IMPACT OF WEATHER ON TRANSIT-DEPENDENT BUS RIDERS IN ORANGE COUNTY, CALIFORNIA

A Thesis
Presented to the
Faculty of
California State Polytechnic University, Pomona

In Partial Fulfillment
Of the Requirements for the Degree
Master
In
Urban and Regional Planning

By
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2023
COMMITTEE MEMBERSHIP

THESIS: IMPACT OF WEATHER ON TRANSIT-DEPENDENT BUS RIDERS IN ORANGE COUNTY, CALIFORNIA

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ACKNOWLEDGEMENTS

I would like to first thank Dr. Richard Willson for mentoring me at the start of my thesis journey. I would also like to thank Charles Main, Kevin Khouri and Steve Hossack at OCTA for helping me with any questions I might have regarding transit ridership data. I would like to especially thank Jorge Duran and Dr. Frank Wen for agreeing to serve on my thesis committee, and for providing helpful feedback during the defense process. Lastly, I would like to thank my thesis committee chair, Dr. Dohyung Kim, for his support and guidance. Without his continual reassurance, this paper would not have been possible.
ABSTRACT

In the coming years, “new normal” weather conditions forecasted for the Greater Los Angeles area include increased temperatures and infrequent, yet extreme rainfall. This has implications for transit ridership in the region, as existing research has shown that extreme rainfall and heat can have significant impacts on transit ridership levels. However, research has also shown that a subclass of transit users (known as transit-dependent users) is limited to public transit as their primary mode of transportation. To date, little research has been conducted on the effects of extreme weather conditions on the ridership turnout of this group.

This study investigates how extreme heat and rainfall affect the ridership turnout of transit-dependent bus riders in Orange County, California. Weekday weather and ridership data was gathered over two approximately year-long study periods from February 2019 to February 2020. Transit-dependency was measured by utilizing 2019 census data to explore the socioeconomic and demographic characteristics of the areas surrounding bus stops. To evaluate the relationship between variables, two ordinary least-squares (OLS) regression models were constructed for heat impacts and rainfall impacts. The results of the models indicate that extreme weather mostly does not have a significant impact on the ridership patterns of transit-dependent bus riders, with exceptions for retail workers (higher ridership during extreme heat, lower during extreme rainfall), construction workers (lower ridership during extreme rainfall), residents with long commute times (higher ridership during extreme rainfall), and limited English-speaking households (lower ridership during extreme heat). As new climatic conditions emerge, transit agencies and municipalities within Orange County can utilize this information to provide improved service and amenities to residents who rely on transit.
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CHAPTER 1: INTRODUCTION

Public transit is an important means of transportation for Americans, especially in the Los Angeles Metropolitan Area. Despite a car-centric reputation, the region is home to many transit users with the largest regional transit provider (Los Angeles County Metropolitan Transportation Authority, or L.A. Metro) boasting the second highest total number of trips in the country for the first half of the 2023 fiscal year (Bonina, 2023). Other transit agencies in the immediate area, such as the Orange County Transportation Authority (OCTA), Foothill Transit, and Riverside Transit Agency also provide transit services to the area. These agencies combine to provide essential transit services to the largest greater urban area in California.

Although the region itself is highly diverse with residents coming from a variety of backgrounds, research has shown that this diversity is not entirely reflected when it comes to transit users. According to one recent study, nearly eighty percent of the individuals who accessed L.A. Metro transit services in 2016 did not have access to a person vehicle, while forty-four percent reported having a household income below $15,000 a year (Manville et al., 2022). This is mirrored in the rider characteristics of other nearby transit agencies such as OCTA, whose own survey found that approximately seventy percent of its riders did not have access to a personal vehicle (OCTA, 2018). What these findings suggest is that a certain segment of transit riders has no choice but to ride transit; they lack the ability to choose another, possibly faster mode of transportation such as car travel. This population has generally been referred to as transit-dependent (Jiao & Wang, 2020). Because they rely exclusively on public transit for mobility, it is imperative that transit agencies study their travel patterns and behavior to best design a transit system with their needs in mind.

Existing research has looked at the causes of transit-dependency and identified multiple
factors. Jiao (2017) identifies lack of personal vehicle access as a defining feature of transit
dependency, as well as being within the age range of 12-15 years old and living in non-
institutionalized group quarters. Other studies link low-income status with lack of vehicle access
and greater transit-dependency (Lachapelle, 2015, Manville et al., 2022). The research on transit
rider behavior in Greater Los Angeles noted that greater personal vehicle access is strongly
associated with choosing not to take transit among low-income residents (Manville et al., 2022).
Based on these studies, it appears that income, vehicle access and youth all play a role in
determining a person’s likelihood to use transit.

While these factors are known to influence a person’s likelihood of using transit, another
well-documented variable that often impacts transit ridership outcomes is weather. Multiple
studies have found that increased rainfall depresses transit ridership, while increased heat
increases ridership (Guo et al., 2007, Stover & McCormack, 2012, Arana et al., 2014). This is
especially important for transit agencies to consider given the climate of Southern California and
the impending consequences of climate change. In the coming years, higher temperatures are
expected in the summer months in Los Angeles County (Burillo et al., 2019, Kim et al., 2021).
At the same time, rainfall is predicted to simultaneously become less frequent and more extreme
(Gershunov et al., 2019), with extremes likely leading to a higher risk of hazardous events such
as flooding. These changes have the potential to significantly impact daily travel behavior for all
Southern Californians, including those who rely on public transit.

An interesting area of study to consider, therefore, is how the demographic and
socioeconomic factors leading to higher transit ridership interact with weather impacts on transit
ridership. To date, few studies have looked at the influence of extreme weather on transit-
dependent riders. One study by Ngo (2019) looked at the impact of high temperatures and
rainfall on bus riders of various incomes in Lane County, Oregon. The results of this study indicated that higher precipitation is associated with lower ridership turnout among low-income riders, while high heat is associated with higher ridership. Because Ngo’s study is located in a specific context (a medium-sized city in the Pacific Northwest), subsequent research that analyzes the same weather impacts upon transit-dependent riders in a different setting would be enlightening.

The purpose of this study is to determine the extent of ridership change among transit-dependent bus riders with respect to extreme weather in the context of Southern California. The area chosen for this study was Orange County, which is located within the Los Angeles Metropolitan Area and has transit services provided by OCTA. This location was chosen because of stop-level bus ridership being available to the researcher at the time of study. By performing this analysis, it is believed that more information can be gleaned on the travel patterns of transit-dependent riders as they respond to inclement weather conditions, which can help OCTA transit planners make well-informed decisions during seasonal service changes.

This study is divided into six chapters. The first chapter introduces the concepts of transit-dependent riders, predicted extreme weather in Southern California, and the need for more information on how the latter will impact the former’s likelihood to take transit. The second chapter goes over the existing literature on the various factors that influence transit ridership and the extent to which they interact. The third chapter details the methodology of gathering data measuring transit dependency, weather, and bus ridership, as well as the statistical model built to determine the relationship between changes in transit ridership and transit-dependency with respect to extreme weather impacts. The fourth chapter reports the results of the previously mentioned model. The final two chapters attempt to explain any significant
relationships between transit ridership, weather, and transit dependency that were detected by the model, as well as provide policy recommendations for OCTA on how to best plan for transit-dependent populations in the face of extreme weather. Study limitations and opportunities for future research are also included in the final chapter.
CHAPTER 2: LITERATURE REVIEW

History of Public Transportation in America and Southern California

Public transit in the United States has a long history that is tied to the expansion of the country’s urban areas. As America’s cities grew throughout the 19th and 20th centuries, new technological innovations often lead to attractive new mass transportation modes that promised better, more efficient ways of moving people from trip starting point to destination. These included first the steam ferry service in the early 1800s, followed by horse-drawn omnibuses and finally electrified transit in the form of electric streetcars nearly a half-century later (Young, 2015). The electric streetcar was especially important in encouraging what Young refers to as the “forces of centralization and dispersion in American cities”. Essentially, this meant both the process of centralizing major commercial activities in a singular urban downtown core, as well as dispersing other urban forms, such as manufacturing centers and residential districts, to areas surrounding the core.

Electric streetcars and the interurban railway networks that supported them allowed for greater distances to be traveled in shorter periods of time when compared to modes such as the horsecar, leading to the development of “streetcar suburbs” in cities like Boston and Baltimore (Ward, 1964) (Wilson, 2019). In the 20th century, this suburban “dispersal” process continued at an increasingly rapid pace with the invention of the automobile and the construction of extensive freeway networks designed to accommodate commuters. Research on 20th-century American urban growth has indicated that urban freeway systems, coupled with a greater reliance on the automobile as a primary means of transportation, were at least partly responsible for the greater rate of urban decentralization during this time-period (Mieszkowski & Mills, 1993). However, this shift toward freeways and automobile usage did not mean that public transport investment
was entirely abandoned. Several actions were taken by the federal government during the period between 1960 and 1974 that led to sustained investment in urban mass transit (Weiner, 2008). These included the Urban Mass Transportation Act of 1964 which established the Federal Transit Administration: a federal agency that provides financial and technical assistance to local public transit systems (U.S. Department of Transportation, 2023). It is through the sustained guidance of federal programs such as this, as well as careful actions and planning at the local level, that public transportation has remained a viable travel mode option for residents in all major U.S. cities.

