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IMPACTS OF AREA-WIDE AIR POLLUTION ON MULTIMODAL TRAFFIC VOLUMES IN UTAH

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16. Abstract

During area-wide episodes of poor air quality, people may reduce their transportation-related emissions by driving less, reducing their exposure to emissions by walking/bicycling less, or going about their lives as usual. These three reactions have different consequences for transportation, health, and the environment. This study investigated the aggregate effects of air pollution on multimodal traffic volumes by comparing associations of the daily air quality index with pedestrian and automobile traffic volumes (collected at many different locations) and system-wide bus/rail ridership over a two-year period in two regions of Utah, United States. We used multilevel modeling to measure how these relationships differ by mode and across locations, while controlling for weather and investigating built/social environmental characteristics. Overall, we found strong evidence that pedestrian volumes declined by 10% or more, on average, on days where the air quality was “unhealthy for sensitive groups” (orange). There was some evidence that automobile traffic volumes increased on poor air quality days, especially on the way to mountainous recreation areas surrounding urban valleys. Decreases in bus/rail ridership were not statistically significant. Overall, there was more evidence for “risk averse” reactions than for “altruistic” travel behavior changes, suggesting that newer or stronger policies may be needed in order to reduce driving and encourage more sustainable and healthful travel behavior changes in regions when faced with periods of area-wide poor air quality.

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Impacts of Area-Wide Air Pollution on Multimodal Traffic Volumes in Utah

Patrick A. Singleton
Associate Professor
Civil and Environmental Engineering
Utah State University

Prachanda Tiwari
Graduate Research Assistant
Civil and Environmental Engineering
Utah State University

Keunhyun Park
Adjunct Professor
Landscape Architecture and Environmental Planning
Utah State University

September 2024

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ABSTRACT

During area-wide episodes of poor air quality, people may reduce their transportation-related emissions by driving less, reducing their exposure to emissions by walking/bicycling less, or going about their lives as usual. These three reactions have different consequences for transportation, health, and the environment. This study investigated the aggregate effects of air pollution on multimodal traffic volumes by comparing associations of the daily air quality index with pedestrian and automobile traffic volumes (collected at many different locations) and system-wide bus/rail ridership over a two-year period in two regions of Utah, United States. We used multilevel modeling to measure how these relationships differ by mode and across locations, while controlling for weather and investigating built/social environmental characteristics. Overall, we found strong evidence that pedestrian volumes declined by 10% or more, on average, on days where the air quality was "unhealthy for sensitive groups" (orange). There was some evidence that automobile traffic volumes increased on poor air quality days, especially on the way to mountainous recreation areas surrounding urban valleys. Decreases in bus/rail ridership were not statistically significant. Overall, there was more evidence for "risk averse" reactions than for "altruistic" travel behavior changes, suggesting that newer or stronger policies may be needed in order to reduce driving and encourage more sustainable and healthful travel behavior changes in regions when faced with periods of area-wide poor air quality.

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EXECUTIVE SUMMARY

Many regions experience episodes of unhealthy area-wide poor air quality due to wildfire smoke or high concentrations of particulate matter or ozone from transportation emissions and other sources. Governments often use hard and/or soft policies to encourage travel behavior change and reduced driving during these events, such as mandatory telework or encouragement to trip chain or postpone unnecessary trips. Individually, people may want to: 1) reduce their contribution to transportation-related emissions by driving less (an altruistic response); 2) reduce their exposure to air pollution by walking less (a risk averse response); or 3) go about their daily activities as usual. Unfortunately, our understanding of the effectiveness of the travel behavior change strategies at a population-wide level is limited by a lack of research on how area-wide poor air quality affects travel amounts using different modes, measured in the same locations.

Thus, this study had two primary objectives: (1) To measure the effects of area-wide air pollution on multimodal traffic volumes and study how these effects differ by mode by building separate models for walking, driving, and transit to observe the difference in effects across modes. (2) To explore locational variations in the effects of area-wide air pollution on multimodal traffic volumes, by using multilevel modeling to represent the locational variations in each mode-specific model. To achieve these objectives, we studied two regions in the state of Utah, United States. Specifically, we assembled detailed daily data on pedestrian and automobile traffic volumes (from many different locations) and system-wide bus/rail transit ridership for a two-year period; we linked these multimodal traffic volumes with air pollution data and weather control variables; and we used multilevel modeling to measure how the air quality–traffic volume relationship differs by mode and across locations.

Overall, we found strong evidence that walking decreased on days with poor air quality, with pedestrian volumes declining by up to 10% or more (on average) when the air pollution was “unhealthy” (orange, air quality index >100). Automobile traffic volumes did not change nearly as much as did pedestrian volumes, but the evidence did suggest some increases in driving as air quality declined (results differed between the two study areas and within the second study area). Although our models found general decreases in system-wide bus and rail transit ridership, the decreases were not statistically significant. By looking at variations in air pollution’s effects on traffic volumes in different locations, we also uncovered some interesting findings. Notably, several locations where automobile traffic volumes increased on days with worse air quality were on highways en route to mountainous skiing, hiking, and recreational areas. This could reflect a trend of people driving into the mountains to escape urban valley air pollution.

Overall, there was more evidence for “risk averse” reactions than for “altruistic” travel behavior changes because walking and public transit usage decreased while driving increased slightly on days with greater area-wide air pollution. This suggests that newer or stronger policies may be necessary in order to encourage more sustainable and healthful travel behavior changes. There could be more requirements or options for teleworking or flexible hours to reduce car commuting. Transit agencies could implement fare-free days to encourage transit use during periods of poor air quality. Also, there are several opportunities for future research to build upon this study’s work to advance knowledge and policy-making around the relationship between area-wide poor air quality and multimodal travel behavior.

1. BACKGROUND

1.1 Introduction

In many parts of the world, air pollution can frequently reach unhealthy levels, affecting both urban and rural downwind communities and negatively impacting public health, out-of-home and outdoor activities, recreation, and tourism. The transportation system is the major cause of pollutants like fine particulate matter (PM2.5) and ground-level ozone (Climate Watch, 2019). Road traffic exhaust emissions have been the major concern as they are associated with the production of PM2.5 and tropospheric ozone (Colvile et al., 2001).

During area-wide air pollution events (smog, haze, dust, and wildfire smoke), governments often resort to hard and soft policies to induce behavior changes in people (Teague et al., 2015; Cummings & Walker, 2000). For example, air quality alerts are often issued to spread awareness regarding high pollution levels and to encourage (or discourage) travel behaviors that would contribute to reduced (or increased) transportation emissions, e.g., carpooling, trip chaining, teleworking, postponing trips, or using public and active transportation modes (UDOT, 2022).

However, without detailed study of the link between air pollution and travel behavior, the design of policies is far from effective. Although research on effects of the transportation system on air quality and air pollution is plentiful (e.g., Caiazzo et al., 2013; Kryzanowski et al, 2005), research emphasizing the reverse link—i.e., how air pollution measurements impact multimodal traffic volumes and other aggregate outcomes of individuals' travel behaviors and transportation choices—is comparatively limited. In order to improve public health as well as manage the public's responses to such air pollution events, it is important to know how people's travel behaviors are affected by area-wide air pollution.

Theoretically, there are a variety of ways in which traveler behaviors may be affected by area-wide air pollution events, associated information, and any policy actions. First, people may exhibit no behavioral response, especially if the pollution event is minor or few options for alternative behaviors or activity schedules exist. Second, people may reduce their automobile travel or use of other polluting travel modes in order to minimize their contribution to the air pollution issue. Third, people may increase their use of encapsulated motorized modes, switching from exposed active modes in an attempt to reduce their exposure and inhalation of air pollution. One might call the second option an "altruistic" response, while the third option is a "risk averse" response (Noonan, 2014). The altruistic response prioritizes the overall good of society even if it comes at one's individual benefit (forgoing automobile usage to reduce air pollution even if it increases one's exposure to emission), while the risk averse response prioritizes one's individual benefit over the common good of society (taking up automobile usage to decrease one's exposure to emissions even if it contributes to more air pollution). The conflict between these two responses highlights the challenge of information dissemination and soft/hard policies that seek to mitigate episodes of area-wide air pollution through travel behavior change.

In addition to the severity of the air pollution event, the population-wide response depends on the interplay of various factors, including (but not limited to) the existing transportation and built environment structures. Thus, an investigation into the relationship of air quality and multimodal traffic volumes—with consideration for varying responses across built environment contexts—is needed to effectively manage the travel behavior response during episodes of poor air quality. This study addresses the need by employing multilevel modeling to study the aggregate effects of air quality on motor vehicle and pedestrian volumes and transit ridership in different locations.

Note that we could have taken a disaggregate approach to study the impact of air quality on traffic volumes by studying people's behavior at an individual level, which could have considered awareness, psychological, and other personal factors (Zhao et al., 2018; Li & Kamargianni, 2017). But for this study we chose an aggregate approach as it allowed us to analyze the overall impact of air quality on traffic volumes across different modes. This approach provides a broader perspective and helps identify general trends in population-level travel behavior response during periods of bad air quality. The aggregate approach helps us overcome one of the major disadvantages of the individual-level approach: probable selection of a non-representative sample of the population. Also, people's self-reported behavior in surveys might not match their actual behavior, and to track those individual behaviors over long periods of time is demanding. Furthermore, an aggregate approach could be more relevant in exploring the interplay between air quality's effect on traffic volumes and the built environment.

1.2 Literature Review

As active transportation use (walking and cycling), automobile, and public transit modes involve different levels of exposure to air pollutants (both the total exposure and exposure/inhalation rate) (Chaney et al., 2017; Morabia et al., 2009; Good et al., 2016) and different contribution levels to emissions (Colvile et al., 2001), people's responses regarding the use of each mode might be different. Thus, we have streamlined a brief literature review into three sections. Separate sections review literature on active transportation, driving, and public transit to highlight potential similarities and differences in modal reactions to increased levels of area-wide air pollution.

1.2.1 Active Transportation

In the domain of exploring the relationship between air pollution and active transportation, a few studies have been conducted in different locations around the world. Doubleday et al. (2021) examined the impact of wildfire smoke events on pedestrian and bicycle counts at eight city counters in Seattle, WA. They calculated the difference between pre-, during-, and post-wildfire smoke periods for two smoke events in the summers of 2017 and 2018 and found that wildfire smoke events decreased daily average bicycle counts by 15%–36% across the eight counters, and 32%–45% across the two pedestrian counters. Similarly, Saberian et al. (2017) analyzed cyclist counts at 31 points across different cycle paths in the city of Sydney, Australia. The authors concluded that when an air quality alert was issued, the amount of cycling was reduced by 14%–35%. Holmes et al. (2009) analyzed traffic counts at 30 multi-use trail points from May 2004 through August 2006 in Indianapolis, IN. They employed fixed effects regression and found that both high levels of ozone and fine particulate matter (PM) were significantly associated with lower levels of trail traffic. Kim (2020) investigated how PM2.5 and PM10 affect bike sharing in different seasons in Seoul, South Korea. The study concluded that high PM levels in spring and winter negatively affected bike sharing but showed no significant association with bike sharing during summer. Chung et al. (2019) examined the effect of PM10 for different air quality grades (good, moderate, and bad) on pedestrian volume data collected from 1,223 street locations in Seoul during October 2015. They used multiple regression and concluded that when PM increased by 1%, pedestrian volume decreased by 0.121%. Acharya and Singleton (2022) studied the non-motorized trail volumes in Logan, Utah, and found a measurable but small deterring impact of air pollution events on utilitarian active transportation.

Although the above-mentioned studies were conducted in different settings at different time-points, they all reached similar conclusions: walking/cycling activities decrease during the episodes of poor air quality. However, it is interesting to note the different approaches and control variables employed by the studies. Saberian et al. (2017) subdivided trips by purpose and stratified the effects of air pollution for leisure and commuter trips. This allowed the authors to deduce that cycling for leisure was reduced more (38%) than cycling to work (20%). These studies have included a mix of explanatory variables to control for the effects of time and weather. However, we see no consistency in the addition of controls. For example, seasonal control was lacking in all except Kim (2020), who addressed this by creating different models for different seasons. On the other hand, Holmes et al. (2009) explored the distinction of effects due to air pollution itself and that of air quality alerts. They isolated the effect of public alerts by estimating the probability of a public announcement being made as a function of the air quality level parameters. However, the study did not find the coefficient on the corrected air pollution advisory variable to be significant.

1.2.2 Automobiles

Another stream of research focuses on the effect of air pollution levels and/or air quality alerts on encapsulated and motorized modes such as automobiles. Using driving data from the Atlanta Regional Commission in central Atlanta, Noonan (2014) studied the relationship of household-level daily vehicle miles traveled (VMT) and regional ozone. The author hypothesized that daily VMT would fall on ozone alert days. However, there was no significant discontinuity at the ozone cutoff point of 85 parts per billion (ppb). In another study in Salt Lake and Davis counties in Utah, Tribby et al. (2013) analyzed motor vehicle traffic data to examine the relation between daily traffic and air quality alerts. They ran ANOVA and multiple regression methods for summer and winter traffic separately. The authors found that there was no significant reduction in daily motor vehicle traffic during yellow and red days of air pollution. They concluded the ineffectiveness of air quality alerts on reducing traffic volume during days of poor air quality. The authors found similar reactions to alerts for both PM2.5 and ozone. They also noted an unintended consequence of the alerts as they found an increase in the average traffic volume for yellow and red days, which was significant for traffic counters near the mountain regions. The authors attributed the increase in traffic to the presence of mountains nearby that provide an easy escape for Salt Lake residents from the air quality problem.

1.2.3 Public Transit

Welch et al. (2005) studied the effects of ozone action day public advisories on train ridership in Chicago. For the study, they used a fixed effects regression model to analyze the effect of ozone action days on hourly Chicago Transit Authority train ridership. The effect was deemed significant and even sizable during some parts of the day, but the overall effect of ozone action days on ridership was not significant. Cutter and Neidell (2009) studied the response of traffic to the “Spare the Air” program in the San Francisco Bay Area and found that total daily traffic was reduced by 2.5%–3.5%. This was accompanied by two large increases in BART (Bay Area Rapid Transit) at 9 am and 6 pm. The results suggested that air quality advisories reduced traffic volume and slightly increased the use of public transit, which supported the role of voluntary information programs on change in traffic volumes.

1.2.4 Research Gaps

To conclude, the most pronounced changes in traffic volumes in response to area-wide poor air quality are reductions for open and active modes, especially for discretionary trips. This conclusion, however, does not clarify if the decrease in pedestrian/cyclist volume is accompanied by an increase in other modes such as driving and transit. Since the existing studies on driving (Noonan, 2014; Tribby et al., 2013) show insignificant changes in volume during days of bad air quality, it leads us toward a gap in the literature: the lack of research about traffic volume changes for different modes measured in the same location. As the response to air quality depends on the available substitute mode options, demographics, and other built environment characteristics, any conclusions about modal shifts are potentially inappropriate if made by comparing studies from different sites (e.g., active mode studies from Seoul, Sydney, and Seattle versus motorized mode studies from Atlanta and Salt Lake City versus transit studies in Chicago and Bay

Area). Thus, there is a need for research exploring traffic volume changes for different modes in the same location.

Also, the reaction to changes in air quality is likely affected by characteristics of a place, such as the availability of transit, the built environment, and the sociodemographic characteristics of the location. Most studies have not explored spatial variations in the relationships between air quality and traffic volumes. Although Tribby et al. (2013) concluded that stations near mountains react differently to stations near downtown, their conclusion was derived by calculating differences between the mean values of traffic for different air quality categories for individual stations. Their approach does not allow us to explore the variation of the air quality–traffic volume relationship according to different locational characteristics. Chung et al. (2019) also controlled for spatial units, but they did so for weather parameters and calculated a single defining relationship between air quality and traffic volume for the entire area. Thus, a methodological gap to be filled is modeling variations in the relationship between air quality and traffic volume for different locations.

