Transportation Research Part D 137 (2024) 104504

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

The impacts of extreme weather events on U.S. Public transit ridership

By Nicole S. Ngo *, Shahinur Bashar

School of Planning, Public Policy, and Management, University of Oregon, United States

ARTICLE INFO

Keywords:
Extreme weather
Public transit
Climate change

ABSTRACT

Climate change is expected to dramatically change weather patterns across the U.S. To understand its impact on public transit, we use regression analysis to investigate: 1) the relationship between public transit ridership and very hot and cold days and days with heavy precipitation across 48 U.S. cities between 2002 and 2019, 2) how this relationship has changed over time, and 3) if there are differences in this relationship based on sociodemographic characteristics. We find a modest reduction in unlinked passenger trips (UPT) per capita, our proxy for public transit ridership, for each additional very hot day, very cold day, or day with heavy precipitation. The greatest reductions associated with very hot days occur toward the end of our study period and in lower-income cities. We also find greater reductions in UPT on buses associated with several consecutive days of cold and heat, but less so with rail.

1. Introduction

Climate change has dramatically affected weather patterns in the U.S. leading to more intense and longer heat waves, less extreme cold events, and heavier precipitation (US EPA, 2021). Numerous studies have shown the severe impacts of these extreme weather events on daily life and the costs associated with them (U.S. Global Change Research Program, 2023). There are also concerns about impacts on social welfare, including the inequitable distribution of impacts across the U.S., with lower-income households being less resilient to extreme weather events (e.g., they are less likely to have air conditioning).

This study examines the effects of extreme weather events, specifically very hot days, very cold days, and heavy precipitation, on urban mobility, an important aspect of social welfare since it reflects accessibility. We focus specifically on one key mode of transportation which is often used by lower-income households: public transit. While the price and accessibility of using transit varies greatly based on locale, overall in the U.S. it remains many communities' primary mode of transportation, especially among those who lack car ownership (The Urban Institute, 2020). In a survey, almost half of public transit riders said they used public transit because other alternative modes were too expensive, including owning a vehicle (American Public Transportation Association, 2017).

Numerous studies have documented the importance of weather on travel mode and usage (Böcker et al., 2013; Singhal et al., 2014r). While a growing literature has used micro-level data (e.g., bus-stop level ridership data, smart card usage) to further examine spatial inequities in access related to weather (Arana et al., 2014; Ngo, 2019; Wei, 2022; Wei et al., 2018; Zhou et al., 2017), there still remain gaps in the literature regarding the heterogenous effects of extreme weather events on public transit ridership over a range of geographies or across different socioeconomic indicators. Additionally, with the massive growth of shared mobility services (e.g., ride-

* Corresponding author.
E-mail address: nngo@uoregon.edu (B. Nicole S. Ngo).

https://doi.org/10.1016/j.trd.2024.104504
Received 8 April 2024; Received in revised form 28 August 2024; Accepted 2 November 2024
Available online 8 November 2024

hailing services, bike sharing, e-scooters) in the past decade, we may also expect this relationship to vary over time as people have more access to other transportation modes.

This study adds to the literature by evaluating the effects of extreme weather events in the U.S. between 2002 and 2019 across a wide geographic range of cities and observing important sociodemographic differences. We focus on this study period because it is before the COVID-19 pandemic, when public transit ridership declined greatly due to stay-at-home orders. Further, 2002 is the earliest year for which the National Transit Database (NTD), our source of U.S. public transit ridership data, has publicly available data.

We address three research objectives. First, we assess the average effects of extreme weather events on unlinked passenger trips (UPT) per capita, which we use as a proxy for public transit ridership, among 48 U.S. cities. We choose cities with the highest levels of UPT and further examine if there are differences based on bus or rail, the most common forms of public transit. Second, we determine if or how this relationship changed during the near two-decade study period. Finally, we investigate if there are heterogeneous effects across cities or public transit systems based on two important sociodemographic indicators: income and population.

We use ordinary least squares (OLS) regressions and observe the impact of an additional very hot or cold day, which we define as days when and where the daily maximum temperature is $\geq$ the 90th percentile or $<$ the 10th percentile (respectively), in a given month, year, and city on UPT per capita. While the threshold for "extreme weather" is subjective, the 10th and 90th percentiles of historical measurements are commonly used (Herring, 2020). We also examine the impacts of days with heavy precipitation, which we define as days when precipitation is $\geq$ the 90th percentile. We observe effects at the month-year level since data on UPT are only available at this time scale. Several control variables (e.g., education, race, income) are included using data from overlapping 5-year American Community Surveys (ACS), as well as dummy variables for each year, month and city, and city-year trends to capture both time-invariant characteristics across cities and temporal trends. Further, we use alternative specifications to examine the impacts within each season, of different temperature and precipitation thresholds, and of several consecutive days of very hot or very cold days, or days with heavy precipitation. The latter has been explored less in the literature, but relates to concerns about increasing heat waves in the U.S.

