures in all of the models for all respondents, residents of urban areas, and residents of suburban/rural areas, respectively: the 20 DVs and the three air quality metrics (AQI number, AQI category, perceived air quality). Note that the two middle columns (AQI: yellow and orange) contain coefficients for the two AQI color categories (green as the base category) from the same set of models. In the following paragraphs, we interpret and discuss the air quality results for each type or set of activity/travel behavior outcomes. We focus on the results from the second (urban) and third (suburban/rural) tables since a major objective is observing differences for residents of different neighborhood types.

To begin, there were no significant associations between air quality and whether or not someone stayed at home or traveled for both urban and suburban/rural areas. Although not significantly different from zero ($p = 0.10$), the magnitude of the estimated coefficient for orange AQI among urban residents was fairly large, suggesting that people who experienced an orange air quality day were almost four times as likely to stay at home (odds ratio $OR = e^B = 3.98$) than on a day with green air quality. Recall that this situation reflects only 1% of the person-day observations in the dataset, so the study may have lacked the power to detect a significant effect for this (and other) outcomes on orange days.

There were few consistent patterns of association found between measures of air quality and activity participation. In both urban and suburban/rural areas, total activities as well as semi-mandatory/discretionary activities did not seem to be linked to air quality. The only significant associations were for mandatory activities (work and school) in urban areas; the models showed positive associations with AQI number and yellow AQI, implying that people tended to participate in slightly more mandatory activities on days with more air pollution or on yellow (vs. green) air quality days. Specifically, in urban areas, the model predicts a 3% increase in mandatory activities for every 10-point increase in AQI ($e^{10B} = 1.03$), and 17% greater participation in mandatory activities on yellow days compared with green days ($e^B = 1.17$). We are unsure how to explain this finding. In northern Utah, air pollution levels often start to elevate during clear days after a snowstorm, so it could be that some workers or students were not commuting on snowy days and started to on clear days when the air quality turned to yellow. While not significant, it is notable that the estimated coefficients among urban residents for discretionary activities were negative in all of the models. If true, this could imply that, on days with elevated levels of perceived or measured air pollution, people tend to forego discretionary activities like shopping, eating out, or indoor/outdoor exercise. This would match our expectation that the need for and scheduling of discretionary activities is more flexible; they could be shifted to other (better air quality) days or even canceled. Urban residents have more flexibility due to greater accessibility.

Table 5.4 Model results for air quality measures (all)

		AQI		*AQI: Yellow*		*AQI: Orange*		*Perceived AQ*	
Dependent variable	*Model*[a]	*B*	*p*	*B*	*p*	*B*	*p*	*B*	*p*
Stayed at home (did not travel)	BL	0.00115	0.766	-0.0661	0.685	0.8612	0.246	-0.0158	0.863
Activities: Total out-of-home	QP	0.00033	0.669	0.0203	0.519	-0.1450	0.464	-0.0106	0.550
Mandatory	QP	**0.00213**	**0.026**	**0.1172**	**0.003**	-0.1265	0.605	0.0034	0.880
Semi-mandatory/discretionary	QP	-0.00061	0.734	-0.0787	0.285	0.1117	0.800	0.0056	0.893
Discretionary	QP	-0.00108	0.479	-0.0118	0.851	-0.3884	0.362	-0.0397	0.266
Number of trips (#): Total	QP	0.00071	0.256	0.0293	0.256	0.0050	0.973	-0.0039	0.784
Distance traveled (miles): Total	LL	-0.00070	0.535	-0.0160	0.730	*-0.4548*	*0.083*	-0.0133	0.608
Travel time (minutes): Total	LL	0.00076	0.345	0.0466	0.161	-0.1769	0.347	0.0128	0.492
Active mode user	BL	0.00576	0.109	**0.3308**	**0.029**	0.1913	0.828	-0.0847	0.313
Number of trips (#)	QP	0.00122	0.406	-0.0474	0.448	*0.4168*	*0.057*	-0.0230	0.508
Distance traveled (miles)	LL	-0.00102	0.638	-0.0756	0.402	-0.1674	0.678	**0.1309**	**0.007**
Travel time (minutes)	LL	0.00143	0.554	-0.0393	0.695	0.5613	0.211	-0.0269	0.624
Public mode user	BL	-0.00261	0.620	-0.0916	0.672	1.2524	0.177	0.0905	0.453
Number of trips (#)	QP	**0.00338**	**0.026**	0.0925	0.167	*0.4744*	*0.055*	0.0377	0.328
Distance traveled (miles)	LL	0.00198	0.389	0.0329	0.738	0.2740	0.490	**0.1615**	**0.003**
Travel time (minutes)	LL	**0.00742**	**0.007**	0.1606	0.179	0.6850	0.154	*0.1172*	*0.082*
Private mode user	BL	-0.00564	0.282	-0.0234	0.915	**-2.1170**	**0.027**	0.0209	0.866
Number of trips (#)	QP	0.00079	0.232	0.0253	0.350	0.0367	0.846	0.0024	0.875
Distance traveled (miles)	LL	-0.00014	0.903	-0.0009	0.985	-0.5088	0.119	-0.0341	0.208
Travel time (minutes)	LL	0.00099	0.261	0.0519	0.148	-0.3058	0.210	0.0221	0.274