1.3 Research Objectives

The above-mentioned gaps point us toward a need for this study to explore the relationships between air quality and traffic volume for different modes in the same area, and allowing for the possibility that each count location could have a different reaction to air pollution. Thus, this research addresses these needs by focusing on the following objectives:

1. To measure the effects of area-wide air pollution on multimodal traffic volumes and study how these effects differ by mode by building separate models for walking, driving, and transit to observe the difference in effects across mode.
2. To explore locational variations in the effects of area-wide air pollution on multimodal traffic volumes by using multilevel modeling to represent the locational variations in each mode-specific model.

The remainder of this report is structured as follows. Chapter 2 describes the two study areas, the multifaceted data, and the analysis methods employed. Chapter 3 presents results for the analyses in study area 1. Chapter 4 presents results for the expanded analyses in study area 2. The concluding Chapter 5 discusses the findings in relation to the study's objectives and offers both implications for policy and recommendations for future research.

2. DATA AND METHODS

2.1 Setting and Study Areas

To meet the objectives of this research project, we started by defining two study areas in the state of Utah in the western U.S. The first study area includes Cache County, which lies in the northernmost part of Utah. The second area includes the counties of the Wasatch Front region (Weber, Davis, Salt Lake, and Utah). All of the counties involved in the study are listed in Table 2.1 along with their 2020 population (U.S. Census Bureau, 2023).

Table 2.1 Counties in study areas

Study Area	***County***	***2020 Census Population***
Study Area 1	Cache	133,154
Study Area 2	Weber	262,223
	Davis	362,679
	Salt Lake	1,158,238
	Utah	659,399

The reasons behind the demarcation of our geographical scope into two areas are transit accessibility and area coverage of the regions. Cache County (study area 1) is not served by the Utah Transit Authority (UTA); instead, it has its own local transit system, Cache Valley Transit District (CVTD). Thus, transit accessibility in study area 1 is not as robust as in study area 2. Also, the lack of data availability from the Smart Location Database, which used pre-2020 census data and transit information from General Transit Feed Specification (GTFS) feeds, meant some of the built environment variables related to transit service were not available in this study area. Secondly, study area 1 is a smaller region with a small dataset, which allowed us the leverage to build a model explaining the spatial distributions of the effect of air quality on multimodal traffic volumes. This model was then efficiently replicated for study area 2.

Study area 1 includes a university town in an agricultural area. Logan is the biggest town in study area 1 and also home to Utah State University. Study area 2 includes the majority of the state's population in one long and narrow urban area. The region is fast-growing and home to the state's largest city and the capital, Salt Lake City. The second largest metro area in the state, Provo, also lies in study area 2. The prominent universities in the area are University of Utah, Brigham Young University, Weber State University, and Utah Valley University.

Both study areas experience summertime wildfire smoke (mostly from California and the Pacific Northwest) as well as wintertime inversions that trap pollutants from transportation, agriculture, and industry in snow-covered urban valleys adjacent to recreational mountain areas. During summer, ozone levels get high in Utah as vehicle emissions and industrial sources mix with sunlight and heat. Smoke from various western North American wildfires (the Dollar Ridge Fire in July 2018 is one notable example) also contribute to pollution in summer. An ozone concentration of 70 ppb—the eight-hour National Ambient Air Quality Standard (NAAQS) standard—is often exceeded in the Wasatch Front (Utah DEQ, 2022a).

During winter months, areas in the Wasatch Front also experience high levels of particulate matter PM2.5 with daily average values reaching up to 60–80 µgm-3. The PM2.5 pollution is related to the formation of persistent cold air pools in Utah's bowl-shaped basins. These conditions are related to stratification and capping inversion of air, which in turn leads to pollutants being trapped near the surface (Baasandorj et al., 2017). Study area 1 is similar, as high particle concentrations result from severe cold temperature inversions, a mix of rural and urban sources, and a confined geographical area (Silva et al., 2007). Due to these pollutants, the PM2.5 concentration of 35µgm-3—the 24-hour National Ambient Air Quality

Standard (NAAQS) standard—is often exceeded in the region, leading to some of the worst non-fire-related air quality within the state of Utah and sometimes the entire U.S. (Wang et al., 2015). The counties comprising study area 2 are designated as serious non-attainment areas for PM2.5, and Cache County in study area 1 was only redesigned as a maintenance area in 2021 (Utah DEQ, 2022a).

2.2 Data and Variables

In line with our objective of measuring changes in daily multimodal traffic volumes in response to area-wide air pollution for multiple modes across various locations, we assembled a variety of data. The following subsections describe how we obtained multimodal traffic volumes—daily motor vehicle volume from traffic count stations, daily pedestrian volumes from traffic signals, and public transit ridership (across entire service areas) from transit agencies—assembled air quality data and weather from atmospheric sensors, and combined these data with locational information about the built environment around each count location. A two-year period from January 2018 through December 2019 was selected for this study. Extending the timeframe to include the COVID-19 pandemic could have led to erroneous conclusions about the relationship between air quality and multimodal traffic volumes because of the difficulty in controlling for COVID effects. Thus, this analysis did not consider time periods during the COVID-19 pandemic.

2.2.1 Multimodal Traffic Volumes

Motor vehicle traffic volume counts on various streets and highways were taken from continuous count stations (CCSs) maintained by the Utah Department of Transportation (UDOT). The stations record the number of vehicles passing a given station by using sensor devices such as inductive loops and overhead microwave radar sensors. The UDOT counts provided the number of vehicles crossing each location per day for CCSs distributed throughout Utah. The motor vehicle traffic volume data had some missing observations spread across locations and times. To minimize the effects of missing data on our analysis, we set a minimum threshold of complete data for 73 days (10% of a possible 730 days). After using this threshold to filter out count stations, six stations in study area 1 and 72 stations spread across study area 2 were selected for the analyses. The remaining missing data from the filtered stations were then omitted.

Pedestrian volumes come from a novel big data source: pedestrian push-button data obtained from high-resolution traffic signal controller logs. In Utah, such real-time and archived data are available from nearly all traffic signals throughout the state. A recent research project compared push-button data with ground-truth pedestrian volumes collected from over 10,000 hours of video at 90 signalized intersections throughout Utah. The project developed a set of simple regression models to convert push-button data to estimated pedestrian crossing volumes. Details of these methods are provided elsewhere (Singleton et al., 2020; Singleton & Runa, 2021), but the methods had good accuracy (correlation of 0.84, mean absolute error of 3.0 pedestrians per hour).

The pedestrian volume estimates contained several sites with a large number of observations having zero or missing values. Common possible reasons were faulty stations, power outages, weekends, few users in a particular area, or no data before a certain date. To deal with these observations, we inspected the frequency and pattern of zero observations and determined which were likely missing versus true zeros. In study area 1, this was done manually. In study area 2, there were too many sites (up to 1,983) to do a manual inspection. Therefore, after some preliminary manual inspections, we constructed several flags to help us identify sites with likely true zeros: mean daily volume less than or equal to 50, 0 contained within two standard deviations of the mean, at least 10% of observations between 1 and 10, maximum difference of 3 between the mean with versus without zeros, and maximum difference of ±1 between the standard deviation with versus without zeros. At all other sites we assumed zeros were missing. We also wanted to only study signals with a sufficient number of true non-zero observations (at least 10%, 73 days) and not too many (likely true) zero observations (no more than 10%, 73 days). After all of this filtering, we ended up using daily estimates of pedestrian volumes at 39 signals in study area 1, and 1,435 signals in study area 2.

Daily transit ridership was obtained from the transit service provider operating in each study area. For study area 1, the Cache Valley Transit District (CVTD) provided the total daily transit ridership across all of its bus routes for each day throughout the study period. For study area 2, the Utah Transit Authority (UTA) provided the total daily transit ridership across each of its commuter rail (FrontRunner) and light rail (TRAX) routes for each day during the two-year study period. We also attempted to get bus ridership data from UTA, but its officials were not confident of the accuracy or completeness of the day-to-day daily bus ridership statistics.

Note that the transit ridership datasets have a different structure than the pedestrian and automobile traffic volume data, as they capture area-wide ridership rather than location-specific ridership. We are using system-wide data for transit ridership rather than location-specific/route-specific data because we would have had to use boarding/alighting data in order to be location/route specific. Boarding/alighting data would capture only those trips starting or ending at that particular location, whereas the pedestrian and automobile volume data capture every trip passing through a point. Thus, to maintain consistency in the nature of data used for analysis across each mode, we opted for system-wide data for transit, even if it meant forgoing a locational analysis (objective 2) for transit ridership.

2.2.2 Air Pollution, Weather, and Control Variables

Daily air quality information (air quality index, based on concentrations of air pollutants measured from sensors) was obtained from the U.S. Environmental Protection Agency (EPA). In 2012, the Utah Division of Air Quality (UDAQ) revamped its air quality categorization in line with the EPA standard and created six color-based categories, as described in Table 2.2. The Air Quality Index (AQI) is a common-scale health-based representation of pollution due to ozone, particulate matter, and oxides of nitrogen, sulfur, and carbon. At most air quality monitoring stations in Utah, only nitrogen dioxide, ozone, and fine particulate matter (PM2.5) were tracked.

During the study period (2018–2019), the highest daily AQI value was 169 (red). However, only a few dates at a few locations were in the range of 150–169. Adding a new color-coded category to our analysis for a few samples would weaken the statistical potency of our model. Thus, only three color categories (green, yellow, and orange+) were considered in our analysis, and the limited observations in the range of 150–169 AQI (red) were put under the orange+ category.

Table 2.2 Air Quality Index (Utah DEQ, 2022b)

Color	*AQI range*	*Health concern*	*Description*
Green	0–50	Good	Air quality is satisfactory, and air pollution poses little or no risk.
Yellow	51–100	Moderate	Air quality is acceptable. However, there may be a risk for some people, particularly those who are unusually sensitive to air pollution.
Orange	101–150	Unhealthy for Sensitive Groups	Members of sensitive groups may experience health effects. The public is less likely to be affected.
Red	151–200	Unhealthy	Some members of the public may experience health effects; members of sensitive groups may experience more serious health effects.
Purple	201–300	Very Unhealthy	Health alert: The risk of health effects is increased for everyone.
Maroon	301–500	Hazardous	Health warning of emergency conditions: everyone is more likely to be affected.

Travel behaviors are also influenced by weather and climatic factors (Böcker et al., 2013; Runa & Singleton, 2021). Therefore, to control for atmospheric environmental impacts on multimodal traffic volumes, daily weather data (about precipitation, snow, temperature, etc.) were obtained for various stations throughout the study areas from the National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA). To account for seasonal differences and behavioral adaptation to weather expectations, a maximum temperature difference variable was created as a measure of how much warmer the maximum temperature observed in a day was compared with the 30-year average of daily maximum temperature on the same day. Since the study areas experience both rain and snow throughout the year, a combined precipitation variable was created categorizing days with no rain and no snow, light rain, light snow, heavy rain, and heavy snow.

Besides the weather controls, additional control variables were introduced to account for temporal variations in traffic volumes and travel patterns. A seasonal categorical variable, which distributed 12 months into four seasons, was created. Days-of-the-week were categorized into Saturday, Sunday, and weekdays to control for the effects of weekends on traffic. Also, holidays in Utah during the study period were identified (Office Holidays, n.d.).

Some unique aspects about the assembly of air pollution, weather, and control variables in each of our study areas are discussed in the following subsections.

2.2.2.1 Study Area 1: Air Quality and Weather Stations

For our initial investigation in study area 1, air quality data from a single monitoring station in Smithfield (a suburb of Logan) was used. The air quality station was 15.4 km and 21.5 km apart from the farthest pedestrian signal and motor vehicle count station, respectively. Also, because the major air quality issue in study area 1 was particulate matter, we considered AQI for PM2.5 only.

Weather data were obtained from two weather stations: one located at Utah State University in Logan that reported daily precipitation (in mm), snowfall (in mm), and maximum and minimum temperature (in °C), and another located at the Logan–Cache Airport, where a dataset containing historical temperatures for the last 30 years was obtained. The weather station was 6.2 km and 28.1 km apart from the farthest pedestrian signal and automobile count station, respectively. From the data, we constructed a combined precipitation/snow categorical variable, reflecting days with no rain and no snow, light rain (1–25 mm) or heavy rain (>25 mm) but no snow, and light snow (1–50 mm) or heavy snow (>50 mm). We also constructed a variable reflecting the difference from normal for maximum temperatures (°C).

2.2.2.2 Study Area 2: Air Quality and Weather Station Matching

Since the air quality and weather stations in study area 2 were not in the same locations as the pedestrian signals and motor vehicle traffic count stations (and we had a large number of available air quality and weather stations to choose from), we had to match stations with each other. The minimum distance approach for each air quality and weather attribute was employed to match stations and link data. For example, assume a traffic station (T1) had two weather stations (W1 and W2) at a distance of 5 km and 9 km, respectively. (The maximum threshold distance between weather stations and traffic stations was set at 15 km for our study). Ideally, we would take all the weather data from W1, because it was closer. But if W1 only recorded temperature data, then for other missing weather records (such as snow, precipitation) we matched it to the next nearest weather station (W2). If W2 did not contain such records, the record would be registered as missing. Similarly, if the same traffic station (T1) had three possible air quality stations (A1, A2, and A3) at distances of 10, 16, and 25 km, respectively (our distance threshold for air quality stations was set at 30 km), we would choose air quality data from A1. Only if A1 had missing air quality data (for one or more attributes), the next nearest air quality station, A2, would be considered. This individual attribute matching helped us to decrease the number of missing records.

Because study area 2 had more severe air quality issues across multiple pollutants, we took the AQI values for three primary pollutants with many measurement stations: nitrogen dioxide, ground-level ozone, and fine particulate matter. When data were available for at least two of these three pollutants (i.e., only one was allowed to be missing), we used the maximum AQI value as our measure of air pollution.

From the weather data for study area 2 (which were in °F and inches), we constructed a combined precipitation/snow categorical variable, reflecting days with no rain and no snow, light rain (>0.0–0.5 in) or heavy rain (>0.5 in) but no snow, and light snow (>0.0–2.0 in) or heavy snow (>2.0 in). We also constructed a variable reflecting the difference from normal for maximum temperatures (°F).

As universities can have a significant impact on pedestrian volumes, we identified the presence of universities near the pedestrian signals. Although "near-university" pedestrian volume locations were selected manually, most were within a 1,200-m (0.75 mi) radius of the center of each campus. (This was an enhancement of the work for study area 2 over the analysis in study area 1.) In study area 2, there were four major universities with large campuses: University of Utah, Brigham Young University, Weber State University, and Utah Valley University. For universities, we also inspected dates during main terms when classes were in session. From this we created a logical variable which was true for signals near universities on the days during university breaks (e.g., winter/holiday, spring, summer). This variable accounted for the low pedestrian volumes at signals near universities during the breaks.

2.2.3 Count Station-Level Variables

Recall our second objective, to measure variations in the air quality–traffic volume relationship across locations. We also collected built and social environment variables at each traffic count location. Information regarding population and employment density, commercial and residential land uses, transit stops, park coverage, schools, and places of worship were collected from the EPA's Smart Location Database (US EPA, 2021). Similarly, sociodemographic attributes like average household size and median household income were obtained from the American Community Survey (ACS) 2016-2020 (US Census Bureau, 2022).

Since we had built and social environment variables for each U.S. Census block group, we had to transform those variables into our spatial unit of analysis: traffic volume stations. For that we used an area-weighted averaging process. First, we created a 400-m (0.25-mi) circular buffer around each pedestrian signal, and then took the area-weighted average of the attribute for the Census block groups included in that buffer. A similar approach with a buffer of 2,000 m (1.25 mi) was used for the motor vehicle count locations.