Our results show small, but statistically significant reductions in public transit ridership across extreme weather events. We also show greater impacts on bus ridership than on rail and negative impacts if there are at least four consecutive days of a heat or cold, but not of precipitation. Further, we find even mildly cold weather or smaller amounts of precipitation is associated with reductions in ridership. Examining impacts over our entire study period, we show consistent reductions in UPT per capita on days of heavy precipitation, but only find reductions on very cold days after 2008 and on very hot days between 2016 and 2019. Finally, when and where the median income is lower, we find decreases in ridership on very cold days, while in more populated cities we find negative effects on days with heavy precipitation.

Many policymakers highlight public transit as a way toward reducing greenhouse gas emissions from private vehicles (Welle et al., 2023). Yet, our results suggest climate change could hinder efforts to expand public transit usage, especially for buses. More work is needed to ensure public transit remains accessible in all types of weather, which could include expanding bus shelters or ensuring shade at important transit stops (Wang et al., 2024), otherwise, people who rely on transit may find it more difficult to access, leading to missed social and economic opportunities.

2. Literature review

Many studies focused on how weather affects public transit ridership use different methodological approaches (Böcker et al., 2013). Several studies use data from smartcards, which provides detailed trip data on how people travel or daily ridership data. Many of them show negative effects on public transit ridership when it rains or is very hot, but more mixed results during more mild changes in weather. For example, one study by Arana et al. (2014) in Gipuzkoa, Spain found a negative relationship between public bus trips and precipitation and wind, but a positive relationship with temperature. Several studies in Brisbane, Australia, which also used smartcard data, found reductions in bus and rail ridership as the heat index increased, while inclement weather negatively affected transit ridership, especially on weekends (Tao et al., 2018; Wei et al., 2018) and among older adults (Wei, 2022). Another study across three megacities in China found a positive relationship between temperature and metro ridership, but a negative relationship with precipitation, with weekend ridership being more sensitive to weather relative to weekdays (Jiang & Cai, 2023). A couple studies in Shenzhen, China found that metro stations in urban areas were more sensitive to outdoor weather (Zhou et al., 2017), as well as evidence of a non-linear relationship between temperature increases and metro ridership, including a decline in ridership during a week-long heat wave in 2016 (Wang et al., 2024). The latter study is one of the few to observe the impacts of several consecutive days of heat on public transit ridership.

Other studies have observed impacts on public transit ridership at a more aggregate scale, and showed similar findings of negative associations between rainfall, or any other inclement weather, and public transit ridership. A study in Chicago using bus and rail transit ridership data found weekend trips were more sensitive to changes in weather than weekday trips (Guo et al., 2007). Another study in Washington found weather variables had different impacts on transit ridership depending on the season, specifically cold temperatures, rain, and snow were associated with reduced transit ridership (Stover & McCormack, 2012), while a study by Li et al. (2018) also found precipitation, snowfall, and unusual winter temperatures had negative impacts on metro ridership in Nanjing Metro, China, especially on weekends. One study in Brisbane showed rainfall had a negative effect on bus ridership but a positive relationship during consecutive rainy days (Kashfi & Bunker, 2015), while a study in Chicago found a 3 % to 5 % drop in public transportation ridership during the heavy rainy days during the summer (Changnon, 1996).

Fewer studies have used survey data to observe this relationship between weather and public transit ridership to better understand changes in travel behavior. A study in Sweden based on survey data found heavy rain was associated with reduced travel (Liu et al., 2015). Another study that used survey and ridership data found that people were more likely to choose subways or private vehicles instead of buses on days with poor weather (Wu & Liao, 2020).

Relatedly, there has been less work investigating the impacts of extreme weather events on public transit ridership across multiple geographies, as well as by varying sociodemographic characteristics (Wang et al., 2024). Yet, a literature review focused on transportation more broadly and extreme weather events, including heat waves and heavy precipitation, found these events can severely affect transportation systems and behavior from the local to global level, highlighting the importance of transportation planning in the context of climate change (Gössling et al., 2023). One of the few studies to observe this relationship among, public transit ridership, extreme weather events, and sociodemographic characteristics focused on a medium-sized county and found reductions in bus ridership on very cold or hot days and days with heavy precipitation, with greater impacts in low-income neighborhoods, parks and commercial areas (Ngo, 2019). A study by Sabir, van Ommeren, and Rietveld (2013) is also one of the few studies to account for income when analyzing the relationship between bus ridership and weather, while another study observed the importance of socio-economic characteristics on metro ridership in China and found they were only significant on weekdays, but not weekends (Jiang & Cai, 2023).

This study complements the existing literature by observing the impacts of very hot days, very cold days and days of heavy precipitation on public transit ridership throughout the U.S. We observe how the relationship between these extreme weather events and UPT per capita varies across different transit modes (e.g. bus versus rail) and different sociodemographic characteristics (e.g., income, population) over a near two-decade period. Further, we examine how several consecutive days of extreme weather, which has been explored less in the literature, affects public transit ridership.