A similar transit origin story can also be observed at the regional level in Southern California. Streetcars were a primary means of transportation in Los Angeles in the early 20th Century, acting as a method to connect growing single-family subdivisions that were developing quickly at the time (Elkind, 2014). Eventually, local developer Henry Huntington would pioneer the creation of a single system, the Pacific Electric Railway Company, that stretched from oceanfront properties in the west all the way to mountain and foothill communities in the north and east (Elkind, 2014). However, this popularity would not last. A new car culture would emerge in the 1950s, 60s and 70s, driven by postwar population growth and contributing to travel patterns that were complex and less linear. As a result, the last Pacific Electric streetcar ceased operations in 1961, leaving buses to become the primary means of public transportation in the region (Elkind, 2014).
Who Rides Public Transportation?

When discussing trends in public transportation, it is important to analyze who exactly is using public transportation regularly. Looking at nationwide data, several key trends emerge. The 2019 American Community Survey reports the bus as the most popular primary commuting mode at 46% of all transit riders, followed by subway and long-distance train. Demographic characteristics of the seven most transit-heavy metros collected by the survey reveal that women commute by transit more than men and that the most common age group of transit commuters is 25 to 34 years old. Among ethnic groups, Black and Asian commuters made up 21.7% and 14.8% of the transit commuting population, respectively, while constituting 11.9% and 12.1% of all other workers (Burrows et al., 2021). The percentages of Hispanic/Latino commuters using transit and using other modes within the seven most transit-heavy metros were similar at 24.9% and 24% respectively (Burrows et al., 2021). This overrepresentation of minority groups among transit users may be tied to greater overall rates of racial/ethnic diversity found in large American metro areas. Additional findings include the New York Metropolitan Area having the largest share of its population as transit commuters compared to other cities at 31.6%, as well as the percentage of commuters using transit having declined nationally from 12.1% in 1960 to 5% in 2019 (Burrows et al., 2021).

Additional statistics collected by the American Public Transit Association have shed further light on transit commuter characteristics and travel motivations. Households making less than $15,000 annually in 2014 were overrepresented amongst transit users when compared to their share of the general population (21% vs. 13% respectively), while shares of transit users and the general population making over $100,000 annually were roughly the same (Clark, 2017) (Figure 1). Common trip purposes for riders included work (49%), shopping (21%), and other
recreational spending (17%) (Clark, 2017). Most used public transit five days a week (50%), with a majority stating that they accessed transit services by walking to a stop or station (69%) (Clark, 2017). Importantly, when asked about which alternative mode they might use if transit were not available, the most common response was that no trip would be made, signifying a lack of vehicle access among transit riders that aligns with previously mentioned statistics discussing income (Clark, 2017). This linkage of public transit and poverty is not new: U.S. policymakers have long examined the lack of mobility options as a precursor to public transit use, as well as the possibility of transit improvements as a means for increased economic mobility (Kain & Meyer, 1970, Zhao & Gustafson 2013). These statistics therefore reaffirm the notion that poor individuals are overrepresented among transit users, at least at the national level.

**Figure 1:** Income of General U.S. Households and Transit Rider Households

![Graph showing income distribution of general U.S. households and transit rider households.](image)

Source: American Public Transportation Association, 2017
At the local level of Orange County, California (the focus area of this paper), transit rider characteristics both emulate and diverge from nationwide findings. Results from the Orange County Transportation Authority’s (OCTA) 2018 agency-wide onboarding survey found that most trips (39%) were made for home-to-work commuting purposes, and that most respondents accessed and egressed bus stops by walking. A majority of riders also self-reported as being from a low-income household (making less than $30,000 annually), not having access to a vehicle (82.5%), and being younger than 34 (51.1%), all of which align with national statistics. However, unlike national findings the most common ethnic group for Orange County transit riders was not white, but Hispanic/Latino at 64.4%, reflecting a disproportionate share of the rider population when compared to their percentage of Orange County as a whole (34%) (U.S. Census, 2022). While the prevalence of Hispanic/Latino residents on Orange County public transit may make sense given how much more Hispanic/Latino the State of California is compared to the rest of the country, the fact remains that transit riders, both in Orange County and elsewhere, are more likely to be disadvantaged when it comes to factors like vehicle access and socioeconomic status. As such, analysis of variables that impact this vulnerable, transit-dependent population is important for their and the county’s societal well-being.

An important trend to consider is the increasing rate of decline bus service use (and public transit use as a whole) prior to the COVID-19 pandemic. In January 2018, a report prepared by the UCLA Institute of Transportation Studies for the Southern California Association of Governments (SCAG) region found that transit ridership across both bus and rail modes began falling modestly in 2007, with increases in the rate of decline picking up in 2013 (Manville et al.). The report also yielded key insights regarding travel patterns, with findings suggesting that a relatively small number of people and neighborhoods (primarily lower-income foreign-born
residents) made up the majority of trips across the SCAG region (Manville et al.). This has implications for bus network design, as it would suggest that targeted investment in communities comprising these residents would yield a greater amount of ridership capture when compared to other communities. Furthermore, the report notes that this declining trend appears unrelated to both transit fares and service levels, with both having stayed relatively flat and increased (respectively) during the period in which this measured decline was occurring (Manville et al., 2018). Instead, the report points to a dramatic increase in vehicle ownership levels among foreign-born residents, with foreign-born households from Mexico constituting the largest decline in share of households without vehicles at 66 percent (Manville et al., 2018). Since Hispanic and Latino residents as of 2021 made up the largest share of the resident population in the SCAG Region (Southern California Association of Governments), it could be wise to prioritize tracking travel behavior and travel mode choice patterns in this population group moving forward.

**Factors that Influence Travel Behavior**

Understanding travel behavior to identify how it can be influenced is considered a key component of the transportation planning process (Meyer, 2016). As a result, much transportation planning research has focused on the factors that predict how people will travel. Early internal determinants of travel behavior identified by researchers include social class position, life cycle status, and residential location (Fried et al., 1977). However, more contemporary research has focused on the built environment. In particular, land use policies that prioritize smart growth have been noted as an attempt to counter the typical “sprawl” development patterns associated with car use (Handy et al., 2005). These policies prioritize higher levels of developmental density and pedestrian friendliness, both of which work to
advertise non-vehicular modes of travel such as walking or transit (Handy et al., 2005) as well as lower vehicle miles traveled, or VMT (Zhang et al., 2012). As more of these policies are implemented in urban areas across the country, it will be useful for policymakers to study whether they achieve their goal in encouraging a behavioral shift in commuters away from cars.

Since this paper concerns transit, it is worth highlighting the factors that influence transit ridership specifically. Taylor and Fink (2003) note that influences on transit ridership are categorized as either external influences such as socioeconomic status and residential/employment density, or internal factors such as service quantity (number of revenue vehicle hours) and customer safety. Multiple studies have also singled out the role that the built environment has played in influencing transit investment and subsequent ridership. In particular, Ryan and Frank (2009) demonstrate that the walkability index of an area is significantly associated with transit ridership. For their study, walkability was calculated through a combination of land use density and street network density (p. 48). Another built environment factor identified as encouraging ridership is the number of parks near a transit stop (Chakour & Eluru, 2013), with researchers citing the increase in walkability brought about by pedestrian activity in parks as a likely explanation.

The external impact of socioeconomic status on transit ridership and travel behavior in general is a key focus of this study, and another area that has been previously covered by research. Income and employment have been shown to be negatively associated with transit ridership (McNally & Kulkarni, 1997, Pasha et al., 2016, Wang & Woo 2017). In their analysis of both downtown and suburban Atlanta, Wang & Woo (2017), note that poverty had both spread over time in a decentralized pattern away from the urban city core and is associated with higher rates of transit usage, suggesting that income may have a greater effect on inducing ridership
than urban form. Additional factors related to socioeconomic disadvantage that have shown to be associated with transit ridership include lack of personal vehicle access (Giuliano, 2005, Clark, 2017), increased fare prices (Gkritza et al., 2011, Erhardt et. al., 2022) and single-family household status (Wang & Xu, 2020). Research by Lyons et al. (2016) also uncovered a significant negative relationship between ridership and the proportion of the population that telecommutes, which is unsurprising given the higher likelihood that telecommuters are to be high-income (He & Hu, 2015). Still, other factors have shown to be complicated in their influence on transit ridership, such as rising fuel costs. While some studies have shown fuel price increases to be negatively associated with ridership (Hare & Machemehl, 2007, Maghelal, 2011), other have failed to find to find a significant relationship (Chiang et al., 2011) or have identified a negative relationship on certain modes of transit only (Maley & Weinberger, 2009). This variability in results suggests further study is needed to clarify how these two variables associate with one another.