2.2.4 Descriptive Statistics and Maps

A map of the pedestrian signals, automobile traffic volume count stations, weather station, and air quality station for study area 1 is shown in Figure 2.1. Similarly, a map of the pedestrian signals, automobile traffic volume count stations, weather stations, and air quality stations in study area 2 are shown for each individual county in Figure 2.2 for better representation. The summary of descriptive statistics for all of the variables and all of the modes is shown in Table 2.3 for study area 1. The summary of descriptive statistics of the associated variable for study area 2 is shown for each mode (walking, driving, and transit) in Table 2.4, Table 2.5, and Table 2.6, respectively.

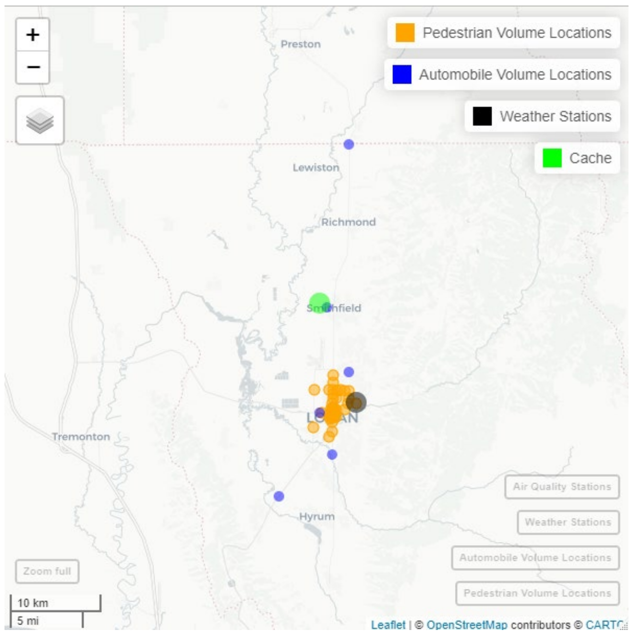

Figure 2.1 Data collection locations in study area 1 (Cache County)

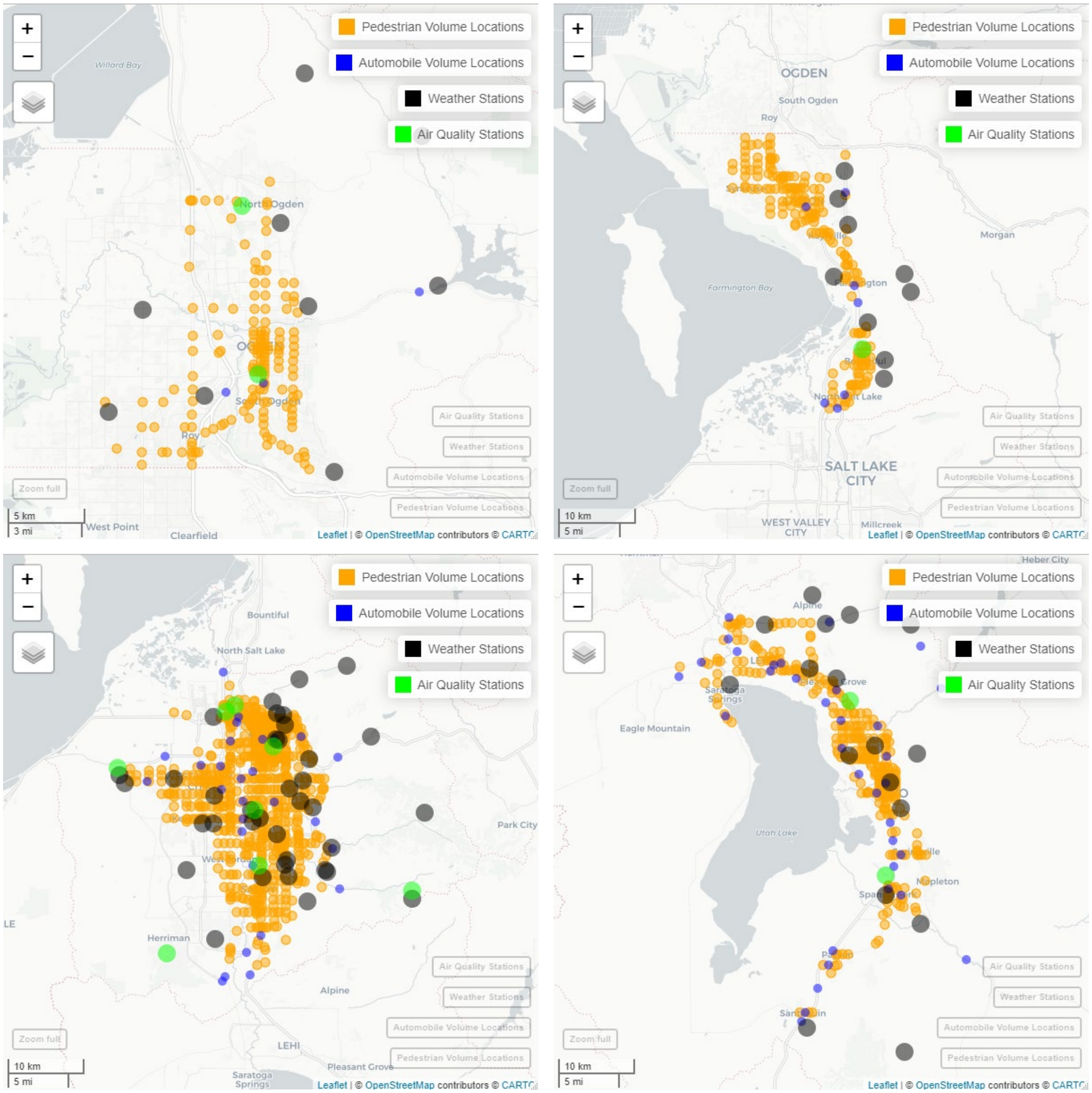

Figure 2.2 Data collection locations in study area 2, in Weber County (top left), Davis County (top right), Salt Lake County (bottom left), and Utah County (bottom right)

Table 2.3 Descriptive statistics, study area 1

Variable	*Mean*	*SD*	*#*	*%*
Multimodal traffic volumes				
Pedestrian volumes	379	1,033		
(N = 27,157 = 39 locations × 730 days – missing data)				
Automobile traffic volumes	12,489	8,410		
(N = 3,987 = 6 stations × 730 days – missing data)				
CVTD bus ridership	4,708	1,991		
(N = 608 = 1 system × 730 days – Sundays – missing data)				
Temporal variables (730 days)				
Day of Week: Weekday			522	71.5
Saturday			104	14.2
Sunday			104	14.2
Holiday: True			24	3.3
Season: Winter			180	24.7
Spring			184	25.2
Summer			184	25.2
Fall			182	24.9
Precipitation: No rain / no snow			532	73.0
Light rain (1–25 mm)			117	16.0
Heavy rain (>25 mm)			2	0.3
Light snow (1–50 mm)			57	7.8
Heavy snow (>50 mm)			21	2.9
Max temperature (°C) difference from average	0.04	4.73		
Air quality index: Green (AQI = 0–50)			626	85.7
Yellow (AQI = 51–100)			88	12.1
Orange (AQI = 101–150)			16	2.2
Built and social environment variables				
(39 pedestrian volume locations, ¼-mile buffer)				
Percentage of residential parcels	20.0	13.3		
Percentage of commercial parcels	33.1	17.1		
Percentage of vacant land	6.6	4.0		
Population density (1,000 people/mi^2)	5.0	2.1		
Employment density (1,000 jobs/mi^2)	9.5	6.3		
Intersection density (#/mi^2)	88.0	37.1		
% 4-way intersections	44.6	21.4		
Number of bus stops	6.1	3.7		
Number of schools	0.2	0.5		
Park acreage	1.1	2.8		
Household income (median, $1,000)	37.4	9.0		
Car ownership (mean)	1.6	0.3		

Table 2.4 Descriptive statistics (pedestrian volumes), study area 2

Variable	***Mean***	***SD***	***#***	***%***
Pedestrian volumes				
(N = 951,701 = 1,435 locations × 730 days – missing data)	296	714		
Temporal variables (730 days)				
Day of week: Weekday			522	71.5
Saturday			104	14.2
Sunday			104	14.2
Season: Winter			180	24.7
Spring			184	25.2
Summer			184	25.2
Fall			182	24.9
Holiday: True			24	3.3
Spatial-temporal variables (N = 635,830)				
Near university on break				
(ref. = Not near university, not on break)			9,587	1.0
Precipitation: No rain / no snow			691,103	72.6
Light rain (>0.0–0.5 in)			163,998	17.2
Heavy rain (>0.5 in)			16,216	1.7
Light snow (>0.0–2.0 in)			56,594	5.9
Heavy snow (>2.0 in)			23,790	2.5
Max temperature (°F) difference from average	0.4	8.6		
Air quality index: Green (AQI = 0–50)			585,469	61.5
Yellow (AQI = 51–100)			338,064	35.5
Orange (AQI = 101–150)			28,168	3.0
Built and social environment variables				
(1,435 pedestrian volume locations, 400m buffer)				
Population density (people/acre)	7.6	4.7		
Employment density (jobs/acre)	7.5	9.4		
Employment and household entropy	0.7	0.2		
Street intersection density (#/mi^2)	102.8	52.0		
Job access, by car (# within 45 min)	76,475	35,560		
Number of children (#/household)	0.8	0.4		
Number of workers (#/household)	1.6	0.7		
Vehicle ownership (cars/household)	1.9	0.4		
Median household income ($10,000s)	6.9	2.5		
Unemployment rate (%)	3.9	2.7		
Non-white or Hispanic race/ethnicity (%)	28.6	16.7		
Number of bus transit stops (#)	5.0	3.9		
Number of rail transit stops (#)	0.1	0.4		
Size of parks (acres)	10.0	42.4		
Number of schools (#)	0.4	0.7		

Table 2.5 Descriptive statistics (automobile traffic volumes), study area 2

Variable	***Mean***	***SD***	***#***	***%***
Automobile traffic volumes				
(N = 34,418 = 72 stations × 730 days – missing data)	66383	66816		
Temporal variables (730 days)				
Day of week: Weekday			522	71.5
Saturday			104	14.2
Sunday			104	14.2
Season: Winter			180	24.7
Spring			184	25.2
Summer			184	25.2
Fall			182	24.9
Holiday: True			24	3.3
Spatial-temporal variables (N = 34,418)				
Precipitation: No rain / no snow			24,470	71.1
Light rain (>0.0–0.5 in)			6,412	18.6
Heavy rain (>0.5 in)			666	1.9
Light snow (>0.0–2.0 in)			1,988	5.8
Heavy snow (>2.0 in)			882	2.6
Max temperature (°F) difference from average	-0.2	9.0		
Air quality index: Green (AQI = 0–50)			21,703	63.1
Yellow (AQI = 51–100)			11,730	34.1
Orange (AQI = 101–150)			985	2.9
Built and social environment variables				
(72 automobile traffic volume locations, 2km buffer)				
Population density (people/acre)	4.3	3.4		
Employment density (jobs/acre)	3.1	3.1		
Employment and household entropy	0.6	0.1		
Street intersection density (intersections/mi^2)	54.1	37.5		
Employment access, by automobile (jobs within 45 min)	60,070	36,488		
Number of children (children/household)	1.0	0.4		
Number of workers (workers/household)	1.6	0.3		
Vehicle ownership (cars/household)	2.2	0.3		
Median household income ($10,000s)	8.2	2.4		
Unemployment rate (%)	3.3	1.5		
Non-white or Hispanic race/ethnicity (%)	26.0	16.9		
Number of bus transit stops (#)	35.8	43.5		
Number of rail transit stops (#)	0.7	1.6		
Size of parks (acres)	93.8	149.6		
Number of schools (#)	4.6	4.2		

Table 2.6 Descriptive statistics (transit ridership), study area 2

Variable	***Mean***	***SD***	*#*	*%*
UTA TRAX rail ridership				
(N = 719 = 1 system × 730 days – holidays – missing data)	46,508	16,172		
UTA FrontRunner rail ridership				
(N = 616 = 1 system × 730 days – Sundays – holidays – missing data)	16,570	4,768		
Temporal variables (730 days)				
Day of week: Weekday			522	71.5
Saturday			104	14.2
Sunday			104	14.2
Season: Winter			180	24.7
Spring			184	25.2
Summer			184	25.2
Fall			182	24.9
Holiday: True			24	3.3
Precipitation: No rain / no snow			542	74.3
Light rain (>0.0–0.5 in)			113	15.5
Heavy rain (>0.5 in)			11	1.5
Light snow (>0.0–2.0 in)			47	6.4
Heavy snow (>2.0 in)			16	2.2
Max temperature (°F) difference from average	1.2	8.3		
Air quality index: Green (AQI = 0–50)			417	57.4
Yellow (AQI = 51–100)			290	39.9
Orange (AQI = 101–150)			20	2.8

2.3 Analysis Methods

The three different modes (pedestrian, automobile, and bus/rail transit) being analyzed had datasets that were distinct in their locational representation. Pedestrian and automobile data covered multiple locations across two years, while bus/rail transit ridership had a single regional aggregate for two years. Because of this difference in the nature of datasets, we employed general regression modeling for bus/rail transit ridership and multilevel modeling for pedestrian and automobile traffic volumes.

For bus/rail transit ridership, in line with the first objective to examine the relationship between air quality and traffic volumes, for each study area we estimated a simple regression model, as represented by Eq. 1. The dependent variable (Y_{ij}) was the natural log of the daily total bus/rail transit ridership in each study area (only bus in study area 1; two types of rail in study area 2), and the independent variables (x_i) were air quality, weather, and temporal controls.

$$Y_i = \beta_0 + \beta_1 x_i + R_i \qquad (1)$$

Since the datasets for pedestrian and automobile traffic volumes covered multiple locations across a span of two years, multilevel modeling was an appropriate approach for our analyses. Multilevel models can adequately represent the two-level nature of our data: daily counts Y_{ij} (level one), nested within locations (level two). Such models also allow clear specifications of variations in model coefficients at level one (across level two units j), including fixed and random intercepts (β_{0j}), slopes (β_{hj}) for h level-one variables (x_{ij}), and cross-level interactions in which level-two variables (z_j) affect level-one slopes. In other words, multilevel models can represent variations in the air quality–traffic volume relationship (slope) across locations and due to locational characteristics. A simple multilevel model with one level-one variable and level-one residuals R_{ij} is represented in the following Eq. 2:

$$Y_{ij} = \beta_{0j} + \beta_{1j} x_{ij} + R_{ij} \qquad (2)$$

In line with the first objective to examine the relationship of air quality and traffic volume for each mode, we estimated separate multilevel models for pedestrian volumes and for automobile traffic volumes. The dependent variable (Y_{ij}) was the natural log of the daily (pedestrian or automobile) traffic volume, and independent (level one) variables (x_{hij}) were air quality, weather, and temporal controls. Different specifications for air quality were considered, but the best-fitting and most intuitive results were found for dummy variables representing the green, yellow, and orange AQI categories (Table 2.2). For pedestrian and automobile models, we allowed the intercept (but not the slopes) to vary across locations. (Recall for bus/rail we resorted to general linear regression as we had aggregate public transit ridership data, but not for particular locations.) For pedestrian volumes (39 locations in study area 1, and 1,435 locations in study area 2), we used a random effects intercept model (Eq. 3), in which the intercept coefficient (β_{0j}) varied randomly following a normal distribution for level-two residuals (U_{0j}). For motor vehicle volumes in study area 1 (six locations), the few sites meant we used a fixed effects intercept model (Eq. 4), in which a different intercept coefficient was estimated for each station k. But the increased number of motor stations in study area 2 (72 locations) allowed us to use the random effects intercept model (Eq. 3).

$$Y_{ij} = \beta_{0j} + \sum_h \beta_h x_{hij} + R_{ij} \qquad \text{(3a), where}$$
$$\beta_{0j} = \gamma_{00} + U_{0j} \qquad \text{(3b).}$$

$Y_{ij} = \beta_{0j} + \sum_h \beta_h x_{hij} + R_{ij}$ (4a), where

$\beta_{0j} = \sum_k \gamma_{0k} D_k$ (4b), and

D_k is a dummy variable equal to 1 for station k and 0 otherwise.