3. Data and methods

3.1. Data

3.1.1. Public transit ridership

We obtain data on UPT from the U.S. Federal Transit Administration's (FTA) NTD. The NTD is the main source of data on transit systems throughout the U.S. and any beneficiary of grants from the FTA must submit data to the NTD. This currently includes over 800 transit providers, representing a comprehensive dataset of transit agencies throughout the U.S. We use the complete monthly ridership dataset between January 2002, the first month data are publicly available, through December 2019 to avoid the COVID-19 pandemic period, when lockdowns dramatically changed travel behavior in the U.S. The complete monthly ridership data adjusts historical data, specifically between 2002 and 2011, for agencies that changed their methodology for collecting data.[1] This study focuses on the 48 cities with the highest levels of UPT, which we use as a proxy for public transit ridership, across a variety of modes (e.g., bus, rail, ferry). We use UPT since it best reflects public transit ridership relative to other measures captured by the NTD[2] and has been utilized in other studies (e.g., Hall, Palsson, and Price 2018) to observe impacts on ridership. To further assess if certain modes of public transportation are more sensitive to extreme weather relative to others, we observe how effects differ between the two most common forms of public transit: bus[3] and rail.[4] The list of cities in our sample are in Table S1 in the supplementary material, and we focus on the 48 U.S. cities with the highest levels of UPT.

3.1.2. Weather and sociodemographic characteristics

We gather data on daily maximum temperature (^{o}F) and precipitation (in.) from Climate Data Online which is run by the National Oceanic and Atmospheric Administration's National Centers for Environmental Information[5] (NOAA, 2024). Given our sample includes an almost two-decade period, we gather data from the largest local airport in a given city since weather stations at airports tend to be more reliable, with consistent daily data collection. If weather data were not available from the largest airport, we consider the next largest airport in the area.

Since weather varies dramatically across the U.S., we find the number of extreme weather events by first calculating the 10th and 90th percentiles for daily maximum temperature in each city across the entire study period. This helps account for climate differences across U.S. cities. Days when daily maximum temperatures are $<$ the 10th percentile or $\geq$ the 90th percentiles are considered "very cold" or "very hot" days respectively. Similarly, we find the 90th percentile for daily precipitation, and when precipitation is above or equal to this threshold, these are days of "heavy precipitation". For example, the 90th percentile for daily maximum temperature and precipitation in Houston, TX is 94°F and 0.28 in. (respectively) based on daily weather data between 2002 and 2019 at the George Bush Intercontinental/Houston Airport. A day when daily maximum temperature or precipitation is $\geq$ these thresholds is considered a very hot day and a day with heavy precipitation (respectively). We also use these percentile thresholds to address possible nonlinearities in the relationship between extreme weather events and public transit ridership. For example, the effects of a 10°F increase in temperature from 60°F to 70°F likely differs from a temperature increase from 90°F to 100°F. In our analysis, we focus on evaluating

[1] Source of public transit ridership data: https://www.transit.dot.gov/ntd/data-product/monthly-module-adjusted-data-release.

[2] The NTD also collects data at the month-year level on vehicle revenue miles, vehicle revenue hours, and vehicles operated in maximum service (peak vehicles).

[3] Bus transit includes trips by motorbus, bus rapid transit, and commuter bus.

[4] Rail transit includes trips by light rail, streetcar, commuter rail, hybrid rail, and heavy rail.

[5] Source of weather data: https://www.ncdc.noaa.gov/cdo-web/#t=secondTabLink.

differences in impacts on UPT per capita between a very hot day versus a not very hot day, which allows for more flexibility in our model, including possible nonlinearities.

Next, since UPT is at the month-year-city level, we aggregate our weather data up to the same level by summing the total number of days the daily maximum temperature is < the 10th percentile or ≥ the 90th percentile for that month, year and city. The weather data are then merged with the UPT data at the month-year-city level. The list of airports from which we retrieve weather data are in Table S1 in the supplementary material.

To control for sociodemographic characteristics in a given city, we collect data from the 5-year ACS. This includes the earliest publicly available 5-year ACS (2005 to 2009), the 2010 to 2014 5-year ACS, and the 2015 to 2019 5-year ACS. Data from the 2005 to 2009 5-year ACS is associated with UPT data between 2002 and 2009, and data from the latter two 5-year ACSs correspond to the years they overlap with. Specifically, we gather data on median household income (adjusted for inflation to 2019), the number of people who live below the poverty level[6] per capita, the proportion of people with a high school degree or higher by age 25, who are Black, Asian, White, American Indian, and/or Hispanic/Latino, are under the age 18, over the age of 65, who are unemployed, and who use a car, van, or truck to commute work.

3.2. *Regression analysis of public transit ridership on extreme weather*

3.2.1. *Main specification*

We are interested in how the number of very hot days, very cold days, and days of heavy precipitation affect UPT per capita, which we use as a proxy for public transit ridership. We use the following OLS regression:

$$\begin{aligned} uptpc_{cym} = {} & \alpha_1(tmax < p10)_{cym} + \alpha_2(tmax \geq p90)_{cym} + \alpha_3(prcp \geq p90)_{cym} + \alpha_4 highschool_{cy} + \alpha_5 medianinc_{cy} + \alpha_6 Black_{cy} \\ & + \alpha_7 Hispanic_{cy} + \alpha_8 AmIndian_{cy} + \alpha_9 Asian_{cy} + \alpha_{10} poverty_{cy} + \alpha_{11} under18_{cy} + \alpha_{12} over65_{cy} + \alpha_{13} unemp_{cy} + \alpha_{14} car_{cy} \\ & + \boldsymbol{year_y} + \boldsymbol{month_m} + \boldsymbol{city_c} + \boldsymbol{city^*year_{cy}} + \varepsilon_{cym} \end{aligned} \tag{1}$$