**Weather as an Influence on Travel Behavior**

An important factor influencing transit ridership, and a primary focus in this research, is weather. Weather has been shown to be influential in altering travel behavior in general, as well as travel by public transit specifically (Böcker et al., 2012). Higher amounts of precipitation have extensively been shown to be associated with reduced car traffic, both in the form of rain precipitation effects (Keay & Simmonds, 2005, Cools et al. 2010) and snow precipitation effects (Datla & Sharma 2010, Call 2011). Travel destination also plays a role when car users are deciding to make a trip during precipitation events; at least two studies have shown that driving to leisure destinations, such as sporting games, decreases when precipitation is high compared to non-leisure destinations (Brandenburg & Arnberger 2001, Cools et al. 2010). In contrast to
precipitation, higher temperatures have been shown to be associated with increased traffic intensity, although it is unclear whether destination type also plays a similar role regarding this variable (Böcker et al. 2012, Cools et al. 2010).

Similar trends have been observed with weather impacts on active travel behavior. Multiple studies have shown that certain weather impacts such as increased precipitation have a negative effect on active transport methods such as walking or cycling, while other impacts such as increased temperature can have a positive effect (Lin et al. 2019, Saneinejad et al. 2012, Böcker et al., 2012). Existing research has focused on the contrast in active transport behavior between cyclists and pedestrians in response to weather. At least one San Francisco study has shown that precipitation has a significantly larger negative effect on walking than it does on cycling (Cervero & Duncan, 2003), while another study conducted in Sweden found that precipitation impacts on walking were insignificant (Liu et al., 2015), which suggests that additional research is needed to determine if there are other variables at play.

Researchers have also teased out additional group differences in behavior within active transport users relating to demographic categorization, seasonal change, and trip type. When examining commuter survey data in the Greater Toronto Area, Saneinejad et al. (2012) found areas where respondents differed by demographic category in how they reacted to weather impacts while actively commuting to work. Examples of these include age (younger cyclists tend to be more sensitive to colder temperatures than older cyclists) and gender (male cyclists are more likely to travel in rainy conditions than female cyclists) (Saneinejad et al., 2012). Seasonal impacts have also been identified, although results appear to vary by geographic location. Hotter climates tend to produce more active transport users in the winter months (Shaaban & Muley, 2016) while in cooler/temperate regions individuals tend to choose active transport when weather
is “non-abnormal”, or neither too hot nor too cold (Liu et al., 2015). Finally, research on active transport trip purposes in Melbourne, Australia by Ahmed et. al (2013) found that weather was a significant factor influencing a commuter’s decision to cycle or not cycle for approximately 70% of casual cyclists as opposed to 30% of committed cyclists. This again demonstrates how whether a trip is leisure-based or more serious (work-related) is influential for travelers in deciding to use active transportation during inclement weather conditions.

**Weather as an Influence on Transit Ridership**

In addition to these forms of transport, public transit is also a mode that has been studied (albeit in a more limited sense) with respect to weather impacts on usage. Like vehicle and active transport usage, inclement weather has been shown to have a significant effect on transit ridership, albeit with variations at different temporal levels of measurement (Stover & McCormack 2012, Singhal et al., 2014). At the seasonal level, Stover & McCormack (2012) found after looking at bus ridership trends in the Greater Seattle Area that rainfall was significantly related to ridership decrease in all four seasons, while temperature was positively associated with ridership (lower temperatures associated with lower ridership) in the winter months. Although these findings correspond with previously mentioned studies focusing on temperature and ridership, it is also important to consider other seasonal variables besides weather that have been shown to be associated with transit use, such as semester-based school systems and seasonal businesses (Kashfi et al., 2015). As a result, more research appears to be needed that takes these non-weather seasonal variables into account.

A week-level analysis of transit ridership in New York City found that rainfall, while negatively impacting ridership across all time periods, has a significantly pronounced effect on AM ridership during weekdays and midday/PM ridership during weekends (Singhal et al., 2014).
In addition, snow was found in this model to be significantly associated with higher transit ridership during the week, as well as lower ridership on weekends. The authors of this study speculate that a reason for this weekday trend may be commuters shifting their travel mode from vehicle to transit (subway) to avoid slowdowns caused by inclement weather (Singhal et al., 2014). Other research has attempted to explain the decrease in ridership on weekends as being related to trip purposes. According to Guo et al. (2007), longer duration, time-flexible and non-commuting trips are more likely to be impacted by adverse weather conditions than short, time-constrained commuting trips. Since the former trip type matches descriptions of leisure trips, it is reasonable to assume that, like active and vehicle-based transportation, trip purpose plays an important role in influencing a transit rider’s decision to travel during inclement weather conditions.

Research has also revealed differences in transit rider behavior at the transit mode level. Analyses of transit networks in Chicago and Brisbane found that in addition to the inclement weather trends mentioned earlier, sensitivity to weather was also more pronounced on buses than on trains (Guo et al., 2007, Wei et al., 2018). This makes intuitive sense, as trains are generally a sturdier form of transportation that could conceivably be viewed as more resilient to the elements than buses. Even so, studies of New York City’s transit network have revealed that cooler and warmer temperatures had positive and negative impacts on subway ridership, respectively, while rainfall had a negative impact on both subway and bus ridership (Cravo & Cohen, 2009, Singhal et al., 2014). A possible explanation for these trends may be uncomfortable passenger conditions brought about by heat trapped in enclosed subway corridors when outside temperatures are hot, as well as pleasant warm conditions brought about by the same enclosed spaces during cold outside temperatures.
Weather and Transit Riders’ Socioeconomic Characteristics

There is limited research analyzing the intersection of transit ridership, socioeconomic status, and weather impacts. One in-depth study conducted by Ngo (2019) examined the impacts that extreme weather events, such as above average heat/coldness and rainfall, had on low-income transit commuters. To accomplish this, Ngo examined bus ridership data over a period of five years in the Lane County Transit District (LCTD), the primary public transit agency serving Lane County, Oregon. Ridership data was collected by the researcher through a public records request from the agency, who used automatic passenger counter (APC) technology installed in buses to record the number of boardings and alightings per bus stop (Ngo, 2019). This functioned as the dependent variable of the study.

For the independent variables of interest (weather, income), weather was measured via average daily maximum temperature and precipitation readings across weather stations at the city level in Lane County (Ngo, 2019). Measurements above and below the 10th and 90th percentiles of maximum temperature and precipitation levels were used to represent extreme weather impacts (Ngo, 2019). To measure the income levels of bus users, mean annual household income data was collected at the census tract level. Tracts where the mean household income was less than $50,000 were designated as “low-income”, a decision partly influenced by the high number of tracts surrounding the University of Oregon containing students whose household income was less than this amount (Ngo, 2019).
To determine relationships between variables, statistical analysis was employed in the form of negative binomial regression modeling (Ngo, 2019). Additional control variables were employed in the model to minimize bias and reduce standard errors, which included dummy variables for each season, day-of-week, day-of-year, and month-year, as well as federal holidays (Ngo, 2019). The purpose of these was to account for temporal/seasonal trends in bus ridership. A dummy variable representing each bus stop was also included for the purpose of accounting for non-temporal bus stop characteristics such as stop type or stop traffic level (Ngo, 2019).

The results of this study revealed that bus ridership experienced statistically significant
average overall decreases of 1.4 percent and 0.3 percent when daily average maximum temperatures were less than 50 degrees Fahrenheit or above 85 degrees Fahrenheit respectively (Ngo, 2019). When average maximum temperatures were within the range between 50 degrees and 70 degrees Fahrenheit, no significant changes in ridership were observed. The findings somewhat contradict earlier studies described in this literature review, which note how increases in temperature were associated with increases in transit ridership. Additionally, a reduction in ridership of 5.1% was also recorded when precipitation was greater than 1 inch, which is in line with previously mentioned trends (Ngo, 2019). Differences in ridership with respect to weather impacts on weekends vs. weekdays were recorded, with bus ridership showing an increase of 1.1 percent during very hot temperatures in comparison to weekday ridership during the same conditions, which produced a decrease of 2.2% (Ngo, 2019). This may be related to differences in trip travel behavior on weekdays vs. weekends, and how different trip destinations (i.e. leisure trips) may influence mode choice in different ways when certain weather conditions occur.

Regarding income, the study found that bus ridership decreased by 1.6% in low-income areas on very hot days, with no significant effects recorded for very cold days (Ngo, 2019). On days with heavy precipitation, bus ridership in low-income areas increased by 1.9-2.7%. For areas where income was not considered “low” (between $50,000 and $75,000), ridership decreased by 2.2% and 1% during very cold and hot days, respectively, while also increasing by 2.2% in the same areas during high precipitation days (Ngo, 2019). Impacts within seasons were also observed, with ridership decreasing by 4.4% during very cold winter days and by 1.6% during high-precipitation winter days, as well as by 1.6% during very hot summer days (Ngo, 2019). In short, the study found that bus ridership levels in lower-income areas tended to be more sensitive to extreme weather events, with ridership in these neighborhoods decreasing at
higher rates during hot days and rainy days relative to higher-income neighborhoods.