To address the study's second objective—exploring variations across locations in the effect of area-wide air pollution on multimodal traffic volumes—we first modified the first objective models and allowed slopes for the air quality dummy variables to vary across count stations. Again, for pedestrian volumes in both of the study areas, this was a random effects slope model (Eq. 5), in which the random coefficients were normally distributed. For automobile volumes in study area 1, this was a fixed effects slope model (Eq. 6), in which different coefficients were estimated for each station. For automobile traffic volumes in study area 2, this was a random effects slope model (Eq. 5) similar to that employed for pedestrian volumes. If the slopes were found to vary across locations—measured using likelihood-ratio tests versus the models for the first objective—we then tested whether g level-two location characteristics (z_{gj}) were significant in predicting the intercept and air quality slope variations across locations. In the terminology of multilevel modeling, these effects are called cross-level interactions (γ_{gh}), because they result in an interaction of a level-two variable (built or social environment) with a level-one variable (air quality). Only variables with significant interaction coefficients were retained in the final models. Due to the lack of public transit data across multiple locations (only system-level data), we could not employ the second objective models for bus/rail transit ridership analyses.

$Y_{ij} = \beta_{0j} + \sum_h \beta_{hj} x_{hij} + R_{ij}$ (5a), where

$\beta_{0j} = \gamma_{00} + \sum_g \gamma_{g0} z_{gj} + U_{0j}$ (5b), and

$\beta_{hj} = \gamma_{h0} + \sum_g \gamma_{gh} z_{gj} + U_{hj}$ (5c).

$Y_{ij} = \beta_{0j} + \sum_h \beta_{hj} x_{hij} + R_{ij}$ (6a), where

$\beta_{0j} = \sum_k \gamma_{0k} D_k$ (6b),

$\beta_{hj} = \sum_k \gamma_{hk} D_k$ (6c), and

D_k is a dummy variable equal to 1 for station k and 0 otherwise.

Model estimation was performed using the "lme4" package in R (Bates et al., 2015).

3. RESULTS, STUDY AREA 1 (CACHE COUNTY)

As defined in Chapter 2, we demarcated our study area into two regions. This chapter explains the model results for different modes in study area 1. First, we built a model for each mode (pedestrian volumes, automobile traffic volumes, and bus ridership) without locational parameters to meet our objective 1. Two additional models were then created to explain the locational variation of relationships between air quality and both pedestrian and automobile traffic volumes. Since we had the overall bus ridership for the region (not for specific stops or routes), we could not explain locational variations of the air quality and bus ridership relationship. Models specific to each mode are discussed in the sections below.

3.1 Pedestrian Volumes

Table 3.1 reports results of the random intercept model for pedestrian volumes. The coefficient estimates for both the yellow (β = -0.053, *SE* = 0.011, *t* = -4.916, *p* = <0.001) and orange air quality days (β = -0.136, *SE* = 0.023, *t* = -5.929, *p* = <0.001) were negative and significant. This implies that pedestrian volumes decreased during episodes of poor air quality (compared with green days), especially on orange days (unhealthy for sensitive groups). The magnitude of decrease during orange days was significantly higher (12.7%) than that on yellow days (5.2%).

Table 3.1 Pedestrian volumes, random intercept model

Coefficients	*Estimate*	*SE*	*df*	*t-statistic*	*p-value*
Intercept	5.092	0.157	38.23	32.356	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.366	0.009	27105	-38.513	<0.001
Sunday	-1.020	0.009	27105	-107.919	<0.001
Holiday (ref. = No holiday)	-0.914	0.019	27105	-49.317	<0.001
Season (ref. = Winter)					
Spring	0.266	0.011	27105	24.874	<0.001
Summer	0.373	0.010	27105	36.192	<0.001
Fall	0.361	0.011	27105	34.074	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.060	0.009	27105	-6.293	<0.001
Heavy rain	-0.157	0.062	27105	-2.521	0.012
Light snow	-0.259	0.013	27105	-19.657	<0.001
Heavy snow	-0.341	0.020	27105	-16.968	<0.001
Max temperature difference from average	0.007	0.001	27105	9.411	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 51–100)	-0.053	0.011	27105	-4.916	<0.001
Orange (AQI = 101–150)	-0.136	0.023	27105	-5.929	<0.001

Notes: *N* = 27,157; # groups = 39; log-likelihood = -21,661; between-group variance = 0.963; residual variance = 0.286.

Table 3.2 reports results of the random intercept and random slope model for pedestrian volumes. By estimating an earlier model (not shown), we found that there were significant random slopes for the air quality variables. A likelihood-ratio test found that the random intercept and slope model (log-likelihood = -21,656) was (marginally) significantly (χ^2 = 9.924, *df* = 5, *p* = 0.077) better fitting than the random intercept only model (log-likelihood = -21,661). Therefore, we estimated several models, each testing cross-level interactions with air quality involving built and social environment variables. As shown in Table 3.2, there were significant interaction effects for three variables: the percentage of commercial parcels, the percentage of 4-way intersections and average car ownership. For the commercial land use variable, there was a positive and significant interaction term with yellow days (β = 0.001, *SE* = 0.001, *t* = 2.072, *p* = 0.042) but not orange days. This implies that the negative effect of yellow air quality days on pedestrian volumes was attenuated in places with more commercial land uses. For the intersection variable, there was a positive and significant interaction term with orange days (β = 0.003, *SE* = 0.001, t = 2.004, p = 0.050) but not yellow days. This implies that the negative effect of orange air quality days on pedestrian volumes (Table 3.1) was attenuated in places with a greater share of 4-way intersections. For the car ownership variable, there was a negative and marginally significant interaction term with yellow days (β = -0.076, *SE* = 0.040, t = -1,935, p = 0.057). This implies that the negative effect of yellow air quality days on pedestrian volumes (Table 3.1) was enhanced in places with greater average household car ownership.

Table 3.2 Pedestrian volumes, random intercept and random slope model

Coefficients	*Estimate*	*SE*	*df*	*t-statistic*	*p-value*
Intercept	-0.105	1.207	33.02	-0.087	0.931
Day of week (ref. = Weekday)					
Saturday	-0.366	0.009	27066	-38.534	<0.001
Sunday	-1.020	0.009	27063	-107.983	<0.001
Holiday (ref. = No holiday)	-0.914	0.019	27063	-49.341	<0.001
Season (ref. = Winter)					
Spring	0.266	0.011	27066	24.897	<0.001
Summer	0.373	0.010	27070	36.218	<0.001
Fall	0.361	0.011	27069	34.095	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.060	0.009	27064	-6.304	<0.001
Heavy rain	-0.157	0.062	27063	-2.525	0.012
Light snow	-0.260	0.013	27065	-19.678	<0.001
Heavy snow	-0.341	0.020	27064	-16.976	<0.001
Max temperature difference from average	0.007	0.001	27075	9.417	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 51–100)	0.008	0.087	69.73	0.096	0.924
Orange (AQI = 101–150)	-0.170	0.195	54.95	-0.871	0.387
Built and social environment variables					
Percentage of commercial parcels	0.007	0.007	32.15	0.877	0.387
Population density (1,000 people/mi^2)	0.322	0.071	29.76	4.532	<0.001
Intersection density (#/mi^2)	0.008	0.004	30.03	2.029	0.051
% 4-way intersections	0.003	0.007	33.00	0.388	0.700
Number of bus stops	0.080	0.035	29.65	2.253	0.032
Number of schools	-0.496	0.229	29.92	-2.172	0.038
Household income (median, $1,000)	0.049	0.016	30.00	3.037	0.005
Car ownership (mean)	0.239	0.411	31.42	0.582	0.564
Cross-level interactions					
Yellow AQI with % commercial parcels	0.001	0.001	71.71	2.072	0.042
Orange AQI with % commercial parcels	0.002	0.002	55.14	1.311	0.195
Yellow AQI with % 4-way intersections	0.0003	0.001	69.94	0.606	0.546
Orange AQI with % 4-way intersections	0.003	0.001	54.63	2.004	0.050
Yellow AQI with car ownership	-0.076	0.040	70.24	-1.935	0.057
Orange AQI with car ownership	-0.091	0.089	56.87	-1.020	0.312

Notes: N = 27,157; # groups = 39; log-likelihood = -21,622; between-group variance = 0.408; residual variance = 0.285; random coefficient variance for yellow AQI = 0.001; random coefficient variance for orange AQI = 0.005.

3.1.1 Posterior Slopes

Because cross-level interaction terms are difficult to interpret in any type of regression model and even more difficult when they affect random slope coefficients, we also calculated what are called “posterior slopes” (Snijders & Bosker, 2012). Since the random air quality coefficients are not estimated by the model (just their mean and standard deviation), we used empirical Bayes estimation to let the model and data give us the “best” estimate of each location’s slope coefficients. Refer to a multilevel modeling textbook (e.g., Snijders & Bosker, 2012) for details on this calculation. Since the air quality coefficients were also interacted with built and social environment variables, we then multiplied each location’s values for these level-two variables with their respective coefficients, and then added them to the random portion obtained through empirical Bayes estimation to get the total value of the posterior slopes for yellow and orange air quality days (vs. green days).

Figure 3.1 plots these posterior slopes, first in a scatterplot (yellow vs. orange) and second in a combined plot versus AQI. The left portion of the figure shows how most locations had a more negative orange coefficient than yellow coefficient (below the diagonal in the lower left quadrant), and how the posterior slopes were positively correlated, which is expected since they are both conditional on the same data at each location. The right portion of the figure shows how air quality coefficients in the orange range (AQI = 101–150) were typically more extreme (most were more negative; some were more positive) than coefficients in the yellow range (AQI = 51–100). In both portions of Figure 3.1, it appears that only a couple of locations had positive coefficients for yellow or orange AQI.

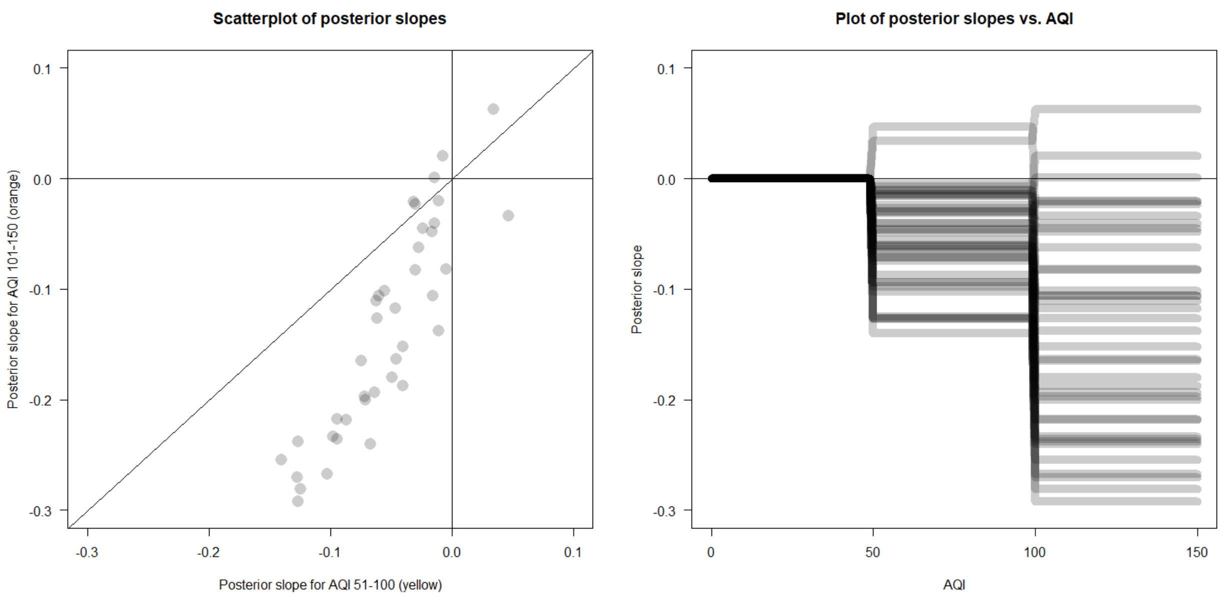

Figure 3.1 Figures showing pedestrian volume model posterior slopes for yellow and orange air quality levels (left: scatterplot; right: plot vs. AQI)

Figure 3.2 plots these posterior slopes for pedestrian volumes on a map for yellow (left) and orange (right) air quality days. In both cases, it appears that locations with positive (or smaller negative) coefficients tended to be concentrated along Main Street (running north–south) and in commercial areas (to the north and in downtown Logan). Locations with more negative coefficients seemed to be located in more peripheral areas, including in the northeast portion of the city, near the Utah State University campus.

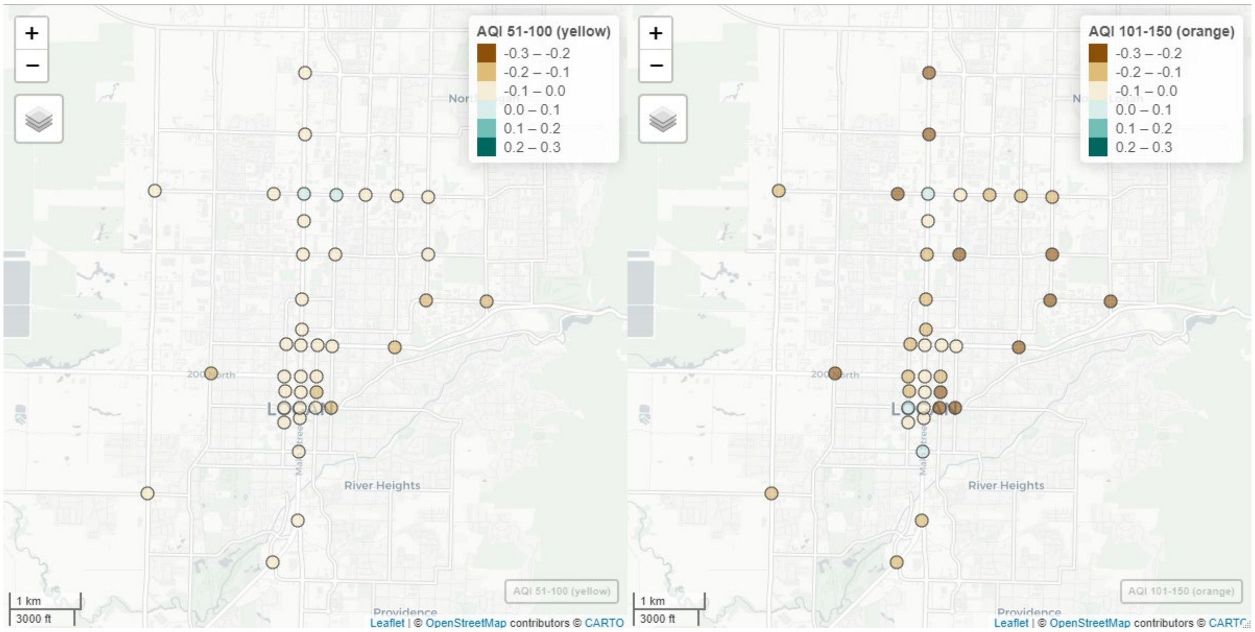

Figure 3.2 Maps showing pedestrian volume model posterior slopes for yellow (left) and orange (right) air quality levels

3.2 Automobile Traffic Volumes

Table 3.3 reports the results of the fixed intercept model for automobile traffic volumes. One of the air quality variables (orange) was positively and significantly associated with automobile traffic volumes ($\beta = 0.049$, $SE = 0.015$, $t = 3.333$, $p = 0.001$). The positive association implies that driving increased (by 5.1%) during unhealthy (orange) air quality days when compared with days with good (green) air quality. The coefficient for yellow air quality was not significantly different from zero, implying no detectable difference in automobile traffic volumes on yellow (moderate) versus green air quality days.