where *uptpc* is UPT per capita in city *c*, year *y*, month *m*. The independent variables of interest are the number of days the daily maximum temperature is less than the 10th percentile ($tmax < p10$) or is greater than or equal to the 90th percentile ($tmax \geq p90$), and the number of days when daily precipitation is greater than or equal to the 90th percentile ($prcp \geq p90$) in a given city, year, and month. The control variables include several sociodemographic characteristics that vary at the city-year level, specifically median household income (*medianinc*) (in 2019 inflation adjusted dollars), the proportion of people who graduated from high school or higher by age 25 (*highschool*), who are Black (*Black*), Hispanic/Latino (*Hispanic*), Asian (*Asian*), American Indian (*AmIndian*), under the age 18 (*under18*), age 65 or older (*over65*), unemployed (*unemp*), use a car, truck, or van to commute to work (*car*), and the proportion of people who live below the poverty level (*poverty*).[7] We also include a dummy variable for each month (***month***) to account for factors that affect UPT at the monthly level (e.g., seasons), as well as dummy variables to account for each year (***year***) to control for annual level factors (e.g. a recession), and a dummy variable for each city (***city***) to account for time-invariant factors that affect UPT per capita within each city. Finally, to account for factors within a city that may vary at the annual level, we also include a dummy variable for each city interacted with a year trend (***city*year***). The error term, ε, represents all other factors that affect UPT. Standard errors are clustered at the city level to account for both heteroskedasticity and autocorrelation within cities (Wooldridge, 2010).

The coefficients of interest are α_1, α_2, and α_3, which represent the effect of an additional day when the daily maximum temperature is < the 10th percentile, ≥ the 90th percentile, and when the daily precipitation ≥ the 90th percentile (respectively) in a given month, year, and city relative to more mild daily maximum temperatures (between the 10th and 90th percentiles) and precipitation levels (below the 90th percentiles). Recall, each of these percentile thresholds is with respect to a given city during our study period. More studies typically find reduced bus and rail ridership during inclement weather (Arana et al., 2014; Li et al., 2018; Ngo, 2019; Stover & McCormack, 2012; Wang et al., 2024; Wei et al., 2018), so we expect the coefficients of interest to be < 0, implying that UPT per capita decreases when more extreme weather events occur in a given month, year, and city. We also observe if there are differences by rail versus bus transit by running equation (1), but the dependent variable is either UPT per capita by bus or rail transit only. We might expect certain transit modes, such as buses, to be more sensitive to extreme weather events given results in the prior literature (Böcker et al., 2013; Wu & Liao, 2020).

Omitted variable bias is a concern if there are factors excluded from equation (1) that are correlated to our independent variables of interest (i.e., the number of days within a given temperature range or above a certain precipitation threshold) and the dependent variable, UPT per capita. To address this, we include several control variables, including sociodemographic characteristics (e.g., age, education, income) and dummy variables for each city. We also control for several time-varying factors. For example, one concern could be that seasonality is correlated to both bus ridership and weather trends, in which case, we include including a dummy variable for each month to account for this. Also, since we focus on a long time period, another concern could be global warming and its

[6] This is based on the poverty to income ratio which represents the income divided by the poverty threshold A number < 1 indicates being below the poverty level in the 5-year ACSs after 2009. The 2005 –2009 5-year ACS, however, shows the number of people who are “poor” or “struggling”. We use this to imply the number of people who live in poverty

[7] The poverty ratio we use for this measure changes after 2009. For the 5-year ACSs in 2010 and after, the poverty ratio represents the proportion of people who live below the poverty level. Prior to this, the ACSs show the number of people who are considered “poor” or “struggling”. We use this to imply the number of people who live in poverty.

differential impact over the years across the U.S. To account for this, we include an interaction between a dummy variable for each city and a year trend as well as dummy variables for each year.

3.2.2. Alternative specifications

Next, we perform four exercises using equation (1) which complement our main findings by providing a more in-depth investigation of the relationship between weather and public transit ridership. First, we examine the impact of heat, cold, and precipitation events. By our definition, these events occur when there have been at least four consecutive days when the daily maximum temperature is $\geq$ the 90th percentile (i.e., a heat event) or is $<$ the 10th percentile (i.e., a cold event), and when daily precipitation is $>$ the 90th percentile (i.e., a precipitation event). We choose four consecutive days since this is in part used by the U.S. EPA to define a heat wave.[8] Since the measure we use slightly differs from how the U.S. EPA defines heat waves, which is based on historical data, we use the term "heat event" instead. Very few studies have observed the impact of consecutive days of very hot or cold days on transit ridership, even though they are becoming more common (Perkins-Kirkpatrick & Lewis, 2020; Wang et al., 2024). We use equation (1), but instead the independent variable of interest is the length of the heat, cold, or precipitation event in a given city. More specifically, our heat event index equals 1 for any heat event lasting 4 consecutive days. If the heat event lasted 5 or 6 days, then the heat event index equals 2 or 3 (respectively). We use this approach to capture the length, and therefore severity, of the heat, cold, or precipitation event.