It should be noted that Ngo described their research as containing limitations. Due to the lack of data relating to passenger trip type or modal split, the researcher concludes that it is difficult to make causal claims related to the outcomes of the study (Ngo, 2019). A solution to this problem identified by the researcher is for future studies to include information from travel surveys to address this gap in knowledge and act as a complement to ridership data (Ngo, 2019). Another limitation is the specificity of the study setting. Since the Pacific Northwest has a specific climate, generalizing the ridership-weather interactions in this study to other climate areas may prove difficult, if not impossible. The demographics of Lane County are also unique, with the largest city in the county, Eugene, acting as home to the University of Oregon and thus as a “college-town” (Ngo, 2019). Since university students are more open to using multiple modes of transportation (Kuhnimhof et al., 2010, Khattak et al., 2011), it is possible that a disproportionately large amount of LCTD riders are students. Such a situation may not be the same in a different area whose largest city does not contain a major university.

Also, Ngo describes the rural-urban divide in population density between the Eugene-Springfield area and the rest of the county as conspicuous (2019). Greater urban density is accepted as leading to higher rates of transit ridership (Cervero & Guerra, 2011), meaning that regions with higher or lower degrees of density may produce different rates of ridership than the ones recorded in Lane County, and may interact differently with other factors such as weather and income. One of the goals of this paper is to explore how weather, income, and transit ridership interact in a setting that is dissimilar from the one evaluated by Ngo, effectively addressing the limitations of that study by applying its methods to a different location to determine if the results are the same.
Summary of Literature Review

American public transportation began with early methods such as electric streetcar and interurban railway networks and continued despite mass adoption of the automobile through investment at the state and federal levels. In the case of Southern California, this investment has resulted in mass transit options such as bus networks becoming the primary transit mode of choice in the region. Data collected by government agencies and advocacy groups has revealed that bus travel is the most used mass transit option and that U.S. transit users are predominantly young, low-income, lacking access to a personal vehicle and (in the case of Orange County, California) Hispanic/Latino. A variety of factors have been shown by research to influence travel behavior and transit ridership, with variables such as urban density, quality/quantity of available transit service, and lower socioeconomic status all having a strong influence on travel behavior generally, and a positive relationship with transit use specifically.

Weather also has been shown to influence transit ridership greatly, as lower temperatures and higher rates of precipitation have been broadly shown to decrease transit ridership. Research on the intersection between transit rider’s socioeconomic status and weather factors has been limited, however Ngo (2019) reveals in her findings that extreme weather does have differing impacts depending on income level of transit users. According to her study, bus ridership in Lane County, Oregon decreased in low-income areas by 1.6% during very hot days and by 1.9-2.7% during heavy precipitation, compared to moderate income areas where ridership decreased by 2.2% during very cold days and 1% during very hot days, as well as increased by 2.2% during heavy precipitation (Ngo, 2019).

The goal of this paper is to address two key gaps in the research surrounding the socioeconomic status of transit riders and weather impacts. First, this paper examines Orange
County, California, a predominantly suburban area. Much of the literature cited in this review focuses on transit ridership impacts in an urban context; by situating this paper in a suburban setting, it is possible that new findings regarding transit use will emerge and contribute to the already existing findings. Secondly, this paper aims to add to the limited amount of research surrounding weather and the socioeconomic characteristics of transit riders. Since research cited in this review paints a picture of transit riders as predominantly low-income, and because climate change is expected to cause greater amounts of extreme weather events for both the nation and Southern California (Meyer & Weigel, 2011, Vaghefi et al., 2017), adding to this body work could be of great social significance in the future.
CHAPTER 3: METHODOLOGY AND RESEARCH DESIGN

This study aims to identify how weather conditions have a differing impact on transit ridership of transit-dependent riders in Orange County. To determine this, two ordinary least squares (OLS) regression models were constructed for two distinct weather conditions, extreme heat and rain. Both have been demonstrated in past studies to have significant impacts on transit ridership (Cravo & Cohen 2009, Stover & McCormack 2012, Singhal et al. 2014). This study aims to add to this literature by investigating the relationship between extreme heat/rain and multiple measures of transit dependency within the context of Southern California.

The geographic location for this study, Orange County, is located immediately east of Los Angeles County and is considered part of the Greater Los Angeles metropolitan area. The county has a mild Mediterranean climate with rainy winters and dry summers that is typical of coastal Southern California, with summer temperatures growing more extreme the further one travels inland. As the county’s primary transit service provider, OCTA has a service area that covers much of the county as well as small portions of eastern Los Angeles County. Most of the agency’s traditional bus service is concentrated in the northern and central portions of the county (Figure 3).
Figure 3: Outline of Orange County, California and OCTA Bus Lines in 2023

Data was collected from the U.S. Census Bureau database (socioeconomic data) and from OCTA’s internal ridership database (transit ridership data). Socioeconomic data was gathered at the census tract level for the year 2019 and functioned as the independent variable in this case, while transit ridership data was gathered at the bus stop level from February 2019 to February 2020 and functioned as the dependent variable. Data collected in 2019 and 2020 was chosen instead of more current data due to concerns with ridership impacts brought on by the COVID-19 pandemic. Transit ridership in the Los Angeles metropolitan area fell significantly during this period and has yet to return to pre-pandemic levels as of April 2023 (Rowlands & Loh, 2023). Because of this real-world context, it seemed appropriate to choose a period of study that was as
recent as possible without being impacted by the outside effects of COVID-19.

Out of 5503 bus stops retrieved from a shapefile detailing OCTA bus stops in June 2019 (Orange County Transportation Authority, 2023), a sample of 297 OCTA bus stops was selected through a multi-step process (Figure 4). First, the number of stops that contained data throughout the entire study period was identified. This was necessary due to regular service changes that occurred throughout 2019 and 2020, causing certain stops to cease operations and no longer record data for the entire yearlong study period. Once this number was identified, stops were randomly selected in a way that avoids overlapping catchment areas. A stop pedestrian catchment area, or service area, has traditionally been defined as the distance that pedestrians are willing to walk (usually 0.25 to 0.5 miles) to access transit services at a particular stop (Zhao et al., 2003). The catchment areas for each stop were set to 0.25 miles. To further ensure ridership data reflected Orange County residents, only stops with catchment areas fully within Orange County were analyzed. Because several stops were geographically close and located within each other’s catchment areas, it was decided that these stops served the same area and were therefore redundant in this analysis. To remove redundant stops, a random selection process was employed that resulted in several areas (typically major intersections) having only one stop instead of multiple. The final 297 stops that resulted from this trimming process are shown in Figure 4.
Figure 4: 2019 OCTA Stops Selected for Analysis

Independent Variables: Transit-Dependency

The independent variables investigated in this study all act as measures of transit dependency. Transit-dependency is generally defined as being confined to using public transit as a means of transportation because of a variety of factors often (but not exclusively) associated with social disadvantage (Fransen et al, 2015). Past studies have identified lack of access to a personal vehicle and low socioeconomic status as characteristics that are especially linked to the likelihood of a person being transit dependent (Grengs 2001, Jiao & Dillivan 2013, Fransen et al 2015). Building on this research, transit dependency is measured here through a series of variables collected at the census tract level that are associated with both personal vehicle access
and low socioeconomic status. Measuring these variables at the census tract level allows the study to analyze the transit-dependent nature of the residents living in each tract through census data, a technique previously employed by Ngo (2019).

A total of seventeen variables were selected as measures of transit-dependency in 2010-2019 Orange County census tracts (Table 1). Data for three of the variables (number of jobs for workers under 29 years old, number of jobs with earnings of $1,250/month or less, number of construction jobs, number of retail jobs, and number of arts, entertainment, accommodation and food service jobs) were taken from the LEHD (2019) Origin-Destination Employment Statistics (LODES) program published by the United States Census Bureau (U.S. Census Bureau Center for Economic Studies, 2019). Because this study looks at the characteristics of residents who travel (or commute) from one destination to another, it was important to gather data at both the trip origin and destination level. Thus, the job destination data represented travel characteristics at the trip destination level, in this case number of jobs found in a particular census tract. Because this data was in census block form, data was aggregated using ESRI ArcMap and Microsoft Excel into a census tract level for consistency purposes. A shapefile detailing 2010-2019 census tract boundaries was downloaded from the Orange County GIS Open Data Portal for this task as well as additional tasks described later in this section (Alexandridis, 2019). The remaining variables measured resident characteristics at the trip origin level and were gathered from the 2019 American Community Survey (5-year estimate), also published by the U.S. Census. These data values already existed at the tract level and as such did not need to be further aggregated.
Table 1: Independent Variables