Table 3.3 Automobile traffic volumes, fixed intercept model

Coefficient	*Estimate*	*SE*	*t-statistic*	*p-value*
Intercept (station 301)	9.060	0.008	1,207.460	<0.001
Difference for station 363	1.084	0.007	147.750	<0.001
Difference for station 510	-0.663	0.007	-91.996	<0.001
Difference for station 511	-0.400	0.007	-55.207	<0.001
Difference for station 620	0.219	0.007	29.726	<0.001
Difference for station 622	0.946	0.007	129.548	<0.001
Day of week (ref. = Weekday)				
Saturday	-0.122	0.006	-19.753	<0.001
Sunday	-0.614	0.006	-98.842	<0.001
Holiday (ref. = No holiday)	-0.320	0.012	-27.073	<0.001
Season (ref. = Winter)				
Spring	0.097	0.007	14.267	<0.001
Summer	0.135	0.007	19.693	<0.001
Fall	0.109	0.007	16.172	<0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.021	0.006	-3.367	0.001
Heavy rain	-0.024	0.039	-0.620	0.535
Light snow	-0.062	0.008	-7.399	<0.001
Heavy snow	-0.123	0.013	-9.742	<0.001
Max temperature difference from average	0.000	0.000	0.348	0.728
Air quality index (ref. = Green)				
Yellow (AQI = 51–100)	-0.003	0.007	-0.474	0.636
Orange (AQI = 101–150)	0.049	0.015	3.333	0.001

Notes: $N = 3{,}987$; adjusted $R^2 = 0.963$.

Table 3.4 reports results of the fixed intercept and fixed slope model for automobile traffic volumes, which involved interaction terms included between the air quality categories and each station. None of the air quality–station interaction terms were significant ($p > 0.10$), which implies that there was no significant difference in the relationship between air quality and automobile traffic volumes across the six count stations. Because no significant slope variation was detected, we did not estimate a subsequent model to predict this variation from built and social environment variables.

Table 3.4 Automobile traffic volumes, fixed intercept and fixed slope model

Coefficients	***Estimate***	***SE***	***t-statistic***	***p-value***
Intercept (station 301)	9.060	0.008	1,170.678	<0.001
Difference for station 363	1.084	0.008	136.704	<0.001
Difference for station 510	-0.660	0.008	-84.793	<0.001
Difference for station 511	-0.399	0.008	-51.036	<0.001
Difference for station 620	0.217	0.008	27.182	<0.001
Difference for station 622	0.943	0.008	120.087	<0.001
Day of week (ref. = Weekday)				
Saturday	-0.122	0.006	-19.745	<0.001
Sunday	-0.614	0.006	-98.815	<0.001
Holiday (ref. = No holiday)	-0.320	0.012	-27.074	<0.001
Season (ref. = Winter)				
Spring	0.097	0.007	14.302	<0.001
Summer	0.135	0.007	19.721	<0.001
Fall	0.109	0.007	16.205	<0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.021	0.006	-3.355	0.001
Heavy rain	-0.024	0.039	-0.618	0.536
Light snow	-0.062	0.008	-7.364	<0.001
Heavy snow	-0.123	0.013	-9.733	<0.001
Max temperature difference from average	0.000	0.000	0.360	0.719
Air quality index (ref. = Green)				
Yellow (AQI = 51–100) (station 301)	-0.011	0.016	-0.704	0.482
Difference for station 363	0.004	0.022	0.167	0.868
Difference for station 510	-0.008	0.022	-0.352	0.725
Difference for station 511	0.004	0.022	0.183	0.855
Difference for station 620	0.019	0.022	0.861	0.390
Difference for station 622	0.033	0.023	1.412	0.158
Orange (AQI = 101–150) (station 301)	0.079	0.036	2.174	0.030
Difference for station 363	-0.031	0.051	-0.604	0.546
Difference for station 510	-0.076	0.050	-1.534	0.125
Difference for station 511	-0.058	0.050	-1.153	0.249
Difference for station 620	-0.018	0.050	-0.367	0.714
Difference for station 622	0.009	0.050	0.184	0.854

Notes: $N = 3{,}987$; adjusted $R^2 = 0.963$.

3.3 Bus Transit Ridership

Table 3.5 reports the results of the linear regression model for bus ridership. Note that we did not run a multilevel model for our public transportation data because we did not have location-specific data, only system-level bus ridership. Since the transit service provider (CVTD) did not operate during Sundays, this variable's estimates are missing from the model. The estimates for both the yellow and orange air quality days were found to be negative but were not statistically significant.

Table 3.5 CVTD bus transit ridership, linear regression model

Coefficients	*Estimate*	*SE*	*t-statistic*	*p-value*
Intercept	8.686	0.026	332.388	<0.001
Day of week (ref. = Weekday)				
Saturday	-1.245	0.025	-49.883	<0.001
Holiday (ref. = No holiday)	-1.238	0.066	-18.829	<0.001
Season (ref. = Winter)				
Spring	-0.078	0.031	-2.512	0.012
Summer	-0.394	0.030	-13.292	<0.001
Fall	0.057	0.031	1.839	0.066
Precipitation (ref. = No rain / no snow)				
Light rain	-0.032	0.027	-1.185	0.237
Heavy rain	0.144	0.231	0.626	0.532
Light snow	-0.069	0.037	-1.843	0.066
Heavy snow	-0.041	0.058	-0.697	0.486
Max temperature difference from average	0.000	0.002	0.065	0.949
Air quality index (ref. = Green)				
Yellow (AQI = 51–100)	-0.017	0.031	-0.556	0.578
Orange (AQI = 101–150)	-0.075	0.063	-1.186	0.236

Notes: $N = 608$; adjusted $R^2 = 0.836$.

4. RESULTS, STUDY AREA 2 (WASATCH FRONT)

Building from the models tested for study area 1, we refined them (by adding some new and some different location-specific variables) for study area 2. The approach taken was similar to that used for study area 1. We first estimated a model for each mode (pedestrian volumes, automobile traffic volumes, and rail ridership), then added locational attributes when possible, and finally graphically analyzed the locational distribution of relationships between air quality and traffic volumes (pedestrian and automobile). Since we had the overall rail transit ridership for the region (for two different rail systems, but not for specific stops or routes), we could not explain locational variations of the air quality and rail ridership relationship.

4.1 Pedestrian Volumes

Table 4.1 reports results of the random intercept model for pedestrian volumes in study area 2 (Wasatch Front region). The coefficient estimate for orange air quality days ($\beta = -0.113$, $SE = 0.003$, $t = -32.302$, $p < 0.001$) was negative and significant, although the coefficient for yellow air quality days ($\beta = 0.006$, $SE = 0.001$, $t = 4.967$, $p < 0.001$) was positive and significant, and of a small magnitude. This implies that, on average, pedestrian volumes increased a little on yellow moderately poor air quality days (an increase of 0.6%) but decreased substantially during episodes of orange unhealthy air quality (a decrease of 10.6%), when compared with green "good" days. The results are similar to those from study area 1 for orange days, but not for yellow days, indicating a potential non-linear or threshold-based relationship between air pollution and walking.

Table 4.1 Pedestrian volumes, random intercept model

Coefficients	*Estimate*	*SE*	*df*	*t-statistic*	*p-value*
Intercept	4.611	0.035	1438	133.205	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.373	0.002	950253	-230.515	<0.001
Sunday	-0.832	0.002	950253	-511.845	<0.001
Season (ref. = Winter)					
Spring	0.291	0.002	950255	178.329	<0.001
Summer	0.314	0.002	950258	182.944	<0.001
Fall	0.279	0.002	950257	170.366	<0.001
Holiday (ref. = No holiday)	-0.654	0.003	950252	-204.299	<0.001
Near university on break (ref. = Not near university, not on break)	-0.728	0.007	950477	-107.440	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.043	0.002	950255	-27.481	<0.001
Heavy rain	-0.064	0.004	950254	-14.593	<0.001
Light snow	-0.220	0.003	950254	-86.468	<0.001
Heavy snow	-0.414	0.004	950256	-111.318	<0.001
Max temperature difference from average	0.0046	0.0001	950301	62.157	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 51–100)	0.006	0.001	950261	4.967	<0.001
Orange (AQI = 101–150)	-0.113	0.003	950254	-32.302	<0.001

Notes: $N = 951{,}701$; # groups = 1,435; log-likelihood = -769,611; between-group variance = 1.72 residual variance = 0.29.

Table 4.2 reports results of the random intercept and random slope model for pedestrian volumes in the Wasatch Front. By estimating a model (not shown), we found there were significant random slopes for the air quality variables. A likelihood-ratio test found that the random intercept and slope model (log-likelihood = -765,326) was significantly better fitting than the random intercept only model (log-likelihood = -769,532). Therefore, we estimated several models, each testing cross-level interactions with air quality involving built and social environment variables.

As shown in Table 4.2, several built and social environment variables had significant and positive interactions with the yellow and/or orange air quality variables: employment density (orange only), employment and household entropy (yellow and orange), number of children (yellow and orange), unemployment rate (yellow only), and near a university (orange only). Given the results from Table 4.1, this means that there were even higher pedestrian volumes at signalized intersections on yellow air quality days (the positive association was amplified) in places with greater mixing of jobs and residents, and in neighborhoods with greater unemployment and more children per household. Conversely, the negative effect of orange air quality days on pedestrian volumes was attenuated (i.e., less of a decrease in walking) in places with greater job density, a higher mix of jobs and residents, near universities, and in neighborhoods with more children per household.

Similarly, some results in Table 4.2 showed built/social environment variables having significant and negative interactions with the air quality variables: street intersection density (yellow and orange), job access by car (yellow and orange), the number of workers (yellow and orange), the percentage of people of non-white or Hispanic race/ethnicity (yellow and orange), the number of rail transit stops (yellow only), and the number of schools (yellow and orange). This means that, on yellow (compared with green) air quality days, places with these characteristics—with more intersections, greater job access by automobile, more rail transit stops, more schools, and neighborhoods with more workers per household and a larger share of non-white or Hispanic populations—experienced smaller increases or even decreases in pedestrian volumes. Similarly, pedestrian volumes decreased more (the negative orange association in Table 4.1 was stronger) on orange air quality days at signalized intersections in these same kinds of places than they did elsewhere.

Table 4.2 Pedestrian volumes, random intercept and random slope model

Coefficients	*Estimate*	*SE*	*df*	*t-statistic*	*p-value*
Intercept	2.472	0.251	1426	9.856	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.372	0.002	948054	-231.640	<0.001
Sunday	-0.832	0.002	947697	-514.947	<0.001
Season (ref. = Winter)					
Spring	0.288	0.002	948809	177.276	<0.001
Summer	0.311	0.002	949405	181.797	<0.001
Fall	0.278	0.002	948578	170.952	<0.001
Holiday (ref. = No holiday)	-0.653	0.003	948136	-205.199	<0.001
Near university on break (ref. = Not near university, not on break)	-0.715	0.007	948293	-101.007	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.043	0.002	948102	-27.935	<0.001
Heavy rain	-0.065	0.004	947789	-14.858	0.012
Light snow	-0.221	0.003	948035	-87.373	<0.001
Heavy snow	-0.419	0.004	948037	-113.170	<0.001
Max temperature difference from average	0.005	0.0001	948690	62.865	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 51–100)	0.088	0.022	1374	3.926	<0.001
Orange (AQI = 101–150)	-0.052	0.058	1329	-0.900	0.368

(Table 4.2 continued)

Built and social environment variables					
Population density (people/acre)	0.076	0.006	1420	11.905	<0.001
Employment density (jobs/acre)	0.034	0.003	1420	9.877	<0.001
Employment and household entropy	0.991	0.192	1423	5.152	<0.001
Street intersection density (#/mi^2)	0.003	0.001	1421	4.965	<0.001
Job access, by car (# within 45 min)	-0.0000016	0.0000009	1422	-1.813	0.070
Number of children (#/household)	0.030	0.089	1425	0.333	0.739
Number of workers (#/household)	0.080	0.047	1419	1.703	0.089
Median household income ($10,000s)	-0.056	0.014	1419	-3.868	<0.001
Unemployment rate (%)	0.018	0.010	1420	1.869	0.062
Non-white or Hispanic race/ethnicity (%)	0.002	0.002	1426	1.273	0.203
Number of bus transit stops (#)	0.085	0.007	1419	12.081	<0.001
Number of rail transit stops (#)	0.364	0.063	1420	5.792	<0.001
Number of schools (#)	0.166	0.033	1420	4.983	<0.001
Near a university	0.541	0.202	1420	2.678	0.008
Cross-level interactions					
Yellow AQI w/ Employment density	-0.0004	0.0004	1351	-1.027	0.304
Orange AQI w/ Employment density	0.002	0.001	1320	2.009	0.045
Yellow AQI w/ Employ./house. entropy	0.037	0.021	1381	1.708	0.088
Orange AQI w/ Employ./house. entropy	0.144	0.055	1326	2.606	0.009
Yellow AQI w/ Street intersection density	-0.0001	0.0001	1347	-1.845	0.065
Orange AQI w/ Street intersection density	-0.0004	0.0002	1293	-2.474	0.013
Yellow AQI w/ Job access, by car	-0.0000005	0.0000001	1357	-5.084	<0.001
Orange AQI w/ Job access, by car	-0.0000010	0.0000003	1322	-3.994	<0.001
Yellow AQI w/ Number of children	0.042	0.009	1385	4.682	<0.001
Orange AQI w/ Number of children	0.063	0.023	1325	2.762	0.006
Yellow AQI w/ Number of workers	-0.029	0.006	1366	-5.174	<0.001
Orange AQI w/ Number of workers	-0.032	0.014	1335	-2.248	0.025
Yellow AQI w/ Unemployment rate	0.002	0.001	1359	1.833	0.067
Orange AQI w/ Unemployment rate	0.004	0.003	1291	1.237	0.216
Yellow AQI w/ Non-white or Hispanic	-0.001	0.0002	1356	-6.006	<0.001
Orange AQI w/ Non-white or Hispanic	-0.001	0.0005	1300	-2.659	0.008
Yellow AQI w/ Rail transit stops	-0.016	0.007	1333	-2.217	0.027
Orange AQI w/ Rail transit stops	0.003	0.019	1250	0.166	0.869
Yellow AQI w/ Schools	-0.025	0.004	1353	-6.309	<0.001
Orange AQI w/ Schools	-0.066	0.010	1291	-6.677	<0.001
Yellow AQI w/ Near a university	0.020	0.024	1402	0.822	0.411
Orange AQI w/ Near a university	0.195	0.063	1398	3.087	0.002

Notes: *N* = 951,701; # groups = 1,435; log-likelihood = -764,851; between-group variance = 0.790; residual variance = 0.288; random coefficient variance for yellow AQI = 0.009; random coefficient variance for orange AQI = 0.056.

4.1.1 Posterior Slopes

We calculated posterior slopes for the pedestrian volume model for study area 2 in a similar approach as discussed in the pedestrian results section of Chapter 3. We then plotted these posterior slopes in Figure 4.1, first in a scatterplot (yellow vs. orange) and second in a combined plot versus AQI. The left portion of the figure shows how: (first) about slightly less than half of the study locations (43%) had negative coefficients for yellow air quality days; (second) most of the locations (71%) had negative coefficients on orange air quality days; and (third) the posterior slopes for yellow and orange air quality days were positively correlated (0.91). The right portion of the figure shows how air quality coefficients in the orange range (AQI = 101–150) are distributed more widely but also more negatively, compared with the coefficients in the yellow range (AQI = 51–100).