Second, we compare results from our main specification focused on extreme weather events to one focused on more mild weather. We use equation (1), but the independent variables of interest are the number of days daily maximum temperature is $<$ 25th percentile or $\geq$ the 75th percentile, or daily precipitation $\geq$ the 75th percentile. We expect smaller, but still negative effects on public transit ridership.

Third, there may be concerns that people adapt quickly to changes in the climate, so we use equation (1) but the 10th and 90th percentile thresholds are determined by the city and year (e.g. the 10th percentile in New York City is different in 2002 versus 2005). This contrasts with the percentile thresholds in equation (1), which are determined in a given city over the entire the study period. We still prefer the latter approach since adaptation likely occurs over a long period of time but compare our results to this alternative specification to provide a range of impacts of extreme weather events on public transit ridership.

Finally, we observe if impacts of extreme weather events are stronger within a particular season since very hot days in the summer may have greater impacts relative to spring for example, when there are fewer very hot days. This has been the focus of other studies in the literature (Stover & McCormack, 2012). To address this, we use equation (1) but run a separate regression for each season.[9]

3.2.3. Heterogeneous effects over time and by population and income

Equation (1) assumes the effects of extreme weather events on UPT per capita is homogenous, however, they likely vary over time. For example, impacts on public transit from extreme weather events may be greater in the past decade due to the growth of shared mobility services, such as ride-hailing services or bike sharing, which could complement or substitute for public transit. To measure heterogenous effects over time, we run separate regressions within each of the following time periods using an equation similar to equation (1): 2002 to 2008, 2009 to 2015, and 2016 to 2019. We choose these periods to capture differences in access to various shared mobility technologies. For example, to observe changes in UPT per capita before and after ride hailing services and bike sharing started to widely penetrate the market, we investigate impacts after 2008 since Uber started in 2009 (Bhuiyan & Milmo, 2022) and the first bikeshare system started in 2010 (NATCO, 2023). Both shared mobility technologies expanded rapidly in the following years (NATCO, 2023), while Lyft also started in 2012 (Lyft, 2023). For consistency, we observe the following seven-year period (2009 to 2015), and then the remaining years (2016 to 2019). While the last period is shorter, it also captures the rapid expansion of micromobility, including the beginning of dockless bikeshares and e-scooters which started in 2017 (NATCO, 2023). We do not include sociodemographic characteristics in these regressions since they are time-invariant during certain time periods (e.g., 2002 to 2008). We then compare coefficients across these regressions and expect UPT per capita in the latter periods, when micromobility and ride-hailing became more prevalent, to be more sensitive to extreme weather events since people could access more alternative forms of transportation.

There is also less information in the literature regarding how the effects of extreme weather events affect public transit ridership across different sociodemographic characteristics. For example, public transit ridership may fluctuate more in higher-income cities due to more transportation alternatives (e.g., a private vehicle, ride-hailing services) or the types of transit available (Taylor et al., 2009; Taylor & Morris, 2015; Wang & Woo, 2017). Further, studies have shown positive correlations between higher incomes and transport demand (Lebrand & Theophile, 2022). To assess if there are differences based on income, we observe if or how these effects might change across different city-level characteristics. First, we use equation (1), but only include cities where and when the median income (in 2019 inflation adjusted dollars) is $<$ the 25th percentile (based on all the cities in our dataset and during our study period). We use these thresholds since "low" and "high" income households are relative to all the households in our sample, so using quartiles could approximate different income classes. For example, according to the 2022 U.S. Census, the income threshold for middle-lower income households was \$58,020, which approximates the 25th percentile of household median income (\$58,028) in our dataset. We run a

[8] Source: https://www.epa.gov/climate-indicators/climate-change-indicators-heat-waves#:~:text=This%20index%20defines%20a%20heat,and%20how%20widespread%20they%20are.

[9] Winter is represented by the months December through February. Spring is represented by March through May. Summer is represented by June through August and Fall is represented by September through November.

separate regression using equation (1), but only include cities where the median income is ≥ the 75th percentile. We then compare coefficients across these two specifications to assess how or if public transit ridership differs between these lower- or higher-income cities.

We use a similar approach based on population, since public transit operates very differently in the most populated U.S. cities (AlQuhtani & Anjomani, 2021; Fraser & Chester, 2017; Jasim et al., 2022). For example, in less populated cities, public transit typically runs less frequently and has a more limited network of stops, so UPT per capita in these cities may be more sensitive to extreme weather events. Our reasoning for using these thresholds is similar to that for income, with these quartiles approximating smaller versus larger major metropolitan areas. For example, the 25th percentile and lower for population in our sample includes cities with populations between 150,000 and 1.2 million while urban areas in the 75th percentile and higher have populations between 4 and 10 million. In separate regressions, we use equation (1) and observe cities where the population is < the 25th percentile (based on all the cities in our dataset and study period), and separately in cities where the population is ≥ 75th percentile. We then compare coefficients across these two regressions based on population size.