<table>
<thead>
<tr>
<th>Category</th>
<th>Transit-Dependency Variable (Census Tract)</th>
<th>Variable Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job Destination</td>
<td>Number of Construction Jobs</td>
<td>Construct_Jobs</td>
</tr>
<tr>
<td></td>
<td>Number of Retail Jobs</td>
<td>Retail_Jobs</td>
</tr>
<tr>
<td></td>
<td>Number of Accommodation and Food Service Jobs</td>
<td>AFS_Jobs</td>
</tr>
<tr>
<td></td>
<td>Number of Jobs with Job-Holders Under 29 Years Old</td>
<td>U29_Jobs</td>
</tr>
<tr>
<td></td>
<td>Number of Jobs with $1,250 Monthly Earnings or Less</td>
<td>LowIncome_Jobs</td>
</tr>
<tr>
<td>Job Origin</td>
<td>Number of Construction Workers</td>
<td>Construct_Workers</td>
</tr>
<tr>
<td></td>
<td>Number of Retail Workers</td>
<td>Retail_Workers</td>
</tr>
<tr>
<td></td>
<td>Number of Arts, Entertainment, Accommodation, and Food Service Workers</td>
<td>AEAFS_Workers</td>
</tr>
<tr>
<td>Transportation</td>
<td>Total Commuting Time for Residents</td>
<td>Commute_Time</td>
</tr>
<tr>
<td></td>
<td>Number of Households with No Vehicle Available</td>
<td>No_Vehicle</td>
</tr>
<tr>
<td></td>
<td>Number of Residents who Commute via Transit</td>
<td>Transit_Commute</td>
</tr>
<tr>
<td></td>
<td>Number of Student Commuters</td>
<td>Student_Commute</td>
</tr>
<tr>
<td>Socioeconomic Status</td>
<td>Median Household Income</td>
<td>Income</td>
</tr>
<tr>
<td></td>
<td>Number of Individuals Living Below Poverty Level</td>
<td>Below_Poverty_Level</td>
</tr>
<tr>
<td></td>
<td>Number of Renter-Occupied Housing Units</td>
<td>Renters</td>
</tr>
<tr>
<td>Race/Ethnicity</td>
<td>Number of Limited English-Speaking Households</td>
<td>Limited-English</td>
</tr>
<tr>
<td></td>
<td>Number of Foreign-Born Residents</td>
<td>Foreign_Born</td>
</tr>
</tbody>
</table>

Variables were grouped into five categories: Job Destination, Job Origin, Transportation, Socioeconomic Status, and Race/Ethnicity. Variables sorted into the Job Destination category included the number of construction, retail, and accommodation/food service jobs located in each census tract. These job types were chosen because of their 2019 median earnings being at the lowest end of all industry earnings for that year (U.S. Census Bureau, 2019), and previous
studies mentioning a link between low-incomes and transit dependency (Pasha et al., 2016, Wang & Woo 2017). Additionally, the number of jobs employing workers 29 years and younger and the number of jobs that paid $1,250 a month or less were also chosen as variables. The reasoning for including jobs paying $1,250 or less was the same as the previous job category variables (relationship between low-income status and transit dependency) while jobs employing younger workers was chosen because of literature indicating that younger commuters are more likely to use transit (Brown et al., 2016). To ensure that data on both ends of commuting trips were collected, variables sorted into the Job Origin category were from two of the same three industries found in the Job Destination category (construction and retail) plus one new similarly low-paying industry (arts, entertainment, recreation, accommodation, and food services). This functioned to represent the residential locations of workers from low-paying and possibly transit-dependent industries.

Variables sorted into the Transportation category were characterized by their association with the ability (or lack thereof) of residents to travel to and from destinations. These were total commuting time per resident in 2019, number of households lacking a personal vehicle, total residents commuting by public transit, and number of students commuting by public transit. Previously identified linkages between these variables and transit-dependent status influenced the selection of these four variables for this category. Lack of vehicle access was chosen due to an established association in the literature between transit-dependency and non-access to vehicular travel (Giuliano, 2005, Clark, 2017), while total residential commuting time was chosen because of research associating longer commute times with higher use of public transit (Macaig, 2017, Liao et al., 2020). Number of student commuters was defined as commuters between the ages of 16 and 24 (U.S. Census Bureau, 2019) and was likewise chosen due to
previously identified factor that this population cohort is more depended on public transit.

The decision to include a category focusing on socioeconomic status was made, like the
decision to include specific job categories, because of the association between low
household income is considered a strong measure of socioeconomic status (Oka, 2023) and as
such was included here. Likewise, number of residents with poverty status was chosen because
of research noting limited income as an important indicator of poverty (Hagenaars, 1988) as well
as findings by Wang & Woo (2017) that demonstration a significant positive relationship
between poverty and high transit ridership. Renter status was selected due to renters being more
likely in the United States to have lower-incomes (DeSilver, 2021) and therefore be transit-
dependent.

Race and Ethnicity were represented through two variables (number of foreign-born
residents and number of limited-English speaking households). Both were chosen because of
OCTA survey findings that show a high number of Hispanic/Latino residents in Orange County
(55.6%) take the bus regularly, more than any other racial/ethnic group (OCTA, 2018). While
there may be multiple reasons why this group takes advantage of transit at higher rates than
others, one of the explanations may lie in a higher rate of transit-dependency among
Hispanic/Latino residents. Such a higher rate of transit-dependency may be due to barriers that
prevent a driver’s license from being obtained, such as undocumented status (Cho, 2022).

The data at the census tract level were aggregated to the bus stop level, which is the unit
of analysis. This was done by first performing a 0.25-mile buffer of the 297 sample bus stops in
ESRI ArcMap representing the stop catchment area. All the census tract segments located within
the buffer were identified and associated with the catchment of the bus stop (Figure 5). If multiple different tract segments were located within a single catchment zone, the value of the independent variable count that fell within the catchment zone was calculated by multiplying the total independent variable value of a tract by the percentage of a tract’s area that fell within the catchment zone. These proportional values were then summed to represent the total count of an independent variable within a stop catchment zone across the tract segments within that zone. For variables that did not represent a simple count (such as income and commuting time) an average of the total value from each tract segment found in a catchment zone was calculated for said zone.

**Figure 5:** Segments of U.S. Census Tracts Located Within a Stop Buffer Zone

**Dependent Variable: Bus Ridership**

To measure the impacts of extreme weather conditions on transit ridership, the dependent variable represents ridership difference between the maximum recorded weather day and on average days. Daily weather and bus ridership data were collected on the same day for multiple
days across two study periods: February 14\textsuperscript{th}, 2019, to February 13\textsuperscript{th}, 2020 for the rainfall model and February 20\textsuperscript{th}, 2019 to February 12\textsuperscript{th}, 2020 for the heat model.

Two types of weather variables were studied: heat (temperature in degrees Fahrenheit) and precipitation (rainfall in inches). These were chosen because of the nature of the alternating hot-cool/wet-dry Mediterranean climate that exemplifies Southern California and Orange County. To determine the impact of these weather variables on bus ridership, the hottest and rainiest weekday out of each study period first needed to be identified.

**Figure 6:** Orange County Weather Stations Providing Daily Maximum Temperature Data
FIGURE 7: Orange County Weather Stations Providing Daily Rainfall Data

Weather data was gathered from the National Centers for Environmental Information, a national weather data archiving agency operated by the National Oceanic and Atmospheric Administration (2019-2020). The data gathering process consisted primarily of retrieving the daily maximum temperature and daily total rainfall readings for several weather stations located throughout the county. Daily maximum temperature data was available at eight weather stations, whereas daily maximum rainfall data was available at seven weather stations. One of the eight weather stations utilized for both temperature and rainfall (Newport Harbor) was missing three days of temperature and rainfall data in February and one day of rainfall data in March, however this station’s remaining data was still included in the analysis to reflect as much gathered data as possible and to preserve daily maximum temperature readings on the coast of Orange County. Data analysis revealed that the weekday with the highest average maximum temperature was
Wednesday, September 4th, 2019 at 96.13 degrees Fahrenheit, and the weekday with the highest average precipitation was Thursday, February 14th, 2019 at 2.58 inches.

Ridership data was retrieved from the Orange County Transportation Authority’s automated passenger counter (APC) database, and the metric selected to measure ridership was average daily boardings per stop. After average daily boarding data on the extreme weather days was collected, ridership data was then collected for the remaining 52 Wednesdays and 53 Thursdays of each study period to represent ridership on days where weather was not at the maximum for temperature and rainfall, respectively. For example, since temperature was highest on Wednesday, September 4th in 2019, ridership data was gathered for all Wednesdays for 52 weeks (from February 20th in 2019 to February 12th, 2020). This accounts for day-of-week ridership variation when measuring the impacts of the extreme weather on ridership. Systemic ridership variation by day of the week is well documented, for example, ridership on Monday tends to be higher than on Friday (McCord & Cheng, 1987).

Only weekday weather and ridership data were gathered because of the greater number of days available to study vs. weekends (five vs. two) and because of generally observed differences in transit ridership levels between weekdays and weekends that may make a full-week analysis not ideal (Walker, 2012). Bus ridership was recorded on the maximum weather day as well as on non-maximum weather days in the study period, with an average of ridership numbers across all non-maximum weather days calculated. The average ridership values were then subtracted from the maximum day ridership value. Thus, negative values of the dependent variable indicate a decline of bus ridership on the extreme weather days. Both sets of difference values were the dependent variables investigated in this study.