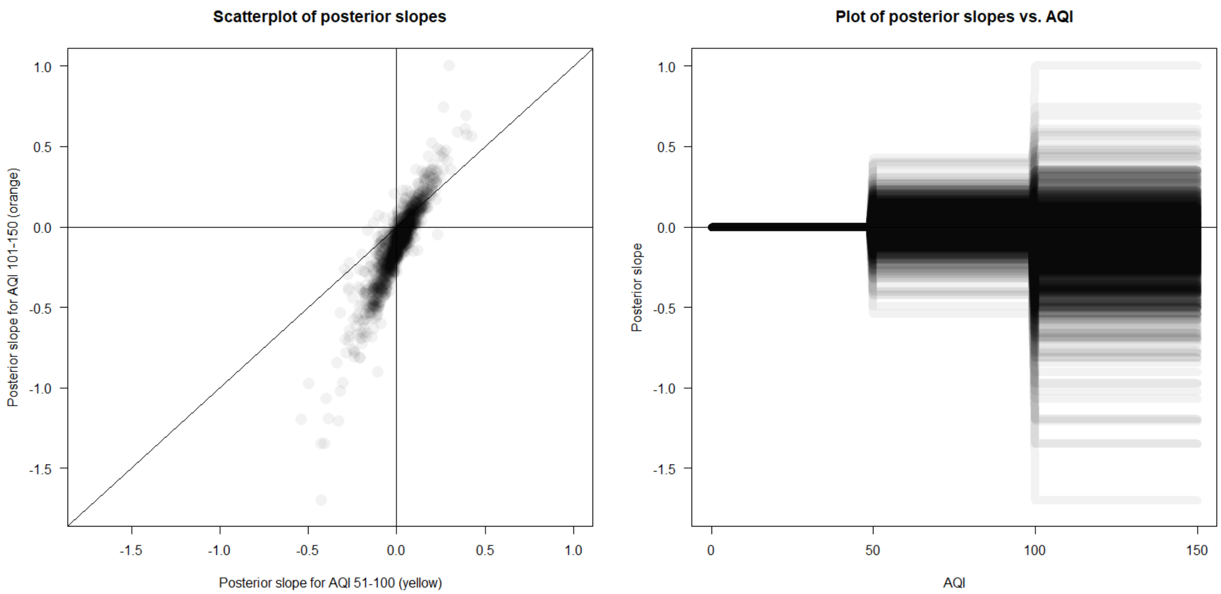

Figure 4.1 Figures showing pedestrian volume model posterior slopes for yellow and orange air quality levels (left: scatterplot; right: plot vs. AQI)

The posterior slopes for yellow and orange air quality levels for pedestrian volumes are mapped in the figures below. Since the number of signals in the pedestrian volume models was high, each map is divided by county. Figure 4.2 plots pedestrian model posterior slopes on a map for yellow (left) and orange (right) air quality days in Weber County and Davis County. Figure 4.3 plots pedestrian model posterior slopes on a map for yellow (left) and orange (right) air quality days in Salt Lake County and Utah County.

Overall, we can notice that there are fewer locations with positive slopes (green dots) and more locations with stronger negative slopes (brown dots) on orange "unhealthy" days, compared with yellow "moderate" days. Some regional differences are also apparent. There are seemingly more locations with decreases in walking (brown dots) on yellow and orange air quality days in Salt Lake County, and more locations with increases in walking (green dots) in Utah County. This is exemplified by the increases seen in downtown Provo (Utah County) compared with the decreases seen in downtown Salt Lake City (Salt Lake County) on orange air quality days.

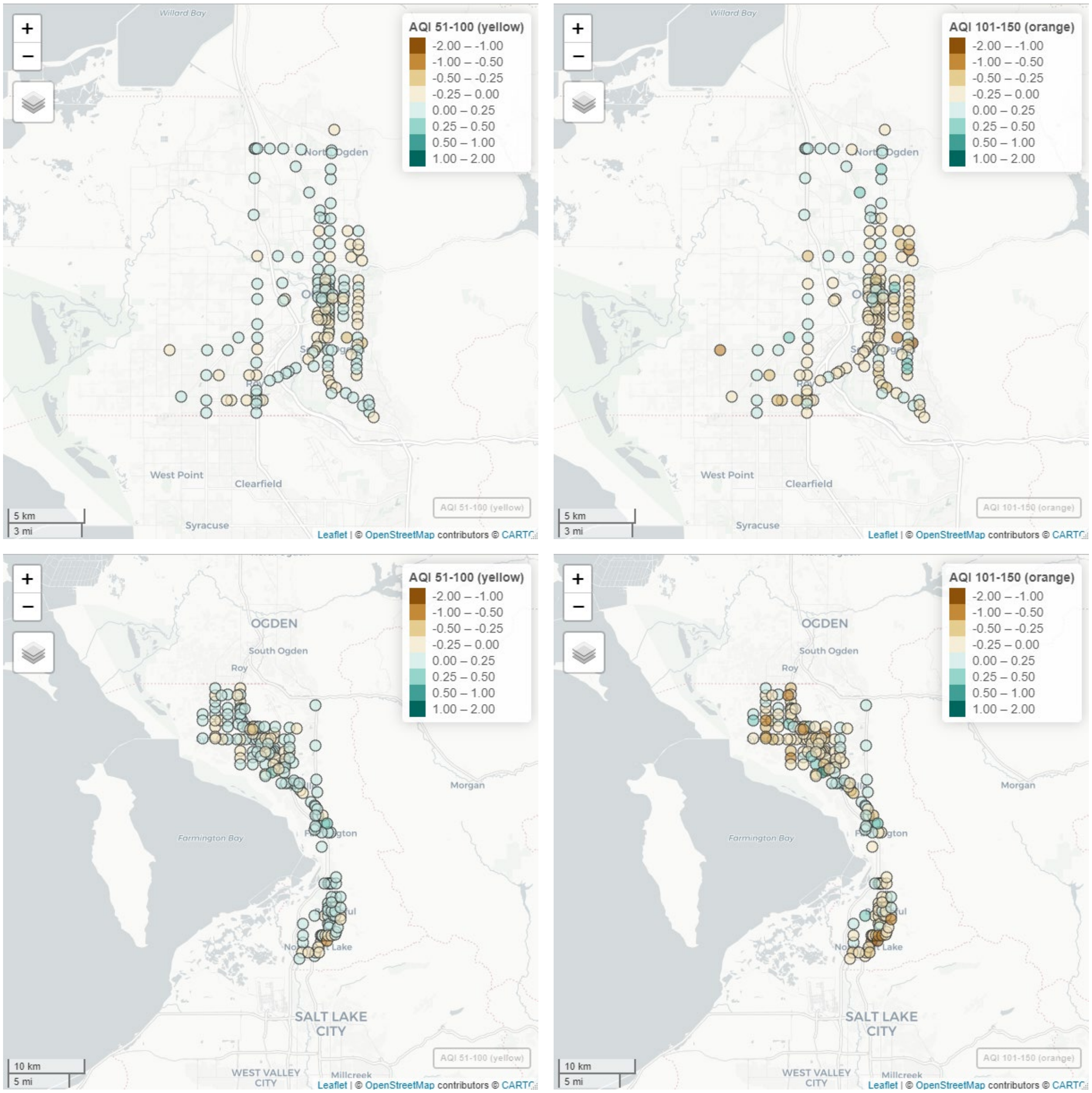

Figure 4.2 Maps showing pedestrian volume model posterior slopes for yellow (left) and orange (right) air quality levels in Weber County (top) and Davis County (bottom)

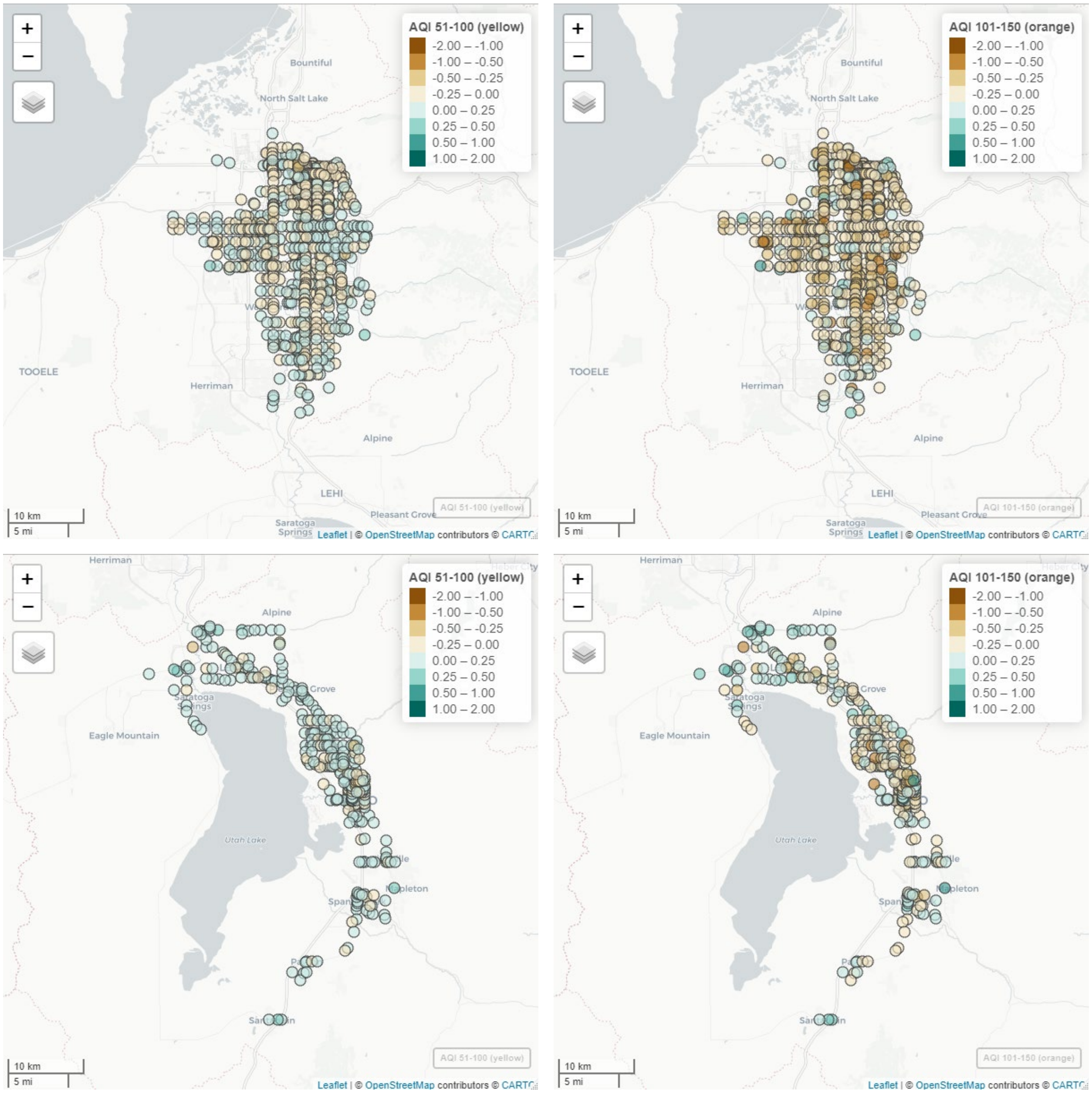

Figure 4.3 Maps showing pedestrian volume model posterior slopes for yellow (left) and orange (right) air quality levels in Salt Lake County (top) and Utah County (bottom)

4.2 Automobile Traffic Volumes

Table 4.3 reports results of the random intercept model for automobile traffic volumes across the Wasatch Front. One of the air quality variables (yellow) was positively and (marginally) significantly associated with traffic volumes ($\beta = 0.007$ $SE = 0.004$, $t = 1.801$, $p = 0.072$). The positive association implies that driving increased by around 0.7% during moderate (yellow) air quality days when compared with days with good (green) air quality. The coefficient for orange air quality was negative but very small and not statistically significantly different from zero ($\beta = -0.001$, $SE = 0.011$, $t = -0.082$, $p = 0.934$). Given the difference, this indicates a presence of a non-linear relationship between air quality and automobile traffic volumes in study area 2.

Table 4.3 Automobile traffic volumes, random intercept model

Coefficients	*Estimate*	*SE*	*df*	*t-statistic*	*p-value*
Intercept	10.580	0.139	71	76.059	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.117	0.005	34333	-24.335	<0.001
Sunday	-0.435	0.005	34333	-89.405	<0.001
Season (ref. = Winter)					
Spring	0.071	0.005	34335	14.536	<0.001
Summer	0.147	0.005	34334	27.422	<0.001
Fall	0.080	0.005	34333	15.968	<0.001
Holiday (ref. = No holiday)	-0.293	0.010	34333	-30.410	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.019	0.005	34333	-4.254	<0.001
Heavy rain	-0.052	0.012	34333	-4.179	<0.001
Light snow	-0.065	0.008	34333	-8.494	<0.001
Heavy snow	-0.137	0.011	34333	-12.416	<0.001
Max temperature difference from average	-0.0014	0.0002	34345	-6.328	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 51–100)	0.007	0.004	34334	1.801	0.072
Orange (AQI = 101–150)	-0.001	0.011	34333	-0.082	0.934

Notes: $N = 34{,}418$ # groups = 72; log-likelihood = -8,535; between-group variance = 1.39; residual variance = 0.094.

Table 4.4 reports results of the random intercept and random slope model for motor vehicle volumes along the Wasatch Front. By estimating a model (not shown), we found there were significant random slopes for the air quality variables. A likelihood-ratio test found that the random intercept and slope model (log-likelihood = -8,239) was significantly better fitting than the random intercept only model (log-likelihood = -8,476). Therefore, we estimated several models, each testing cross-level interactions with air quality involving built and social environment variables. As shown in Table 4.4, there were significant interaction effects for two variables.

- For the unemployment rate, there was a negative and marginally significant interaction term with yellow air quality days ($\beta = -0.013$, $SE = 0.008$, $t = -1.760$, $p = 0.085$); the interaction for orange days was also negative but not significant ($\beta = -0.022$, $SE = 0.017$, $t = -1.272$, $p = 0.210$). This implies that the positive effect of yellow air quality days on automobile traffic volumes (see Table 4.3) was attenuated in places with higher unemployment rates. In other words, places with higher unemployment rates were more likely to see less driving on days with moderate (yellow) air quality.

- For non-white or Hispanic race/ethnicity, there was a negative and significant interaction term with yellow air quality days (β = -0.001, *SE* = 0.001, *t* = -2.029, *p* = 0.049); the interaction for orange days was also negative but barely not significant (β = -0.003, *SE* = 0.002, *t* = -1.633, *p* = 0.110). Similarly, this finding suggests that places with greater shares of populations identifying as non-white or Hispanic were less likely to see increased driving and more likely to see driving reduced on days with moderately poor air quality.

Table 4.4 Automobile traffic volumes, random intercept and random slope model

Coefficients	***Estimate***	***SE***	***df***	***t-statistic***	***p-value***
Intercept	6.745	0.688	76	9.803	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.117	0.005	34217	-24.579	<0.001
Sunday	-0.435	0.005	34210	-90.114	<0.001
Season (ref. = Winter)					
Spring	0.071	0.005	34290	14.714	<0.001
Summer	0.146	0.005	34302	27.325	<0.001
Fall	0.080	0.005	34247	16.121	<0.001
Holiday (ref. = No holiday)	-0.294	0.010	34220	-30.806	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.020	0.005	34229	-4.400	<0.001
Heavy rain	-0.044	0.012	34217	-3.608	0.012
Light snow	-0.067	0.008	34225	-8.775	<0.001
Heavy snow	-0.141	0.011	34226	-12.884	<0.001
Max temperature difference from average	-0.0013	0.0002	34235	-6.098	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 51–100)	0.105	0.027	45	3.807	<0.000
Orange (AQI = 101–150)	0.165	0.063	44	2.626	0.012
Built and social environment variables					
Employment and household entropy	4.856	1.055	72	4.603	<0.000
Unemployment rate (%)	0.177	0.089	68	1.992	0.050
Non-white or Hispanic race/ethnicity (%)	0.010	0.008	69	1.276	0.206
Cross-level interactions					
Yellow AQI w/ Unemployment rate	-0.013	0.008	44	-1.760	0.085
Orange AQI w/ Unemployment rate	-0.022	0.017	42	-1.272	0.210
Yellow AQI w/ Non-white or Hispanic	-0.001	0.001	44	-2.029	0.049
Orange AQI w/ Non-white or Hispanic	-0.003	0.002	42	-1.633	0.110

Notes: *N* = 34,418; # groups = 72; log-likelihood = -8,303, between-group variance = 1.088; residual variance = 0.092; random coefficient variance for yellow AQI = 0.007; random coefficient variance for orange AQI = 0.033.