4. Results

4.1. Summary statistics of public transit ridership, weather and sociodemographic characteristics

Fig. 1 shows annual means between 2002 and 2019 for all the cities in our sample for our dependent variables: UPT per capita across all public transit modes (UPTpc) (solid line), UPT per capita for bus transit (BusUPTpc) (dash line), and UPT per capita for rail transit (RailUPTpc) (dash dot line). It also shows annual means for the independent variables of interest: number of days when daily maximum temperature is < the 10th percentile based on all cities in our sample and study period (“temp < p10” and represented by the short dash line) and ≥ the 90th percentile (“temp >= p90” and represented by the long dash line), and when daily precipitation is ≥ the 90th percentile (“prcp >= p90” and represented by the short dash dot line). The graph shows public transit ridership, especially on buses, slightly declined the few years prior to 2019, as well as small increases in annual mean very hot days and days of heavy precipitation, especially toward the end of the study period, while annual mean cold days fluctuate, but has stayed relatively steady.

Table 1, panel A shows more detailed summary statistics, including the mean, standard deviation, 10th percentile, median, and 90th percentile, for the dependent variable, UPT per capita at the city-month-year level during the study period (2002 to 2019), to highlight the variation in public transit ridership across the U.S. We also present the same detailed summary statistics for our independent variables of interest (also at the city-month-year level during the entire study period), which includes the monthly mean maximum temperature and precipitation, as well as the 10th and 90th percentiles. On average, the 10th and 90th percentiles for daily maximum temperature are 44°F and 90°F (respectively) and for precipitation, it is 0.008 and 0.22 in.. The mean number of days below the 10th percentile and above 90th percentile is 2.8 and 3.4 (respectively), while the mean number of days with precipitation ≥ 90th percentile is 4.9. Next, panel B shows the monthly mean index of cold, heat, and precipitation events in our study period. The mean

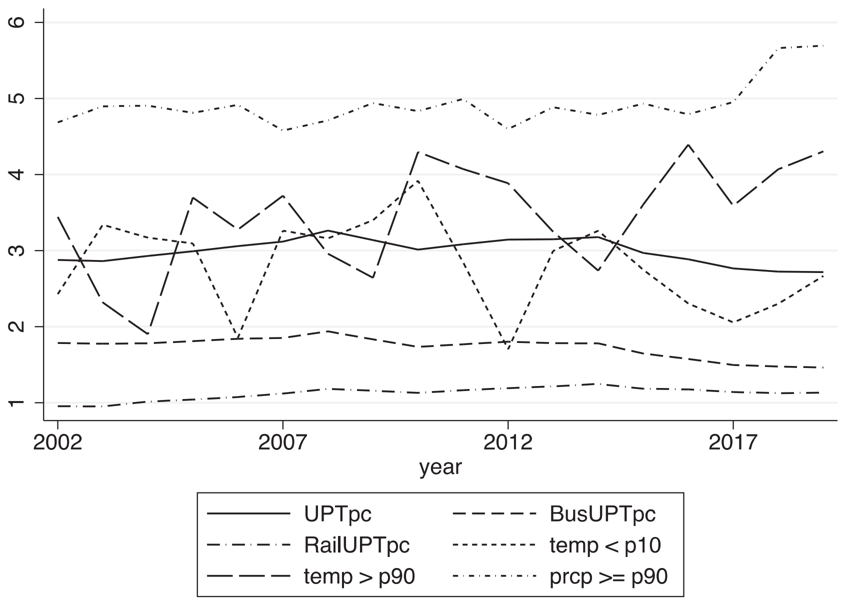

Fig. 1. This graph show annual means between 2002 and 2019 for all cities in our sample for our dependent variables: UPT per capita across all transit modes (UPTpc), UPT per capita for bus transit (BusUPTpc), and UPT per capita for rail transit (RailUPTpc). It also shows annual means for the independent variables of interest: number of days when daily maximum temperature is < the 10th percentile (based on all cities in our sample and study period) (temp < p10) and ≥ the 90th percentile (temp >= p90), and when daily precipitation is ≥ the 90th percentile (prcp >= p90).

Table 1
Summary statistics for the dependent and independent variables.

	1	2	3	4	6
	Mean	Std. dev.	10th percentile	Median	90th percentile
Panel A: Public transit ridership and weather variables (2002 to 2019) (at the month-city-year level)					
Unlinked passenger trips per capita	3	4.4			
Mean maximum temperature (all data) (^{o}F)	69	17	44	72	90
Mean maximum temperature (10th percentile)	47	14	31	45	69
Mean maximum temperature (90th percentile)	89	5.9	83	89	97
Number of days below the 10th percentile	2.8	5.1			
Number of days above the 90th percentile	3.4	5.8			
Mean precipitation (all data) (inches)	0.11	0.09	0.008	0.09	0.22
Mean precipitation (90th percentile)	0.32	0.16	0.03	0.38	0.48
Number of days exceeding the 90th percentile	4.9	7.1			
Panel B: Heat, cold, precipitation events (2002 to 2019) (at the month-city-year level)					
Mean measure of cold events	0.8	2.4			
Mean measure of heat events	1.1	3.1			
Mean measure of precipitation events	2.02	7.5			
Panel C: Sociodemographic characteristics (2005 to 2019) (at the year-city level)					
Median income ($)	66,925	13,538			
Number of high school graduates by age 25 per capita	1.34	0.16			
Number of Black people per capita	0.13	0.08			
Number of Hispanic/Latino people per capita	0.18	0.17			
Number of Asian people per capita	0.05	0.04			
Number of American Indian people per capita	0.01	0.01			
Number of people with incomes below the poverty level per capita	0.21	0.10			
Number of people under age 18 per capita	0.24	0.02			
Number of people aged 65 and older per capita	0.13	0.04			
Number of people unemployed per capita	0.07	0.02			
Number of people who drive their car to work per capita	0.41	0.05			