[a] Models: BL = binary logit, QP = quasi-poisson, LL = log-linear

Bold if p<0.05; *italics* if p<0.10.

Table 5.5 Model results for air quality measures (urban)

Dependent variable	*Model*[a]	*AQI* *B*	*p*	*AQI: Yellow* *B*	*p*	*AQI: Orange* *B*	*p*	*Perceived AQ* *B*	*p*
Stayed at home (did not travel)	BL	-0.00115	0.815	-0.2439	0.248	1.3821	0.104	-0.1458	0.221
Activities: Total out-of-home	QP	0.00036	0.724	0.0376	0.374	-0.1241	0.633	-0.0053	0.814
Mandatory	QP	**0.00331**	**0.007**	**0.1601**	**0.002**	0.0771	0.798	0.0256	0.349
Semi-mandatory/discretionary	QP	-0.00022	0.931	-0.0592	0.572	0.0464	0.938	-0.0090	0.872
Discretionary	QP	-0.00310	0.138	-0.0534	0.529	-0.5475	0.364	-0.0640	0.168
Number of trips (#): Total	QP	0.00068	0.415	0.0404	0.238	0.0773	0.681	-0.0015	0.932
Distance traveled (miles): Total	LL	0.00146	0.332	0.0216	0.726	-0.2633	0.450	-0.0368	0.266
Travel time (minutes): Total	LL	**0.00260**	**0.016**	**0.0922**	**0.037**	0.0815	0.744	-0.0011	0.964
Active mode user	BL	0.00291	0.477	0.1226	0.470	0.4138	0.681	-0.1416	0.129
Number of trips (#)	QP	0.00087	0.574	-0.0526	0.433	*0.4158*	*0.058*	-0.0500	0.172
Distance traveled (miles)	LL	-0.00184	0.426	-0.1272	0.190	-0.1761	0.661	**0.1289**	**0.016**
Travel time (minutes)	LL	-0.00001	0.996	-0.0907	0.401	0.5526	0.218	-0.0693	0.246
Public mode user	BL	-0.00386	0.498	-0.1625	0.492	1.3158	0.172	0.0741	0.569
Number of trips (#)	QP	**0.00374**	**0.022**	0.0938	0.195	*0.4753*	*0.056*	0.0516	0.222
Distance traveled (miles)	LL	0.00119	0.626	0.0125	0.906	0.2590	0.516	**0.1449**	**0.014**
Travel time (minutes)	LL	**0.00874**	**0.003**	0.2069	0.106	0.7188	0.135	**0.1430**	**0.050**
Private mode user	BL	-0.00417	0.447	0.0792	0.731	**-2.3259**	**0.025**	0.0300	0.816
Number of trips (#)	QP	0.00109	0.237	0.0505	0.175	0.1816	0.543	0.0143	0.474
Distance traveled (miles)	LL	*0.00271*	*0.097*	0.0475	0.467	-0.1368	0.808	**-0.0709**	**0.044**
Travel time (minutes)	LL	**0.00358**	**0.003**	**0.1202**	**0.014**	-0.0163	0.969	0.0169	0.520