4.2.1 Posterior Slopes

Figure 4.4 contains plots of the posterior slopes for yellow and orange air quality levels. The left portion of the figure shows that while the majority of locations were clustered near zero for yellow days and slightly below zero for orange days, there were several locations with much stronger positive coefficients for both yellow and orange air quality days. Also, the posterior slopes were positively correlated (0.94), which is expected since they are both conditional on the same data at each location. The right portion of the figure shows how air quality coefficients in the orange range (AQI = 101–150) were typically more extreme (mostly more positive; some were more negative) than coefficients in the yellow range (AQI = 51–100). It also shows that, despite the mean positive yellow coefficient and insignificant orange coefficient in Table 4.3, median locations actually had just barely negative coefficients on yellow days and more noticeably negative coefficients on orange days.

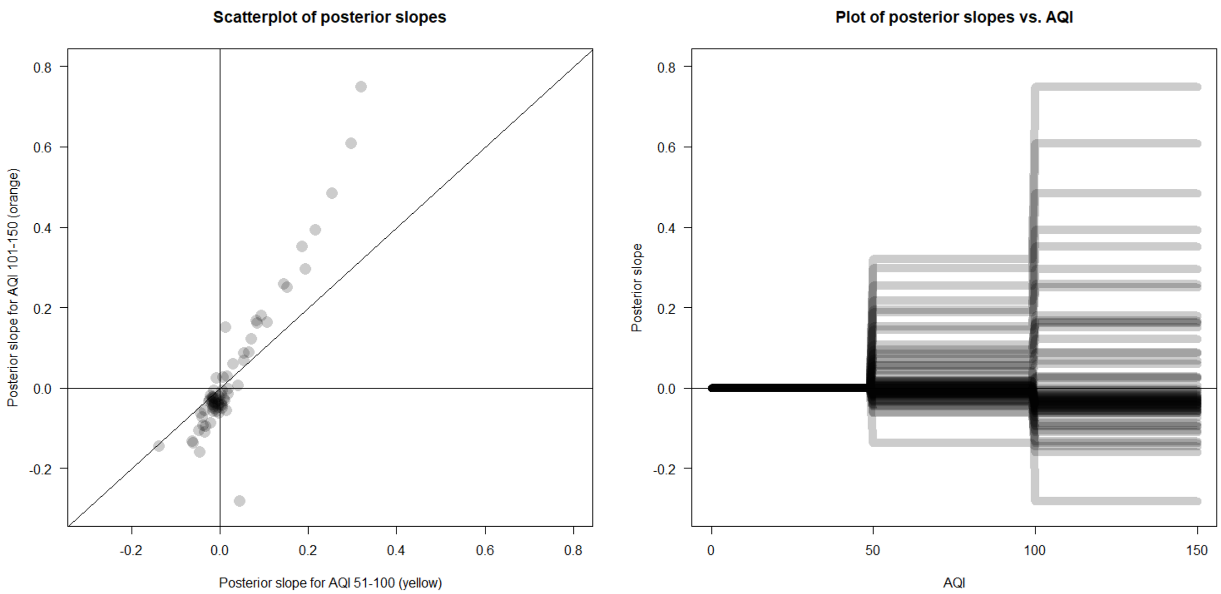

Figure 4.4 Figures showing automobile traffic volume model posterior slopes for yellow and orange air quality levels (left: scatterplot; right: plot vs. AQI)

The posterior slopes for yellow and orange air quality levels for automobile traffic volumes are mapped in the figures below. Figure 4.5 plots posterior slopes for Weber County and Davis County, while Figure 4.6 plots posterior slopes for Salt Lake County and Utah County. In Salt Lake County, very little difference is seen between yellow and orange days. In Weber, Davis, and Utah counties, a few more locations have negative coefficients (brown dots) on orange days than they do on yellow days. Utah County contains most of the locations where the positive coefficient increased greatly from yellow to orange days. Only a few spatial patterns are visible. Locations with more positive yellow/orange coefficients tended to be located on the periphery (especially to the east and northeast) of urban areas like Ogden, Salt Lake City, and in Utah County. These sites tended to be on highways on the way to mountains, including skiing, hiking, and recreation areas. This could reflect a trend of people driving to escape urban valley air pollution.

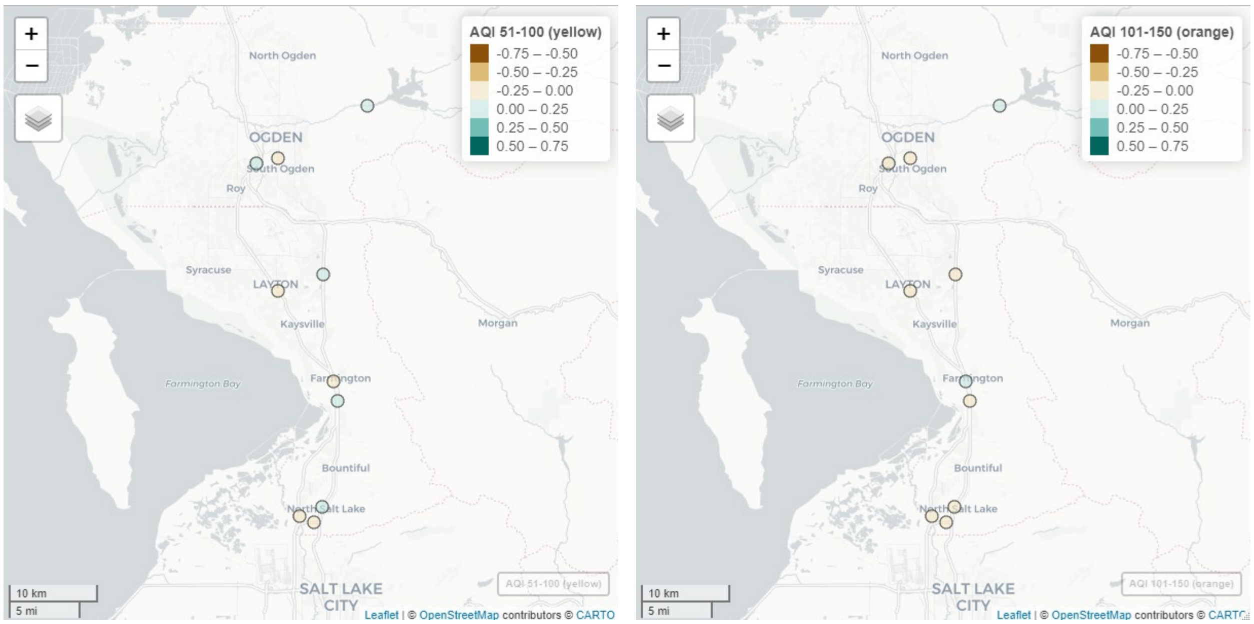

Figure 4.5 Maps showing automobile traffic volume model posterior slopes for yellow (left) and orange (right) air quality levels in Weber County and Davis County

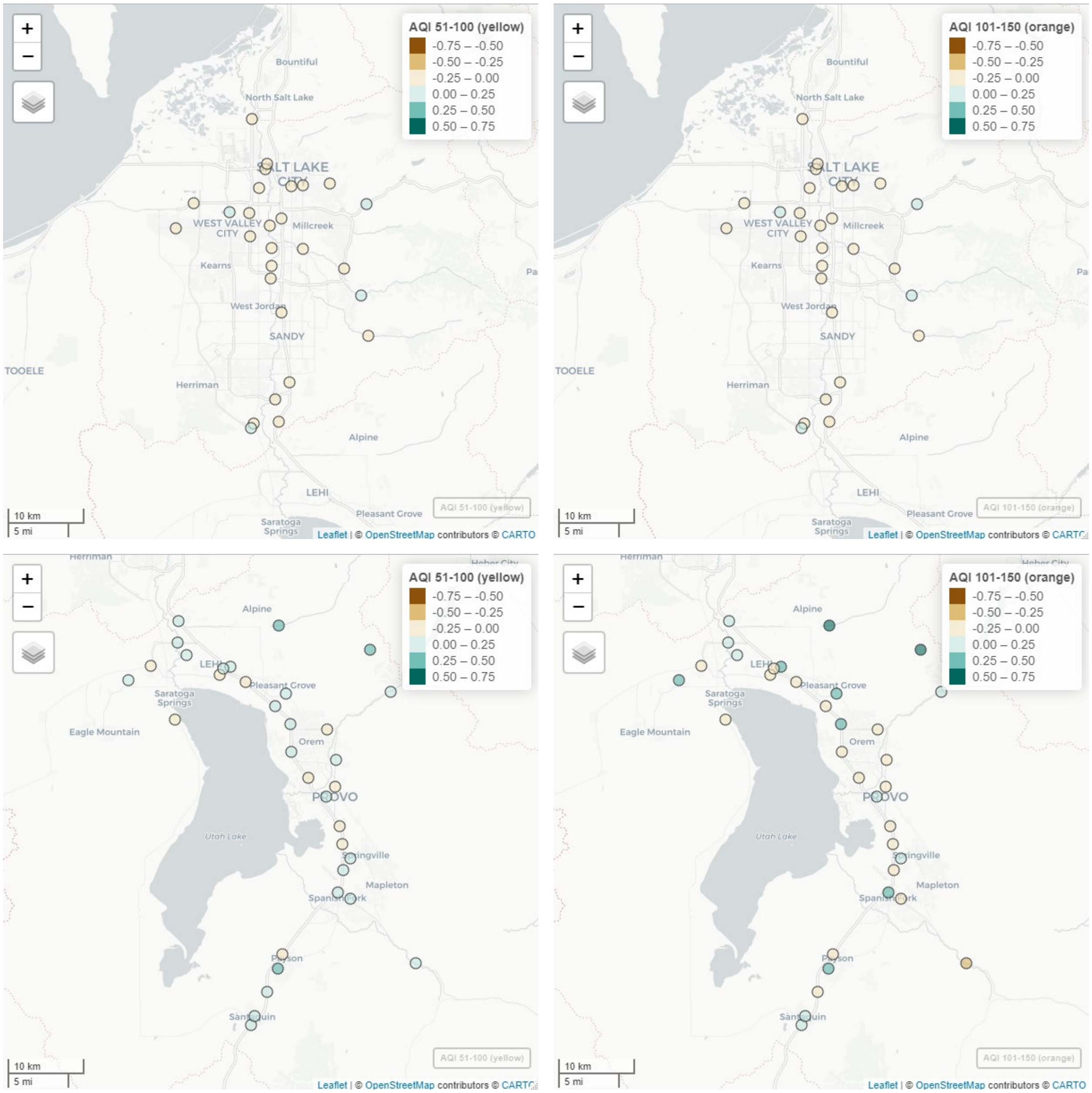

Figure 4.6 Maps showing automobile traffic volume model posterior slopes for yellow (left) and orange (right) air quality levels in Salt Lake County (top) and Utah County (bottom)

4.3 Rail Transit Ridership

Table 4.5 reports results of the model for UTA TRAX light-rail ridership. The coefficient estimates for both yellow air days (β = -0.061, *SE* = 0.065, *t* = -0.947, *p* = 0.344) and orange air days (β = -0.178, *SE* = 0.180, *t* = -0.988, *p* = 0.323) were negative but insignificant. Although the data showed a roughly 6% decrease and 16% decrease in TRAX light-rail ridership on days with “moderate” and “unhealthy” air pollution, these could not be statistically distinguished from zero with high confidence. Similarly, Table 4.6 reports results of the model for UTA FrontRunner commuter rail ridership. The coefficient estimates for both yellow air days (β = -0.004, *SE* = 0.015, *t* = -0.260, *p* = 0.795) and orange air days (β = -0.018, *SE* = 0.040, *t* = -0.462, *p* = 0.644) were again negative but not significant, and with a lower magnitude (0.4% and 1.8% decreases, respectively) for FrontRunner than for TRAX. Overall, although the data show a small (for FrontRunner) to moderate (for TRAX) decrease in rail transit ridership on days with poor air quality (and greater decreases on orange as compared with yellow air days), there was not enough confidence to say that these were not due to random chance. As a reminder, due to the regional nature of transit data, we could not study variations in these relationships across different locations.

Table 4.5 UTA TRAX transit ridership, ordinary regression model

Coefficients	*Estimate*	*SE*	*t-statistic*	*p-value*
Intercept	10.964	0.072	151.587	<0.001
Day of week (ref. = Weekday)				
Saturday	-0.475	0.082	-5.807	<0.001
Sunday	-1.105	0.081	-13.574	<0.001
Season (ref. = Winter)				
Spring	-0.056	0.082	-0.683	0.495
Summer	-0.203	0.086	-2.350	0.019
Fall	0.094	0.084	1.114	0.266
Holiday (ref. = No holiday)	-2.924	0.185	-15.779	<0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.075	0.082	-0.914	0.361
Heavy rain	0.006	0.245	0.025	0.980
Light snow	-0.006	0.124	-0.052	0.959
Heavy snow	0.452	0.213	2.122	0.034
Max temperature difference from average	0.009	0.004	2.507	0.012
Air quality index (ref. = Green)				
Yellow (AQI = 51–100)	-0.061	0.065	-0.947	0.344
Orange (AQI = 101–150)	-0.178	0.180	-0.988	0.323

Notes: N = 719; adjusted R^2 = 0.374.

Table 4.6 UTA FrontRunner transit ridership, ordinary regression model

Coefficients	*Estimate*	*SE*	*t-statistic*	*p-value*
Intercept	9.838	0.016	615.082	<0.001
Day of week (ref. = Weekday)				
Saturday	-0.861	0.017	-50.411	<0.001
Season (ref. = Winter)				
Spring	-0.059	0.019	-3.183	0.002
Summer	-0.066	0.019	-3.401	0.001
Fall	0.094	0.019	4.976	0.000
Holiday (ref. = No holiday)	-1.213	0.039	-31.225	<0.001
Precipitation (ref. = No rain / no snow)				
Light rain	0.009	0.018	0.517	0.605
Heavy rain	0.001	0.051	0.016	0.987
Light snow	-0.006	0.028	-0.226	0.821
Heavy snow	0.039	0.050	0.775	0.439
Max temperature difference from average	0.002	0.001	2.012	0.045
Air quality index (ref. = Green)				
Yellow (AQI = 51–100)	-0.004	0.015	-0.260	0.795
Orange (AQI = 101–150)	-0.018	0.040	-0.462	0.644

Notes: $N = 616$; adjusted $R^2 = 0.849$.

5. DISCUSSION

5.1 Objective 1: Modal Differences in the Effects of Area-Wide Air Pollution on Traffic Volumes

In line with the first objective of our study—to measure the effects of area-wide air pollution on multimodal traffic volumes and study how these effects differ by mode, by building separate models for walking, driving, and transit to observe the difference in effects across mode—we ran multilevel models for pedestrian volumes, automobile traffic volumes, and bus/rail transit ridership. The model results are discussed in two different subsections, one for each study area.

5.1.1 Study Area 1: Cache County

The results obtained from our models in study area 1 (Table 3.1, Table 3.3, and Table 3.5) shed light on the aggregate effects of area-wide air quality on multimodal traffic volumes (the study's first objective), specifically automobile and pedestrian volumes and bus ridership. We found a general decrease in walking and an increase in driving on days with higher levels of air pollution, while our results showed no significant change in bus ridership. For orange days (AQI = 101–150, unhealthy for sensitive groups), an increase of 5.1% in automobile volumes and a decrease of 12.7% in pedestrian volumes are expected compared with green days. Even on yellow days (AQI = 51–100, moderate), the models predict a 5.2% decrease in walking. This could possibly be explained by a tendency of active travelers to avoid exposing themselves to outdoor air pollution by switching from walking (or walking plus public transportation) to driving, an encapsulated mode of travel with sometimes lower exposure to air pollution, at least in terms of minutes. In addition, there could be a reduction in recreational trips made by active modes such as running or visiting parks.