index for cold events is < 1, meaning cold waves on average last less then 4 days. For heat events, the mean index is 1.1, implying they on average last 4 days, and the mean index for precipitation events is 2, meaning they last on average 5 days. Finally, panel C shows the mean and standard deviation for the sociodemographic, or control, variables (at the city-year level) in equation (1). These data are for the period between 2005 and 2019 since 2005 is the first 5-year ACS that is publicly available. Table S2 in the supplementary material shows the summary statistics for sociodemographic characteristics for each of the 5-year ACS surveys used in our analysis.

4.2. Main specification: Public transit ridership and extreme weather events

Results using our main specification in equation (1) are in Fig. 2, which shows the coefficients of interest with 95 % confidence intervals across all types of public transit (represented by the squares). The vertical line represents zero. Coefficients on all the independent variables are in Table S3 in the supplementary material. We focus on statistically significant (i.e., $p < 0.05$) results. We show, on average, an additional day when and where daily maximum temperature in a given month-year-city is < the 10th percentile, UPT per capita decreases by 0.0071 ($p < 0.05$), which represents 0.24 % of mean UPT per capita, relative to days when and where the daily maximum temperature is between the 10th and 90th percentiles. When daily maximum temperature or precipitation is ≥ the 90th percentile, UPT per capita decreases by 0.0023 ($p < 0.05$) and 0.0098 ($p < 0.05$) (respectively), which represents 0.08 % and 0.33 % of mean UPT per capita (respectively). This suggests an additional day of extreme weather events has a small, but consistently negative effect on public transit ridership.

Next, we observe if there are differences based on travel mode, specifically bus or rail. Results are also in Fig. 2, and we find bus UPT per capita (represented by the "x") is associated with reductions of 0.0033 ($p < 0.05$), 0.0019 ($p < 0.01$), and 0.0046 ($p < 0.05$) on very cold days, hot days, and days with heavy precipitation (respectively). For rail UPT per capita (represented by the triangles), we only find a statistically significant reduction on days with heavy precipitation of 0.0036 ($p < 0.05$). This implies that ridership on buses is more sensitive to extreme weather events relative to rail and more closely mimics results focused on all types of public transit ridership.

4.2.1. Alternative specifications

We then observe impacts of cold, heat, and precipitation events, and results are in Table 2, column 1. Recall, we define a cold event in this study as at least four consecutive days when and where daily maximum temperature is < the 10th percentile. An additional day of a cold or heat event is associated with a decline in UPT per capita of 0.0086 ($p < 0.05$) or 0.0041 ($p < 0.01$) (respectively). We find no statistically significant effect from an additional day of a precipitation event. This effect from an additional day of a heat event is larger than the impact of a very hot day from Fig. 2 using equation (1).

We also examine effects for more mild changes in weather. Specifically, we observe days when and where the daily maximum temperature is < 25th percentile or ≥ the 75th percentile, and results are in Table 2, column 2. We find an additional cold day is associated with a reduction in UPT per capita of. 0.0053 ($p < 0.05$). We also find reductions in UPT per capita of 0.0055 ($p < 0.01$) when precipitation is ≥ the 75th percentile, which is smaller than the effect of a day with heavy precipitation in our main results in