[a] Models: BL = binary logit, QP = quasi-poisson, LL = log-linear

Bold if p<0.05; *italics* if p<0.10.

Table 5.6 Model results for air quality measures (suburban/rural)

		AQI		*AQI: Yellow*		*AQI: Orange*		*Perceived AQ*	
Dependent variable	*Model*[a]	*B*	*p*	*B*	*p*	*B*	*p*	*B*	*p*
Stayed at home (did not travel)	BL	0.00487	0.432	0.1995	0.439	-11.7318	0.973	0.1746	0.221
Activities: Total out-of-home	QP	0.00028	0.806	-0.0013	0.979	-0.1725	0.574	-0.0185	0.507
Mandatory	QP	0.00039	0.798	0.0526	0.404	-0.4436	0.293	-0.0408	0.289
Semi-mandatory/discretionary	QP	-0.00096	0.698	-0.0978	0.346	0.2032	0.759	0.0228	0.707
Discretionary	QP	0.00127	0.570	0.0394	0.676	-0.2040	0.735	-0.0051	0.927
Number of trips (#): Total	QP	0.00074	0.428	0.0147	0.708	-0.1085	0.660	-0.0078	0.736
Distance traveled (miles): Total	LL	**-0.00336**	**0.045**	-0.0645	0.358	*-0.7055*	*0.077*	0.0236	0.569
Travel time (minutes): Total	LL	-0.00152	0.206	-0.0123	0.807	*-0.5154*	*0.071*	0.0347	0.243
Active mode user	BL	**0.01538**	**0.038**	**1.1431**	**0.001**	-10.9696	0.974	0.1642	0.392
Number of trips (#)	QP	0.00409	0.342	-0.0120	0.945	NA	NA	0.1595	0.100
Distance traveled (miles)	LL	0.00444	0.443	0.2397	0.316	NA	NA	0.1419	0.267
Travel time (minutes)	LL	*0.01103*	*0.087*	0.2745	0.303	NA	NA	0.2085	0.147
Public mode user	BL	0.00506	0.715	0.2755	0.610	-10.0092	0.985	0.1884	0.550
Number of trips (#)	QP	0.00080	0.858	0.0845	0.638	NA	NA	-0.0358	0.715
Distance traveled (miles)	LL	0.00811	0.246	0.1748	0.531	NA	NA	*0.2666*	*0.071*
Travel time (minutes)	LL	-0.00292	0.724	-0.1606	0.632	NA	NA	-0.0457	0.802
Private mode user	BL	-0.02058	0.231	-1.1664	0.166	9.4508	0.986	-0.0991	0.828
Number of trips (#)	QP	0.00047	0.617	-0.0033	0.934	-0.0570	0.816	-0.0139	0.552
Distance traveled (miles)	LL	*-0.00320*	*0.058*	-0.0576	0.416	*-0.7111*	*0.076*	0.0181	0.665
Travel time (minutes)	LL	-0.00179	0.156	-0.0281	0.594	-0.4728	0.114	0.0295	0.345

[a] Models: BL = binary logit, QP = quasi-poisson, LL = log-linear

Bold if p<0.05; *italics* if p<0.10. NA if the coefficient was unable to be estimated due to the small sample size.