5.1.2 Study Area 2: Wasatch Front

In the case of study area 2 (Table 4.1, Table 4.3, Table 4.5, and Table 4.6), our analysis reports smaller magnitude changes in pedestrian volumes than were observed in study area 1. On average, pedestrian volumes decreased by 10.6% on orange days and actually increased slightly (by 0.6%) on yellow days. Also, automobile traffic volumes increased by only around 0.7% on yellow days, and there was no significant increase or decrease (on average) on orange days. However, follow-up analysis showed that more locations had decreases in automobile traffic volumes than increases on "unhealthy" orange air quality days (Figure 4.4). Although our models found general decreases in rail transit ridership for both of UTA's TRAX and FrontRunner systems on yellow days and stronger decreases on orange days, the decreases were not statistically significant.

These results suggest overall decreases in travel during episodes of area-wide air pollution, either by people foregoing trips or time shifting them to other less polluted days. This result could reflect the effects of air quality alerts (i.e., in news media and on variable message signs), as well as options for teleworking. The simultaneous decrease in walking and decrease in rail transit ridership (even if not significant) is a reasonable finding since many, if not most, public transit riders are pedestrians when going to and from transit stops and stations. The mixed results for automobile traffic volumes (small decreases/increases, with large variations in different locations), when taken alongside pedestrian and trail transit findings, potentially suggest that (like in study area 1) some "risk averse" travel behavior responses (Noonan, 2014) to elevated air pollution levels. Some people, in some places, may switch modes from walking to driving in order to reduce their exposure to air pollution.

5.2 Objective 2: Locational Variations in Relationships of Air Pollution with Traffic Volumes

In line with the second objective of our study—to explore locational variations in the effects of area-wide air pollution on multimodal traffic volumes by using multilevel modeling to represent the locational variations in each mode-specific model—we introduced cross-level interaction variables in the multilevel models. As transit ridership was not available for specific locations within the region (only aggregated for each study area), we could not study the effect of location on the relationship between air quality and transit ridership. We again discuss findings for study area 1 first, followed by study area 2.

5.2.1 Study Area 1: Cache County

In study area 1, we looked at the effect of location on the relationship between air quality and multimodal traffic volumes (the study's second objective), specifically pedestrian and automobile traffic volumes.

For pedestrian volumes, we found significant associations of the percentage of commercial land uses, the percentage of four-way intersections, and average car ownership with the slope of the air quality coefficients (Table 3.2). The positive interactions between yellow days and the percent of commercial parcels, and between orange days and the percent of 4-way intersections (a measure of street network connectivity), inform us that in areas with more commercial land uses and high street connectivity, pedestrian volumes do not decrease as much on poor air quality days. Areas with more connected street grids (Tal & Handy, 2012) and more commercial businesses often allow shorter and more direct walking trips, which can shorten the time exposed to air pollution and thus may make people walking in these areas less sensitive to polluted air. Also, good street network connectivity often implies a business area—coefficients were less negative and more positive along Main Street running north/south through the region (Figure 3.2)—which might involve mostly non-discretionary and work-related walk trips, which we expect to be less sensitive to poor air quality.

On the other hand, there was a significant negative interaction for yellow and negative (but not significant) for orange days with average car ownership. In other words, in neighborhoods with higher car ownership, pedestrian volumes tend to decrease more on poor air quality days. One likely explanation is that greater car ownership provides more opportunities (modal options) for escaping air pollution and shifting from higher-exposure modes like walking to less-exposed modes like driving a personal automobile. Higher car ownership could potentially signify higher income groups whose tendency to take motorized vehicles is high in polluted days (Kim et al., 2023). Conversely, neighborhoods with limited private car access may not have such flexibility of modal shifting.

Compared with walking, we did not find any significant variations across locations for the relationship between air quality and automobile traffic volumes (Table 3.4). This conclusion was likely due to the small number of stations (six) that were available for automobile traffic counts in study area 1 and the relatively small size of our study area (in terms of demographics and diversity). Another explanation could be the different spatial scales at which walking and driving take place. Let us assume that the travel behavioral differences in air quality responses are mostly due to who people are and where they live. If this is the case, then the shorter nature of walking trips will average these differences over a small spatial area, perhaps within one mile. Since automobile trips tend to be longer, then individual or neighborhood differences will be averaged over a larger scale, perhaps five or 10 miles. Thus, the differences that appear when comparing air quality relationships with traffic volumes across locations will be diminished for automobile traffic compared with pedestrian traffic. Given the sparseness of our automobile traffic volume count locations, we could not test this hypothesis.

5.2.2 Study Area 2: Wasatch Front

For pedestrian volumes, we found significant associations of several built and social environment variables with the slope of the air quality coefficients (Table 4.2). In general, pedestrian volumes increased more or decreased less on days with poor air quality in the following types of locations: greater job density, more mixing of jobs and residents, more children per household, greater unemployment, and near universities. The results for job density, children, and university proximity could relate to more mandatory trips (to work or school) being made in those locations; such trips (including escorting children to school) may to be less sensitive to external environmental factors like air pollution because they are not as easy to cancel or reschedule as compared with more discretionary trips for shopping or recreation. As was mentioned for study area 1, a greater diversity or balance of jobs and residents often indicates a more walkable neighborhood (Ewing & Cervero, 2010), so walk trips may be shorter, less exposed to air pollution, and thus less deterred by poor air quality. The result regarding the unemployment rate is not as easily explainable; however, it was of a small magnitude and only marginally significant.

In contrast, pedestrian volumes increased less or decreased more on poor air quality days in locations with the following characteristics: more intersections, better job access by car, more rail transit stops, more schools, and neighborhoods with more workers per household and a larger share of non-white or Hispanic populations. The result for rail transit stops makes sense when viewed in relation to the (albeit non-significant) decrease in rail transit volumes. Transit riders tend to have longer commutes than those using other modes, so they may be most willing to telework if given the opportunity, and thus pedestrian volumes might also go down near transit stops. The result for job access by car also makes sense when viewed in relation to the increase or no change in automobile traffic volumes; if it is easier to get to many places via car, people may be more likely to switch from walking to driving when the air quality is poor. For schools, parents may be more willing to drive their children to school than allow them to walk when there are elevated levels of air pollution. Regarding the finding about race/ethnicity, other research has found that non-white populations in the U.S. perceive greater risks from air pollution caused by automobiles than do U.S.-born white people (Macias, 2016), so it could make sense that their pedestrian travel behavior is more sensitive to area-wide poor air quality.

For automobile traffic volumes, we found significant associations between the variables unemployment rate and percentage of non-white or Hispanic populations with the air quality coefficients (Table 4.4). Specifically, driving did not increase as much or decreased slightly more in neighborhoods with a greater share of the population either unemployed or reporting non-white or Hispanic race/ethnicity. Given that walking increased more or decreased less in areas with higher unemployment, this could mean that there was less mode shifting from walking to driving for people who were unemployed. In contrast, neighborhoods with more non-white or Hispanic populations saw greater reductions in both walking and driving, which again could be related to air pollution and environmental perceptions among these populations (Macias, 2016).

5.3 Policy Implications

This study informs stakeholders in air quality and transportation by highlighting the aggregate behavior of travelers during periods of area-wide air pollution, such as that caused by wintertime inversions, summertime ozone, or wildfire smoke. These findings are especially relevant for efforts to affect changes in travel and other health-related behaviors through air quality alerts. The Utah Division of Air Quality issues alerts that are directly linked to the color-coded AQI levels (Utah DEQ, 2022b). For example, on orange days, the recommendation for sensitive groups is to: “Reduce prolonged or heavy exertion. It’s OK to be active outside, but take more breaks and do less intense activities. Watch for symptoms such as coughing or shortness of breath." Also, the Utah Department of Transportation encourages people to "TravelWise" (UDOT, 2022) and reduce driving on or in advance of poor air quality days by using "soft" travel behavior change strategies such as carpooling, riding public transit, trip chaining, trip shifting, and teleworking. Many employers (including the State of Utah) have mandatory (mostly automobile) trip reduction programs that they can deploy on severe air pollution days. The call to drive less, carpool, and telework is also prevalent on major news media (Maffly, 2020; Mumford, 2022; Roe, 2018) as Utah grapples with poor air quality every winter.

From our study's results in both study area 1 (Cache County, Utah) and study area 2 (Wasatch Front region, Utah), it appears that people are walking less, by 10% or more, on days with unhealthy air quality (AQI > 100). This could be an active risk averse response to the air quality alerts or to seeing or breathing the air pollution. However, we find that people do not seem to be driving less on poor air quality days; instead, motor vehicle traffic volumes were actually higher on yellow or orange air quality days, all else equal and on average. This implies that air quality and travel behavior alerts are not effective at significantly reducing driving, at least as currently employed in these parts of Utah. Some places certainly saw fewer decreases in walking and more decreases in driving, so there are locational variations in these aggregate behavior changes. Overall, there was more evidence for risk averse reactions than for altruistic travel behavior changes (Noonan, 2014).

Overall, more and different strategies may be needed to encourage sustainable and healthy travel behavior changes during episodes of area-wide poor air quality. New policies could include wider use of mandatory employer-based programs. Organizations could be encouraged or required to provide options for telecommuting and flexible work arrangements that can reduce the number of driving trips (Giovanis, 2018; Kitou & Horvath, 2008). In cases of severe air quality, hard policies such as road pricing schemes could be introduced to decrease automobile traffic volumes (Isaksen & Johansen, 2021; Simeonova et al., 2021). Soft policies could include communication campaigns to emphasize the health benefits of reducing automobile usage during poor air quality days, highlighting the collective impact of individual actions on air pollution reduction and public health. UTA could consider implementing free public transit during periods of bad air quality. (CVTD's transit system is already fare-free.) Federal funds through the Congestion Mitigation and Air Quality Improvement program may be available for projects and programs to reduce air pollution emissions, including those that encourage mode shifts and other travel behavior changes.

We also wish to highlight a potential equity or environmental justice issue. Recall our findings that both walking and driving decreased more on days with poor air quality in neighborhoods with higher shares of non-white or Hispanic residents and higher unemployment rates. While there could be localized benefits of reduced driving such as reduced motor vehicle emissions, the reduced mobility overall is potentially troubling because many of the public's essential services and daily needs still must be met through travel. Therefore, this finding suggests policies to enhance public transit services to these communities, both on a short-term and ongoing basis, to allow for continued mobility and participation in society while both reducing exposure to air pollution through walking and reducing contributions to air pollution through driving. In addition, adjusting work policies to encourage telecommuting on days with poor air quality could further benefit vulnerable populations, reducing the need for travel and exposure to harmful conditions.

5.4 Limitations & Future Work

This study had several shortcomings that could be remedied through future work. First, the number of days with very poor air quality (i.e., red "unhealthy" or purple "very unhealthy") was quite limited, and there were only 2%–3% of observations with "unhealthy for sensitive groups" orange air quality levels. The implications of this included a reduction in our models' statistical power to detect the likely small size effects of air pollution on traffic volumes. Considering a longer time frame and picking sites unfortunate enough to have experienced more days with more severe air pollution (including multiple days of red or worse air quality) could improve the statistical significance of the model's estimated coefficients and potentially lead to measuring stronger relationships between air quality and multimodal traffic volumes.

Second, though our study defined the air quality impacts on traffic volumes, it did not distinguish the different impacts that might be present during different seasons (i.e., winter and summer) or due to concentrations of different pollutants (i.e., nitrogen dioxide, ground-level ozone, and fine particulate matter). Owing to the different types of air pollution sources and causes and different travel options available during each season, we might see a different response in each season or because of different air pollutants. For example, people escaping from air pollution by driving to the mountains might be more common in summer than during the winter, or more common in winter in relation to recreational skiing. Also, the shift from automobiles to walking is more convenient in summer than during the cold winter. These hypotheses should be examined in future work.

Third, improved air pollution and weather monitoring and modeling could improve the accurate measurement of our exposure variables. Although we tried to match multimodal traffic count locations with nearby weather and air quality stations, this method still assumed some degree of uniformity of precipitation, temperature, and air pollution across the area. Localized variations in these ground-level conditions—due to topography, heat-island effects, transportation networks, building and green space locations, etc.—were likely obscured in our analysis because of data limitations. On the other hand, one could argue about the appropriate spatial scale at which knowledge of weather and air quality levels might affect travel behavior choices that would manifest in differential multimodal traffic volumes.

Fourth, a lack of robust data for public transit ridership led to several limitations: it did not allow us to build multilevel models for transit ridership; we could not examine bus ridership in study area 2; and we could not investigate locational variations in the relationship between air quality and transit ridership. For example, were there some areas which were more or less significantly affected by air quality? In the case of pedestrians, we could see different regions within study area 2 had a varied response to air quality; the lack of locational data for transit did not allow us to study this possibility.

Fifth, the pedestrian volume models did not account for any similarity in unobserved factors affecting counts for stations that are located closer to each other; i.e., it ignored the spatial structure of the data. Accounting for potential spatial autocorrelation—such as the use of a spatial lag term—in the models would address this limitation. Sixth, all of the models did not account for temporal autocorrelation, although we did attempt to structurally model temporal patterns through the use of temporal control variables representing day-of-week and season. Future work could investigate time series modeling to better address the impact of temporal autocorrelation.

Seventh, this study was done in a particular location (Utah, United States), so its findings may be limited to this or similar locations, e.g., the western U.S., mountain valleys, areas with specific predominant cultural characteristics. At the time of this study, Utah as a state was younger (median age 32 vs. 39 years) and less racially diverse (79% vs. 61% of the population reporting white alone race) than the U.S.

population as a whole (US Census Bureau, 2022), which might have led to different results as different groups of people have diverse beliefs about outdoor air pollution (Johnson, 2002). Also, diverse income groups in various geographical areas show different levels of active travel (Buehler et al., 2020; Ghimire & Bardaka, 2023). Thus, we suggest future work examining other urban areas with more non-automobile transportation options and greater availability of frequent public transportation, larger downtowns, more demographic diversity, etc., as future work might find stronger and/or more significant impacts of air pollution on multimodal traffic volumes.

Eighth, this study did not account for the period during and since the COVID-19 pandemic. After COVID-19, people's ability and adaptation to teleworking changed drastically (Belostecinic et al., 2021). Employees have been more flexible in the policy of teleworking, which means that during the periods of poor air quality, more travelers could respond by opting for teleworking. However, our study did not include the days during COVID-19, as it would have complicated the inference of relationships between air quality and traffic volumes. There were many significant travel impacts during early phases of COVID which might not reflect the true long-term relationship between air quality and aggregate travel behavior. Further studies could look into the relationship between air quality and multimodal traffic volumes during and after COVID by including adequate controls for COVID spread and response, as well as changes in employer policies and employee preferences around remote work and schedule flexibility.

Ninth, although this research explored changes in both pedestrian and automobile traffic volumes as well as system-wide bus and rail transit ridership, due to the aggregate nature of the data it could not explain how the change in volume/ridership for different modes could have been interlinked or precisely why driving increased and walking decreased on poor air quality days. Future work could supplement this aggregate traffic volume analysis with a more disaggregate analysis of travel diaries, travel behaviors derived from location-based services data, and/or travel surveys to understand how and why individuals change their travel patterns in response to poor air quality. The growing availability of big data sources of travel behavior information allows for the study of many people over many days (Xu et al., 2021), and thus break down the boundaries between aggregate and disaggregate analyses. Such studies could be better able to capture behavioral responses to air pollution, such as shifting modes or forgoing or rescheduling trips. We encourage researchers to address these issues in future work.

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