Although an analysis of weekdays in 2019 would have been ideal, data limitations in
OCTA’s ridership database led to the selection of the final study periods. Because the extreme rainfall and heat days fall on different days of the week, the two study periods for each weather model are different in terms of period length and dates chosen.

**Figure 8:** Bus Ridership for Each Study Period Day

*Note:* Upper graph depicts heat model, while lower graph represents rainfall model.
**Figure 9:** Difference in Bus Ridership at Bus Stops Between Extreme Weather Day and Average of Non-Extreme Weather Days

*Note.* Upper graph represents heat model, while lower graph represents rainfall model.

**Statistical Models**

Using the transit-dependency data and bus ridership data, two statistical models were built: one for precipitation impacts and one for heat impacts. The statistical method used for the models was ordinary least squares (OLS) regression. This method was chosen because it
estimates the strength of relationships between variables, which in this case are transit dependency characteristics within each bus stop catchment area (independent variable) and the difference between bus stop ridership on extreme weather days and non-extreme weather days at each stop (dependent variable). Five out of the seventeen variables (jobs with workers under 29 years of age, low-income jobs, number of renter-occupied housing units, number of residents below poverty level, and number of foreign-born residents) were eliminated due to multicollinearity that refers to strong correlation between independent variables rather than the dependent variable. This was identified by a high variance inflation factor (VIF) score of seven or greater, which was generated for each variable after running the models. In addition, 15 stops with outlier dependent variable values were eliminated from the heat impact model to increase the R-square value of this model to an acceptable level (the R-square value of the precipitation model was sufficiently high and therefore did not warrant the removal of outliers).
Table 2: Descriptive Statistics of Independent and Dependent Variables for Rainfall Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Job Destination</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construct Jobs</td>
<td>0.00</td>
<td>4538.25</td>
<td>185.23</td>
<td>466.45</td>
<td>1.09</td>
</tr>
<tr>
<td>Retail Jobs</td>
<td>6.00</td>
<td>8002.88</td>
<td>572.82</td>
<td>963.92</td>
<td>3.10</td>
</tr>
<tr>
<td>AFS Jobs</td>
<td>4.70</td>
<td>5514.34</td>
<td>575.41</td>
<td>924.94</td>
<td>6.77</td>
</tr>
<tr>
<td>U29 Jobs</td>
<td>35.95</td>
<td>20291.93</td>
<td>1650.98</td>
<td>3340.14</td>
<td>89.40*</td>
</tr>
<tr>
<td>LowIncome Jobs</td>
<td>78.27</td>
<td>11723.85</td>
<td>1204.08</td>
<td>1970.86</td>
<td>65.57*</td>
</tr>
<tr>
<td><strong>Job Origin</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construct Workers</td>
<td>0.00</td>
<td>768.65</td>
<td>193.33</td>
<td>105.60</td>
<td>2.45</td>
</tr>
<tr>
<td>Retail Workers</td>
<td>19.02</td>
<td>642.10</td>
<td>324.21</td>
<td>116.33</td>
<td>2.83</td>
</tr>
<tr>
<td>AEAFS Workers</td>
<td>11.05</td>
<td>1027.25</td>
<td>367.96</td>
<td>174.48</td>
<td>5.56</td>
</tr>
<tr>
<td><strong>Transportation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commute Time</td>
<td>2301.36</td>
<td>291585.86</td>
<td>80072.32</td>
<td>39173.85</td>
<td>9.02*</td>
</tr>
<tr>
<td>No Vehicle</td>
<td>0.69</td>
<td>716.19</td>
<td>109.15</td>
<td>103.97</td>
<td>4.10</td>
</tr>
<tr>
<td>Transit Commute</td>
<td>0.00</td>
<td>326.09</td>
<td>76.34</td>
<td>68.08</td>
<td>2.82</td>
</tr>
<tr>
<td>Student Commute</td>
<td>17.78</td>
<td>2936.98</td>
<td>382.04</td>
<td>249.03</td>
<td>4.66</td>
</tr>
<tr>
<td><strong>Socioeconomic Status</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td>4450.21</td>
<td>250081.96</td>
<td>80700.83</td>
<td>24731.34</td>
<td>2.00</td>
</tr>
<tr>
<td>Renters</td>
<td>10.18</td>
<td>5373.31</td>
<td>1056.24</td>
<td>843.10</td>
<td>9.72*</td>
</tr>
<tr>
<td>Below Poverty Level</td>
<td>8.30</td>
<td>5072.38</td>
<td>882.32</td>
<td>795.14</td>
<td>13.44*</td>
</tr>
<tr>
<td><strong>Race/Ethnicity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Foreign_Born</td>
<td>51.08</td>
<td>8897.16</td>
<td>2155.57</td>
<td>1448.80</td>
<td>18.81*</td>
</tr>
<tr>
<td>Limited-English</td>
<td>0.00</td>
<td>730.48</td>
<td>213.73</td>
<td>162.99</td>
<td>9.26*</td>
</tr>
<tr>
<td><strong>Dependent Variable</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in Stop-Level Ridership (Extreme Weather Day minus Non-Extreme Weather Days)</td>
<td>-78.25</td>
<td>18.44</td>
<td>-7.89</td>
<td>11.33</td>
<td>---</td>
</tr>
</tbody>
</table>

Note. Asterisk (*) represents VIF score greater than 7.0.
Table 3: Descriptive Statistics of Independent and Dependent Variables for Heat Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Job Destination</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construct Jobs</td>
<td>0.00</td>
<td>4538.25</td>
<td>185.50</td>
<td>472.53</td>
<td>1.09</td>
</tr>
<tr>
<td>Retail Jobs</td>
<td>6.00</td>
<td>8002.88</td>
<td>557.59</td>
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<tr>
<td>AFS Jobs</td>
<td>4.70</td>
<td>5514.34</td>
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<td>6.63</td>
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<td>U29 Jobs</td>
<td>35.95</td>
<td>20291.93</td>
<td>1624.38</td>
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<td>LowIncome Jobs</td>
<td>78.27</td>
<td>11723.85</td>
<td>1193.22</td>
<td>1970.65</td>
<td>66.54*</td>
</tr>
<tr>
<td><strong>Job Origin</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construct Workers</td>
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<td>Retail Workers</td>
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<td>322.36</td>
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<td>AEAFS Workers</td>
<td>11.05</td>
<td>1027.25</td>
<td>364.40</td>
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<td>2301.36</td>
<td>291585.86</td>
<td>79691.12</td>
<td>39434.25</td>
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<td>2936.98</td>
<td>378.65</td>
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<td>250081.96</td>
<td>80788.34</td>
<td>24905.51</td>
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<td>Renters</td>
<td>10.18</td>
<td>5373.31</td>
<td>1053.62</td>
<td>845.67</td>
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<td>Below Poverty Level</td>
<td>8.30</td>
<td>5072.38</td>
<td>873.63</td>
<td>795.73</td>
<td>13.42*</td>
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<tr>
<td>Foreign_Born</td>
<td>51.08</td>
<td>8897.16</td>
<td>2129.05</td>
<td>1449.20</td>
<td>18.31*</td>
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<td>Limited-English</td>
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<td>719.17</td>
<td>210.41</td>
<td>161.75</td>
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<td><strong>Dependent Variable</strong></td>
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<tr>
<td>Difference in Stop-Level Ridership (Extreme Weather Day minus Non-Extreme Weather Days)</td>
<td>-78.25</td>
<td>18.44</td>
<td>-7.89</td>
<td>5.63</td>
<td>---</td>
</tr>
</tbody>
</table>

*Note. Asterisk (*) represents VIF score greater than 7.0.*

For the remaining independent variables, few differences were noted between the sample of 297 bus stops used for the rainfall model and the sample of 282 stops used for the heat model. The job category with the highest average destination-level count was AFS (575 for the rainfall model, 569 for the heat model) followed by retail (573, 558) and construction (185, 186). This same variable order was also true for the three job categories at the job origin level. The fact that
there are less construction workers and jobs observed than the other categories is somewhat unsurprising, as the construction industry relies on new projects for job growth and Orange County is a fairly built-out environment.

Regarding transportation variables, the minimum total time spent commuting during the year for both the rainfall and heat models was 2,301 minutes, while the maximum for both was 291,586 minutes. The average number of student residents commuting via transit (382 for rainfall, 379 for heat) was higher than the average number of transit commuters overall (76 for rainfall, 75 for heat) which makes sense given previously mentioned research touching on the transit-dependent nature of students and young people. For socioeconomic variables, a relatively wide difference was observed between the lowest median household income observed in both models ($4,450.21) and the highest in both models ($250,081.96), reflecting the nature of income inequality in Orange County. The average median household income of residents living near bus stops in both models ($80,072.32 for rainfall, $80,788.34 for heat) is lower than the 2019 average median household income recorded for the entire county ($94,441) (U.S. Census Bureau), suggesting that bus stops may be disproportionately located in lower income areas throughout the county.