The air quality metrics showed links with a few total (all-mode) travel behavior outcomes. In urban areas, the only (marginally) significant association was between AQI and yellow AQI days with travel time. Specifically, the model predicts a 10% increase in total travel time ($e^{B} = 1.10$), on average, when comparing yellow with green air quality days, or a 3% increase ($e^{10B} = 1.03$) for every 10-point increase in AQI. In suburban/rural areas, there were significant associations between AQI number and orange AQI days for distance traveled and travel time (marginally significant). The model predicts a 3% reduction in total miles traveled for every 10-point increase in AQI ($e^{10B} = 0.97$), and a 50% reduction in total miles traveled (e^{10B} =0.49) on orange days. Meanwhile, there was a marginally significant association between orange AQI days and travel time in suburban/rural areas. The model results predict a 40% decrease in total travel time for orange AQI days ($e^{10B} = 0.60$). These are substantial declines that (as seen later) appear to be being driven by large decreases in travel amounts for private (automobile) modes among suburban/rural residents. If true, this would be quite promising evidence for efforts to reduce emissions from polluting modes on days with poor air quality. However, recall that the sample size for this orange situation is quite low: only 23 person-days.

Turning to active modes of transportation (walking and bicycling), some results were significant. In urban areas, the models present some evidence that the use of active modes increased on days with worse AQI. Among active travelers, the model showed large-magnitude increases in travel on orange air quality days: 51% more trips ($e^{B} = 1.52$). The model also shows that distance traveled by active modes increased on days with poorer perceived air quality. Specifically, urban residents walked or bicycled 14% more ($e^{B} = 1.14$) on days with one-point worse air quality (on a five-point scale). For residents of suburban/rural areas, the models' results also show some evidence that the use of active modes increased on days with worse air pollution. Specifically, these respondents had 17% greater odds ($OR = 1.17$) of using active modes for every 10-point increase in AQI, or more than three times as likely ($OR = 3.14$) on yellow as compared with green air quality days. The models' results also show an average 12% increase ($e^{10B} = 1.12$) in travel time spent walking or biking for a 10-point increase in AQI. There were also positive (albeit not statistically significant) associations between active mode use and perceived air pollution among suburban/rural residents. Overall, these results appear to support an altruistic response to air pollution, although the magnitudes of the effects on orange days should be viewed with caution. Also, the results appear to suggest different responses by neighborhood type: suburban/rural residents were more likely to be active mode users, while urban residents were more likely to increase their use of active modes.

Model results for public transit modes (bus only) in urban areas imply similar altruistic responses to air pollution. No coefficients were significant for choosing to ride the bus, but there were several significant associations between AQI categories (AQI number, orange AQI, and perceived AQI) and travel behavior outcomes (number of trips, distance traveled, and travel time). The model results show that the number of trips by public mode increased on days with poor air quality: a 4% increase for every 10-point increase in AQI ($e^{10B} = 1.04$), and a 61% increase on orange (versus green) air quality days ($e^{B} = 1.61$). There was also a 9% increase in travel time by bus for every 10-point increase in AQI ($e^{10B} = 1.09$). Additionally, the model results show that urban residents spent more time and longer distance traveling using public modes on days with greater perceived air pollution. The model predicts a 15%–16% increase in distance traveled and travel time. In suburban/rural areas, however, we did not find any significant results for public mode, except for a marginally significant association between perceived AQI and distance traveled. Based on the results, respondents rating the air quality one point worse might be expected to increase their transit distance traveled use by 31% ($e^{B} = 1.31$). Altogether, there is some evidence that transit riders in our sample tended to use the bus more on days with worse (measured or perceived) air quality. However, this evidence was concentrated among urban residents, suggesting that transit access and availability might be preconditions for being able to change travel behaviors.

Finally, we come to private mode (automobile) use. In urban areas, there were significant associations between all AQI categories (AQI number, yellow AQI, orange AQI, and perceived AQI) and most travel behavior outcomes (mode users, distance traveled, and travel time). We can see that distance traveled and travel time by private modes increased on days with poor air quality. The results show a 3% increase in the distance traveled ($e^{10B} = 1.03$) and a 4% increase in travel time ($e^{10B} = 1.04$) for every 10-point increase in AQI. Also, on yellow (versus green) days, the model predicts a 13% increase in travel time by private modes. Even air quality perception had a meaningful and significant impact; people rating air quality one point worse might be expected to decrease the distance traveled by private modes by 7% ($e^{B} = 0.93$). On orange days, for urban residents, the model showed a large and statistically significant 90% decrease in the odds ($e^{10B} = 0.10$) of someone being a private mode user; however, recall the sample size limitation. In suburban/rural areas, we only saw two marginally significant associations: between the AQI number and orange AQI days with distance traveled. The model predicted that private mode users drove 3% fewer miles for every 10-point increase in AQI ($e^{10B} = 0.97$), and on orange days a decrease of 51% ($e^{10B} = 0.49$). Recall the small sample size, but also remember the marginally significant decrease in total (all-mode) distance traveled by suburban/rural residents on these days mentioned earlier. Changes in driving amounts seem to be affecting this result.

5.5 Conclusion

In this study, we sought to determine whether and how measured or perceived levels of air pollution affected individuals' daily activity participation and travel behaviors in urban and suburban/rural areas. Although there were not many significant air quality coefficients estimated by the models of activity and travel outcomes (Table 5.4, Table 5.5, and Table 5.6), there were enough for us to make some overarching conclusions. Activity and travel behavior response patterns in both urban and suburban/rural areas exhibited both similarities and differences.

First, the only change in activity participation we observed was that participation in mandatory activities (work and school) appeared to increase on days with worse air pollution in urban areas. While we speculated about this potentially being a side-effect of shifting work or school travel to different days, we are unsure of this result and encourage additional research to identify a more convincing explanation. There was some but not convincing evidence that urban residents made fewer discretionary trips on poor air quality days, which, if true, could imply that greater multimodal accessibility could allow greater flexibility in activity schedules.

Second, there appeared to be some detectable changes in traveler behaviors on days with poorer measured air quality, but the effects were different for active, public, and private modes and for residents of urban and suburban/rural neighborhoods. For active modes in urban areas, not much changed. Meanwhile, people living in suburban/rural neighborhoods were more likely to use active modes (and perhaps increase their active travel duration) as air pollution increased. In contrast, air pollution did not appear to encourage more people to shift to using public transit, but existing transit users in urban areas tended to ride the bus more frequently and for a longer time; whereas no changes in public mode use behavior were measured for residents of suburban/rural areas, likely due to the greater difficulty accessing transit services. For private mode use, in urban areas, people appeared to spend more time driving on poor air quality days, whereas in suburban/rural areas there was some evidence of fewer miles driven.

Third, there were some very large (and sometimes significant) measured changes in travel behaviors on unhealthy (orange) air quality days: more walking/bicycling (urban only), more transit use and users (urban only), and less driving (all areas, especially suburban/rural) and fewer automobile users (urban only). However, the small sample size calls into question the validity of the estimates. Despite our best efforts, our study's natural experiment suffered from a weak "treatment effect." Because few people were exposed to an orange air quality day, our study likely lacked sufficient power to detect significant effects of days with unhealthy air pollution. For instance, we were unable to estimate coefficients for active and public mode travel behaviors in suburban/rural areas on orange days due to sample size limitations.

Fourth, people who perceived the air quality to be worse tended to use active and public transit modes more (longer distances and travel times), but this is only among users of these modes and mostly among urban residents. There were no results suggesting that air quality perceptions shifted people toward walking, bicycling, or riding the bus. It could be that both measured (and announced) air pollution and perceptions of air quality affect peoples' behavioral responses in slightly different ways. We encourage more research investigating air quality perceptions.