Lastly, descriptive statistics for the dependent variable of each model reveal negative values, which is expected since these are difference values not in absolute value form. Given the direction of the difference equation (average ridership on non-extreme weather days subtracted from ridership on extreme weather day) and the average value of the differences recorded for both models (-7.89), it is implied that most non-extreme weather days had higher ridership than the extreme weather day investigated in each model.
## CHAPTER 4: MODEL RESULTS

### Table 4: Results of Weather Models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Rainfall Model</th>
<th>Heat Model</th>
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<th></th>
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<td></td>
<td>Coefficient</td>
<td>Significance</td>
<td>VIF</td>
<td>Coefficient</td>
<td>Significance</td>
<td>VIF</td>
<td>Coefficient</td>
<td>Significance</td>
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<td><strong>Job Destination</strong></td>
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<tr>
<td>Construct Jobs</td>
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<td>0.676</td>
<td>1.026</td>
<td>-0.081</td>
<td>0.168</td>
<td>1.027</td>
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<tr>
<td>Retail Jobs</td>
<td>0.068</td>
<td>0.398</td>
<td>2.149</td>
<td>-0.097</td>
<td>0.262</td>
<td>2.202</td>
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<td>AFS Jobs</td>
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<td>0.673</td>
<td>3.687</td>
<td>-0.046</td>
<td>0.682</td>
<td>3.726</td>
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<td><strong>Job Origin</strong></td>
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<tr>
<td>Construct Workers</td>
<td>-0.14</td>
<td>0.091*</td>
<td>1.828</td>
<td>0.063</td>
<td>0.468</td>
<td>1.822</td>
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<td>Retail Workers</td>
<td>-0.193</td>
<td>0.013*</td>
<td>2.288</td>
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<td>0.02*</td>
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<td>AEAFS Workers</td>
<td>-0.177</td>
<td>0.147</td>
<td>2.031</td>
<td>0.123</td>
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<td><strong>Transportation</strong></td>
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<tr>
<td>Commute Time</td>
<td>0.342</td>
<td>0.009*</td>
<td>4.961</td>
<td>0.36</td>
<td>0.800</td>
<td>4.797</td>
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<tr>
<td>No Vehicle</td>
<td>0.006</td>
<td>0.947</td>
<td>2.751</td>
<td>0.015</td>
<td>0.876</td>
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<tr>
<td>Transit Commute</td>
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<td>0.164</td>
<td>5.691</td>
<td>-0.047</td>
<td>0.609</td>
<td>5.978</td>
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<tr>
<td>Student Commute</td>
<td>0.118</td>
<td>0.225</td>
<td>2.798</td>
<td>-0.148</td>
<td>0.151</td>
<td>2.833</td>
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<td>Income</td>
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<td>0.873</td>
<td>2.588</td>
<td>-0.096</td>
<td>0.221</td>
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<tr>
<td>Limited English</td>
<td>-0.010</td>
<td>0.123</td>
<td>3.130</td>
<td>-0.162</td>
<td>0.088*</td>
<td>3.317</td>
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<td><strong>R²</strong></td>
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<tr>
<td></td>
<td>0.153</td>
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<td></td>
<td>0.096</td>
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</tbody>
</table>

Note. Asterisk (*) represents statistical significance at 95% confidence interval.

None of the job destination variables in the rainfall model was significantly associated with the dependent variable. However, two job origin variables were significantly associated with the dependent variable: number of construction workers and number of retail workers. Both variables were negatively correlated with the dependent variable, meaning that the bus stops in areas with higher numbers of these workers tend to show the decline of ridership on the highest precipitation day. Only one transportation variable (total commuting time) was positively related to the dependent variable at a statistically significant level. The positive correlation means that stops located in areas with high resident commuter times show higher ridership on the maximum precipitation day. No socioeconomic variable was associated with the dependent variable at a
statistically significant level.

Like the rainfall model, the heat model indicates that job destination variables were not associated with the dependent variable. For job origin variables, the number of retail workers was once again associated with the dependent variable, this time positively instead of negatively. This means stops with a higher number of retail workers living nearby saw higher ridership levels on the hottest day of the study period compared to the rest of the year. For transportation variables, none were significantly associated with the dependent variable in this model. One socioeconomic variable (number of limited English-speaking households) was significantly and negatively associated with the dependent variable, meaning that stops with a higher number of limited-English speakers living nearby presented ridership decline on the hottest day.
CHAPTER 5: DISCUSSION

The primary takeaway from the results of both models is the lack of significant correlations between most independent variables and the dependent variable. In total, only five out of the twenty-four independent variables in both models (three and two in the precipitation and heat models, respectively) showed strong associations with changes in transit ridership across weather conditions. This implies that extreme heat and rainfall did not have a highly significant impact on the ridership patterns of transit-dependent bus riders, and that these individuals used transit consistently regardless of the severity of weather impacts. Furthermore, the relatively low R-Square values of the models suggest that the independent variables are limited to fully explain the difference in transit ridership between the extreme weather day and the non-extreme weather days.

Among significantly correlated independent variables, three were found in the precipitation model and two were found in the heat model. This suggests that of the two extreme weather conditions, rainfall plays a more significant role in influencing the ridership patterns of transit-dependent bus riders than extreme heat does. This is also supported by the higher R-Square of the precipitation model, which points to the independent variables having greater power in explaining ridership changes on the rainiest days (See also Figure 8). Such a finding is supported by literature detailing the significant impact of precipitation on transit ridership when compared to other weather variables (Ngo, 2019, Stover & McCormack, 2012, Singhal et al., 2014). It should be noted that Orange County has historically experienced very little rainfall by national standards, with the county seeing approximately 12.4 inches of rain annually from 2013 to 2023 (WeatherWX.com, 2023) compared to the national average during the same period of 31.9 inches (National Centers for Environmental Information, 2023). Because rainfall is so
scarce, an above-average rainfall day may be especially powerful in driving down bus ridership.

It is interesting to note that some variables in the job origin category are significantly associated with changes in ridership, while others are not. The ridership of the bus stops where higher amounts of retail workers reside tends to increase on the hottest day while decreasing on the rainiest day, while the bus stops where higher amounts of construction workers reside only present declines of ridership on the rainiest day. Although the retail worker finding is supported by studies indicating that precipitation depresses transit ridership and heat increases ridership (Stover & McCormack, 2012, Singhal et al., 2014), there is no consensus on this relationship and the finding is debatable. In their research, Stover & McCormack note that a lack of adequate bus shelters in Pierce County, Washington may have played a role in depressing transit ridership during above-average rainfall, which may have also been the case here. With respect to heat, a limitation of the Stover & McCormack study that must be noted is how the climate of Pierce County is much cooler than the climate of Orange County, meaning that increased temperatures may be seen as more pleasant and less extreme/unpleasant by riders in comparison. An association in the minds of transit riders between higher temperatures and pleasant weather could lead to increased ridership levels, while an association with higher temperatures and unpleasant weather (such as extreme heat in the non-coastal areas of Orange County) may not have the same effect. This could potentially explain why most independent variables were not positively associated with the dependent variable in the heat model.

For other job origin categories, it is possible that construction workers may be less inclined to use public transit because their occupations require the transport of tools and other equipment, which may explain why areas with many of these workers saw a decline in transit ridership during the precipitation day but no significant effect during the heat day. AEAFS
workers also may be the most unaffected by extreme weather conditions because of a higher rate of transit-dependency compared to the other job categories, as evidenced by this occupation having the lowest earnings out of the three categories (U.S. Census Bureau, 2019). More individual commuter-level data would need to be gathered on these independent variables to determine the accuracy of these claims.

To the extent that extreme heat and rainfall were shown to influence transit ridership among the transit riders studied, areas with a high amount of retail workers showed the highest sensitivity. This finding implies that retail workers in Orange County may not be as transit dependent as imagined and are able to find other options for commuting when inclement weather such as high rainfall occurs. OCTA can make transit more appealing to retail workers by investing in service that provides more connections between residential areas and commercial areas where many retail jobs are concentrated, while also giving special attention to routes serving retail job centers in the summer as higher ridership rates occur during warmer weather. Increasing route frequencies and spans of service during regular pre-summer service changes can help OCTA manage a seasonal increase in ridership along these routes. At the same time, cities served by OCTA bus routes can contribute by improving bus shelters. Studies have shown that sheltered bus stops see higher ridership during heavy precipitation (Miao et al., 2019). Adding shelters to heavily used stops on routes that serve retail job centers could help in retaining these kinds of workers when heavy rainfall occurs.

The fact that no job destination variables were significantly related to the dependent variable is noteworthy, especially when considering that two out of the three job origin variables (number of construction workers and number of retail workers) were revealed as having significant relationships with the dependent. A potential explanation for this may lie in the
concept of complex trip chaining, which is defined as when individuals take more than one trip between departing for work at the beginning of the day and arriving back at home at the end of the day (Strathman & Dueker, 1995). Examples of these secondary trips include getting food or running errands after a work shift before heading home. It is possible that after the end of their work shift, individuals working at construction, retail and AFS jobs may choose to take these trips instead of immediately going home. As with job origin variables, more research would have to be done at the individual trip level to determine if complex trip-chaining is occurring.