Overall, these results are somewhat encouraging for behavioral responses to air pollution. There is more evidence of altruistic responses than risk-averse responses: more people choosing active modes, more bus use among transit riders, fewer people using automobiles, and potentially dramatic shifts on days with much worse air pollution. This finding suggests that policies to spread awareness of the harms of air pollution from automobile emissions and other soft travel behavior change strategies might be able to encourage people to choose less-polluting modes on poor air quality days.

Notably, we observed that, in urban areas, active and public transportation modes were used more frequently on polluted days, possibly due to the closer proximity of destinations and transit accessibility, making these more feasible travel options. Conversely, in suburban/rural areas, we did not witness a considerable change (except for a greater chance of using active modes), which could be largely attributable to the built environment with larger distances between developed areas, rendering them less walkable for daily travel to work, school, shopping, and other destinations. Furthermore, we should acknowledge that the insignificant changes observed in suburban/rural areas may partly result from the smaller size of these populations in our sample.

We recommend several efforts for future research to advance upon this study. First, most of our participants did not experience a day of unhealthy air quality (orange or worse), so it was difficult to detect significant behavioral shifts due to air pollution. Future studies should try to capture a wider range of air quality levels, although this is difficult when relying upon unpredictable atmospheric conditions. Second, our use of self-report travel diaries had a high respondent burden, was potentially prone to reporting errors, required much data cleaning, and limited the number of days we could study. The use of a GPS-based travel survey could help mitigate many of these issues, and it might also allow for a longer study period to hopefully capture more variation in air pollution levels. Third, our analysis itself could be improved through more advanced statistical methods. For example, we did not account for various natures of our dataset: panel (people observed over multiple days), multilevel (people within households within neighborhoods), or multivariate (multiple potentially correlated dependent variables). In future work, advances such as these could help provide stronger evidence of how activity and travel behaviors are affected by episodes of area-wide air pollution.

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6. CONCLUSION

Recall the four objectives of this research study, to:

1. Understand how measured (or perceived) poor air quality affect individuals' daily travel amounts.
2. Identify what factors (personal characteristics, travel behaviors, and measured air quality) affect perceptions of air quality.
3. Understand patterns of attribution of responsibility of air pollution, the relationship with stated travel behavior changes, and the impact of awareness of consequences, risk perception, self-efficacy, and socio-demographics.
4. Determine whether and how measured (or perceived) area-wide air pollution affects individuals' daily activity and travel behaviors, as well as how those associations differ by neighborhood type.

To achieve these objectives, we developed a multifaceted research approach involving a multi-phase longitudinal (travel) survey data collection effort, followed by data analysis of travel behaviors and perceptions. In this concluding chapter, we summarize the study's key findings, highlight policy recommendations, and offer suggestions for future research.

6.1 Key Findings

Regarding the **first objective**, our initial analysis (see Table 3.3) indicated there was no substantial change in people's travel amounts (number of trips, total time spent traveling) due to variations in air quality, whether objectively measured (AQI) or perceived (terrible-to-good). Why do people seem to not be affected by poor air quality, at least not enough to make detectable changes in overall travel amounts? This could be due to much travel being mandatory trips to work, school, or for life-sustaining activities (e.g., grocery shopping) that cannot be easily rescheduled for another day or conducted remotely. It could also be that air quality does impact travel amounts, but only at levels of adverse air quality beyond what we were able to observe during the winter of 2019. Finally, the effect size of air quality influences on travel behavior may be small, and we may not have had a sufficient sample size to detect a significant effect in Chapter 3.

In a follow-up study (regarding the **fourth objective**), we looked at whether and how measured or perceived levels of air pollution affected more detailed measures of individuals' daily activity participation and travel behaviors in urban and suburban/rural areas. Although there were few significant air quality effects identified (Table 5.4, Table 5.5, and Table 5.6), there were enough for us to make some overarching conclusions.

- First, the only activity change we observed was that participation in mandatory activities (work and school) appeared to increase on days with worse air pollution in urban areas. There was also some evidence that urban residents made fewer discretionary trips on poor air quality days. If true, this could imply that greater multimodal accessibility in urban neighborhoods could allow for greater flexibility in activity schedules.
- Second, there were some detectable changes in mode-specific traveler behaviors on days with poorer measured air quality. In urban areas, people did not change their use of active modes (walking, bicycling, etc.), but suburban/rural residents were more likely to use active modes as air pollution increased. Poorer air quality did not seem to encourage more people to use public transit, but urban transit riders rode the bus more frequently and for a longer time; however, there were no changes for suburban/rural residents, perhaps because it is harder for them to access transit services. For private mode (automobile) use in urban areas, people appeared to spend more

time driving on poor air quality days, whereas in suburban/rural areas there was some evidence of fewer miles driven.

- Third, there is some emerging evidence that unhealthy (orange) air quality more substantially affected travel behaviors. We saw more walking/bicycling (urban only), more transit use and users (urban only), and less driving (all areas, especially suburban/rural) and fewer automobile users (urban only). However, the small sample size calls into question the validity of this particular finding, and more research is needed to substantiate them.
- Fourth, people who perceived the air quality to be worse tended to use active and public transit modes more (longer distances and travel times), but mostly only among urban users of these modes. There were no results suggesting that perceptions of adverse air quality shifted people toward walking, bicycling, or riding the bus. It could be that both measured (and announced) air pollution and perceptions of air quality affect peoples' behavioral responses in slightly different ways.

Overall, the more detailed results of Chapter 5 provide slightly more evidence (compared with Chapter 3) of travel behavior being affected by air pollution. In fact, there was some (albeit not overwhelming) evidence that more people may exhibit altruistic (e.g., drive less, ride transit more) than risk-averse (e.g., walk less, drive more) travel behavior responses to area-wide poor air quality. But the overall conclusion remains the same: among our study population (adult residents of Cache County, Utah), most people did not substantially change their activity and travel behaviors in response to moderately poor levels of area-wide air quality.

Regarding the **second objective**, in Chapter 3 we found several factors associated with perceived air quality. Most notably, people's perceptions of air quality were positively associated with the AQI. In other words, people were at least somewhat aware of actual air pollution conditions. The result is in contrast with some past studies that did not find a link between perceived and objective measures of air quality. We suspect this may be because our study area experiences regular wintertime periods of visible high air pollution (obscuring mountain views) and regular news alerts about air quality levels. Because our study population seems to be aware of air quality issues, this lends support to the hypothesis that the (modest) travel behavior changes observed in Chapter 5 are indeed caused by people's understanding and awareness of air pollution levels.

Regarding the **third objective**, in Chapter 4 we found three classes of individuals based on how they view their (and other people's) transportation mode usages and the impact of those choices on air quality. Individuals in Class I (high internal–high external attributors) showed high preferences for their and other people's reduction in auto driving and increase in use of walking/cycling and public transit, followed by moderate preferences of the same for Class II; whereas Class III individuals (low internal–low external attributors) reported neither an increase or decrease in their or people's usage of transport modes. Consistent with previous research, people with a higher level of education and those identifying as women were more likely to be in Class I and say that they and others are responsible for making transportation changes to improve the environment. People with high self-efficacy (perceived ability to change) were more likely to be high internal–high external attributors, suggesting that people with more travel options and schedule flexibility ascribed more responsibility to people making travel behavior changes. Also, people in Class I reported being more likely to make travel behavior changes, showing the link between psychology, attribution of responsibility for air pollution, and travel behavior. Across all classes, trip-chaining and rescheduling were more commonly reported than mode shifts, suggesting that not all travel behavior changes are similarly easy or equally likely.

6.2 Recommendations

These findings offer several recommendations for transportation policymaking that could help to reduce air pollution and improve air quality through travel behavior change strategies.