Future research can also focus on incorporating alightings into an analysis of transit ridership to develop a better picture of how weather impacts transit ridership at the destination as well as origin end of trips. Alighting data could also illuminate the types of destinations that transit riders are travelling to, and if different trip types (commuting, errands, leisure) are influenced by extreme weather in different ways.

For transportation variables, three out of the four variables (number of households with lack of vehicle access, number of transit commuters, and number of student commuters) showed no relationship with the dependent variable, which suggests that precipitation and heat had no impact on transit riders who are characterized by these backgrounds. Because these variables are associated with transit dependency, it is possible that residents with these characteristics are unchanged in their travel patterns during inclement weather (i.e. they remain transit dependent). The one significant association that did emerge was the positive significant relationship between precipitation and ridership in areas with higher resident commuting times, a finding that does not have an obvious explanation. Precipitation has been found in past studies to shift commuter’s travel mode away from public transport and toward cars (Liu et al., 2015), especially if commuters are walking or cycling (Bocker et al., 2014). It is possible that in this instance,
cycling/walking commuters are shifting their mode to public transit to avoid being impacted by significant rainfall. A more detailed analysis looking at individual trip and commuter characteristics could possibly shed more light on the motivations behind the trip-making decisions of residents in these areas, and why they chose to take public transit during periods of high precipitation.

Few significant relationships were detected for the socioeconomic and race/ethnicity independent variables across both models. The lack of a significant relationship with median household income suggests that weather impacts mostly have little impact on the boarding patterns of transit users across all income groups. Since ridership was shown to be generally highest on bus routes that traversed lower-income cities compared to higher-income cities (OCTA, 2018), it can be inferred that these trends would not change dramatically when high heat or precipitation events occurred. One interesting finding related to limited English-speaking households was that areas with high amounts were significantly associated with decreased ridership on the hottest day (no relationship between this variable and ridership was found for the precipitation model). The fact that this variable did not show a significant relationship with ridership in the precipitation model suggests that this is a transit-dependent population that does not alter its travel patterns even during high amounts of rain. A possible explanation for lower ridership during hotter weather for this population is lack of comfortability brought about by standing and waiting for the bus to arrive. Research by Fraser & Chester (2017) notes that low-density residential areas are more likely to experience higher waiting times for bus service, leaving transit users in these areas possibly more vulnerable to negative health impacts brought about by heat. Extreme heat in areas with high waiting times may be too much of a negative
impact on individuals waiting for transit, thus causing them to either not travel or take another mode.
CHAPTER 6: CONCLUSION

This study’s purpose is to explore if extreme weather conditions have an influence on ridership turnout among transit dependent users. Because climate change is expected to cause abnormal weather conditions such as high heat and rainfall to increase in frequency across Southern California, examining how these changing weather patterns influence the travel patterns of vulnerable groups like transit-dependent bus riders can give transit agencies more insight as to who these groups are and how best to serve them in the future.

The findings of the study indicate that the impacts of extreme heat and rainfall are limited on ridership turnout for many kinds of transit-dependent bus riders. In other words, these bus riders continue to take the bus regardless of inclement weather conditions. Areas that did not see a significant change in bus ridership during these conditions include areas with a high number of vehicle-less households, transit commuters, student commuters, and arts, entertainment, accommodation, and food service workers. Because these groups appear to be particularly transit-dependent, this thesis recommends that transit agencies pay special attention to them when planning their service networks. One way that OCTA can target these populations is by continuing certain strategies aimed at specific populations, such as Youth Ride Free and College Pass. These student-oriented programs offer free and discounted rides to K-12 and college students throughout the county and may prove especially helpful to transit-dependent students during the winter months, when some researchers predict an increase in extreme precipitation events leading to flooding are to occur (Swain et al., 2018).

To recapture riders who are choosing not to take the bus due to weather impacts, OCTA may take into consideration reducing the amount of time spent waiting at stops during high heat and rainfall. An example of this is investing in real-time information displays for passengers,
either through the addition of digital signage or improvements to the OC Bus digital application. Research has shown that passengers waiting for the next bus report a smaller perceived wait time when presented with real-time bus information than passengers who are not presented with such information (Watkins et al., 2011). This may prove easier to implement than increasing frequency by adding buses to routes, given the current bus driver shortage facing transit agencies in the region (Brasuell, 2022). Information can also be given out to passengers on changing weather conditions, as well as services to access in case of a weather emergency. Sami & Keith note in their study on streetcar service that when it came to serving customers during extreme heat, a helpful option would be the ability to provide information on weather forecasts and nearby cooling centers (2023). Information on cooling centers may be especially helpful for extremely low-income and/or homeless transit users who lack adequate access to air conditioning. All this information could be translated into multiple languages in order to recapture limited English-speaking riders who are choosing not to ride transit during inclement weather.

A potential long-term service improvement strategy at the city level can be to encourage the development of transit-oriented communities in areas with high waiting times for transit. Adding to the residential density of these areas could potentially lead to a greater demand for transit, which could in turn spawn a cycle of justified service improvements and better route frequency, shorter waiting times at stops, and less impacts caused by standing outside during extreme weather.

As with rainfall, more robust shelters can be added to stops as a means of providing shade for waiting passengers during hot weather. Examples of highly robust shelters have been noted in South Korea, where a new smart bus shelter model allows passengers to be completely
enclosed in a space that is heated, air conditioned, and provides real-time information via digital signage (Park, 2020). While expensive, this model could be seen as an ideal for cities in Orange County to strive towards when improving existing bus shelters. In addition, an amenity that has shown promise in helping to retain riders and reduce heat impacts is tree canopy. According to a study by Lanza & Durand, increases in tree canopy near bus stops are significantly associated with decreases in ridership decline during hot days (2021). Cities can invest in planting trees near bus stops to serve residents who are experiencing the impact of extreme heat, as well as to help boost local transit ridership. Both tree installations and bus shelter upgrades can be tracked in a database by OCTA using GIS technology to determine whether inadequate shelter amenities are associated with lower ridership at certain stops.

In conclusion, this study recommends that OCTA continue its efforts to serve transit-dependent populations, while also gathering more information on where and when these populations travel. Doing so can help inform regular decision-making processes when it comes to transit planning for transit-dependent riders, as well as work to potentially retain riders who have departed the service due to inclement weather impacts.

An important limitation of this study is the lack of individual-level data regarding transit commuters. Because independent variable data was collected from the U.S. Census for the 0.25-mile buffer zone surrounding bus stops, only associations between aggregate-level data found in these stop buffer zones and stop ridership can be made. It is unclear if every individual who accessed transit at these stops also lives within the buffer zone of said stops. Future studies can address this by using individual trip data to examine the impact of extreme weather, possibly by using smart-card data. This data has been collected by researchers to examine travel patterns of specific rider populations (Morency et al., 2011, Ma et al., 2017), typically by gathering data.
generated when a user swipes a card while boarding. Despite having a cardless system, OCTA has access to individual trip origin-destination data through its 30-Day Pass, which is scanned by users while boarding. Further analysis of this data could provide interesting findings on how trips in certain areas are affected by extreme weather, as well as reveal how OCTA can improve service to recapture certain rider populations who shifted modes due to weather impacts.

The specificity of the study date and location can also be considered a limitation for this study. Research was conducted in Orange County, which has a specific climate that is only found in a select number of locations around the world. Other settings with vastly different climate types, such as the Midwest and East Coast regions of the United States, may not provide the same results if this study were to be replicated there. Instead of heat and rainfall, other factors such as snow, wind and humidity can be studied instead. Furthermore, it should be noted that data was collected in 2019, and therefore does not reflect the most recent ridership, census, and weather data. A future study could replicate the methodology of this paper to consider any demographic or ridership changes that may have happened in Orange County following the period of COVID-19.

Additionally, it should be noted that 3 weekday daily maximum temperature recordings available at observed Orange County weather stations were noted as failing one quality control test by NOAA. While these recordings were ultimately still included in the data analysis, they do raise questions about the accuracy of the weather data available at NOAA stations. Future research can implement additional quality control tests to further validate the accuracy of weather data before performing any analysis.

Subsequent research can analyze the interplay between weekend and weekday transit ridership and the impacts of extreme weather. Because transit ridership has been shown to be
affected differently by weather on weekends as opposed to weekdays (Guo et al., 2007, Tao et al., 2018) it may be worth expanding the scope of the research beyond weekdays to include all days of the week. This can further inform transit planners at OCTA and other agencies on how to plan differently between weekends and weekdays during the months when extreme weather impacts are more likely to occur.

Another fruitful area for future research is examining how weather impacts non-transit-dependent or “choice” riders. Existing research has shown that different types of trips (leisure trips, commuting trips, etc.) are associated with different types of weather in different ways (Guo et al., 2007, Liu et al., 2015). It is therefore reasonable to assume that different kinds of transit riders will respond differently to inclement weather conditions. Because this study focused on transit-dependent riders, an interesting area of research could be examining how non-dependent riders are influenced by extreme weather conditions such as high heat and rainfall.
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