Overall, the results of Chapter 5 are somewhat encouraging for behavioral responses to air pollution. There is more evidence of altruistic responses than risk-averse responses: more people choosing active modes, more bus use among transit riders, fewer people using automobiles, and potentially dramatic shifts on days with much worse air pollution. This suggests that policies to spread awareness of the harms of air pollution from automobile emissions and other "soft" (voluntary) travel behavior change strategies might be able to encourage some people to choose less-polluting modes on poor air quality days. Yet, it could be that travel behavior changes in response to poor air quality would be stronger if more rigorous "hard" (semi-mandatory) policies were implemented. However, public inclination toward soft and benefit-framed policy measures (as opposed to hard or punitive/restrictive policies) suggests that the public may be more willing to make these sorts of changes if they are voluntary. Unfortunately, these soft policies may be less effective at actually solving the air quality problem through behavior change, at least in the short term.

At least we know from the results of Chapter 3 that air quality perceptions are affected by actual air quality levels (AQI). Also, the results of Chapter 4 show that more than half of our respondents understand the impact of their transportation choices on air quality and are willing to shift to more sustainable modes (enthusiasts). Since residents are aware of poor air quality days and how transportation contributes to air pollution, it could be relatively easier to advise them of travel behavior modification strategies on such days. This supports the implementation of programs (such as TravelWise) to encourage individuals to refrain from increased car use during adverse air quality episodes. Furthermore, it provides ideas for policymakers to consider increasing the reliability and accessibility of public transit, providing flexible door-to door-service and other ways of practicing mobility-as-a-service (MaaS) schemes.

Providing options for people to make different travel behavior choices appears to be critical to facilitating travel behavior changes in response to air pollution. In Chapter 5, we observed that, in urban areas, active and public transportation modes were used more frequently on polluted days, possibly due to the closer proximity of destinations and transit accessibility, making these more feasible travel options. Conversely, in suburban/rural areas, we did not witness a considerable change (except for a greater chance of using active modes), which could be largely attributable to the built environment with larger distances between developed areas, rendering them less walkable for daily travel to work, school, shopping, and other destinations. This indicates the benefits of policy measures and investments providing adequate infrastructure for active modes like bike networks, adequate foot paths, and a more robust and reliable public transit service. These recommendations extend beyond just transportation infrastructure planning and design to land use policy as well. The more walkable, bike-friendly, and transit-accessible neighborhoods that can be built or retrofitted, the easier it will be for people to choose to travel less or with a more environmentally friendly mode when faced with episodes of poor area-wide air quality.

6.3 Future Work

There are several opportunities for future research to build upon this work and address some of its limitations.

First, the biggest limitation of this work was its ability to measure a more limited range of air quality levels than anticipated or desired. Despite our best efforts, our study's natural experiment suffered from a weak "treatment effect." Because few people were exposed to an orange (unhealthy) air quality day, our study likely lacked sufficient power to detect significant effects of travel behavior changes on days with unhealthy air pollution. Future studies should try to capture a wider range of air quality levels, although this is difficult when relying upon unpredictable atmospheric conditions.

Second, our use of self-report travel diary surveys had a high respondent burden, was potentially prone to reporting errors, required much data cleaning, and limited the number of days we could study. The use of a GPS-based travel survey could help mitigate many of these issues, and it might also allow for a longer study period to hopefully capture more variation in air pollution levels. A larger sample size might also have aided in the detection of more statistically significant associations and relationships.

Third, our study area (Cache County, Utah) had a high automobile mode share and relatively fewer feasible non-automobile options compared with larger and denser urban areas. Because transportation options seemed to influence people's ability to make travel behavior changes, replicating this study in a larger metropolitan area could help it to detect significant effects and identify greater travel behavior sensitivities to air pollution.

Overall, future work should build upon the successes of this project and conduct research involving larger samples, collected over more days, in a larger region, and using more automated data collection methods. In this way, we may be able to gain more and stronger evidence regarding how and why travel behaviors are (or are not) affected by episodes of area-wide air pollution.