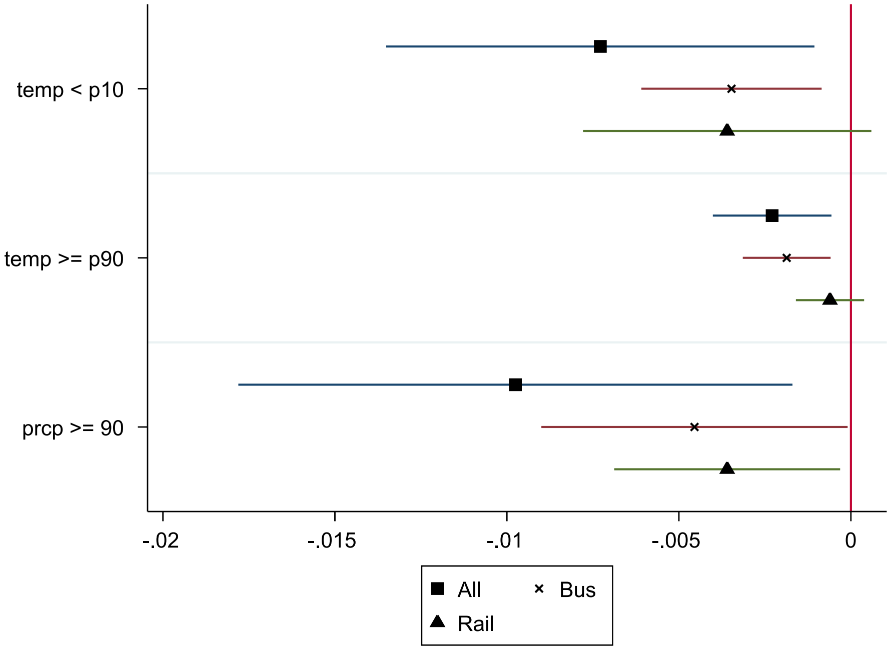

Fig. 2. This graph shows coefficients and their 95 % confidence intervals on the independent variables of interest using equation (1) in a given month-year-city. It represents the effect of an additional day when and where daily maximum temperature is < the 10th percentile ("temp < p10"), ≥ the 90th percentile ("temp >= p90"), or when and where daily precipitation ≥ the 90th percentile ("prcp >= p90"). The square represents impacts on ridership across all modes of public transit in the National Transit Database, while the "X" and triangle represent bus and rail transit (respectively). Each shape represents a separate regression. The vertical line represents zero. The sample size across all transit modes is 10,109 and there are 48 clusters. All coefficients are in Table S3 in the supplementary material.

Table 2
Results of independent variables of interest in alternative specifications.

	1	2	3
	UPT	UPT	UPT
	per capita	per capita	per capita
Cold event	−0.0089* [0.0038]		
Heat event	−0.0041* [0.0015]		
Precipitation event	−0.011 [0.0069]		
Daily maximum temperature < p25		−0.0054* [0.0022]	
Daily maximum temperature ≥ p75		−0.0030 [0.0017]	
Daily precipitation ≥ p75		−0.0056** [0.0020]	
Daily maximum temperature < p10 (city-year level)			−0.0086* [0.0035]
Daily maximum temperature ≥ p90 (city-year level)			−0.0028* [0.0013]
Daily precipitation ≥ p90 (city-year level)			−0.0033* [0.0014]
N	10,109	10,109	10,109
R-squared	0.991	0.991	0.991
Number of clusters	48	48	48

Notes: **p < 0.01, *p < 0.05. This table shows alternative specifications of equation (1). See section 3.2.2. for more information. Coefficients on all the independent variables are in Table S4 in the supplementary material. Each column represents a separate regression.

Fig. 2. We show no statistically significant effect on days when the daily maximum temperature is ≥ the 75th percentile.

Next, we use equation (1), but the 10th and 90th percentiles are determined within a city and year (as opposed to the entire study period as shown in the main results). Results are in column 3 of Table 2, and on very cold and very hot days using these different percentile thresholds, coefficients are statistically similar to the main results in Fig. 2, except the effect on days with heavy precipitation is smaller, showing a reduction in UPT per capita of 0.0034 ($p < 0.05$). Coefficients on all the independent variables for results in Table 2 are in Table S4 in the supplementary material.

Finally, our last alternative specification uses equation (1), but focuses on a given season to see if the impacts of extreme weather effects are stronger. Results are in Table 3 and are statistically similar to those in Fig. 2 for very cold days in the winter season and very hot days in the summer. However, we find no statistically significant effect of days with heavy precipitation in any particular season. Coefficients on all the independent variables are in Table S5 in the supplementary material.

4.3. Heterogeneous effects over time

Next, we observe if this relationship between extreme weather events and UPT per capita varies during our study period. Findings are in Fig. 3, which shows the coefficients and 95 % confidence intervals on the independent variables of interest. Coefficients on all the independent variables are in Table S6 in the supplementary material. We run equation (1) separately for each time period of interest: 2002 to 2008 (squares), 2009 to 2015 (diamond), and 2016 to 2019 (triangle). We consistently find statistically similar reductions in UPT per capita, between 0.0079 and 0.010 ($p < 0.05$), in every time period ($p < 0.01$) for each additional day of heavy precipitation. We also find for each additional very cold day, the size of the effect slightly declining from 0.0098 ($p < 0.05$) in the second period (2009 to 2015) to 0.0068 ($p < 0.05$) in the last period (2016 to 2019). Finally, we find a small reduction on very hot days in only the last period of 0.0024 ($p < 0.05$). These results suggest very cold days and days with heavy precipitation had the greatest impact on UPT per capita starting in 2008, while the impact of a very hot day was only statistically significant starting in 2016.[10]

4.4. Heterogeneous effects by income and population

We then observe if impacts on UPT per capita vary based on certain sociodemographic groups that may be sensitive to extreme weather events. First, we observe if UPT per capita varies in cities when and where the median income or population is $<$ the 25th percentile or $\geq$ the 75th percentile in separate regressions using equation (1). Coefficients on all the independent variables are in Tables S7 and S8 in the supplementary material. Among cities where and when median income is $<$ the 25th percentile (square), we find statistically significant decreases in UPT per capita of 0.004 ($p < 0.01$) from an additional very cold day, but no other statistically significant effects. Regarding differences based on population size, Fig. 4 shows when and where population is $\geq$ the 75th percentile (diamond), UPT per capita reduces by 0.026 ($p < 0.01$) for each additional day of heavy precipitation. However, we find no statistically significant effects if the population is $<$ the 25th percentile (triangle). These results suggest UPT per capita in lower-income cities is more sensitive to very cold weather relative to higher-income cities, while UPT per capita in more populated cities is more sensitive to days with heavy precipitation relative to less populated cities. Both effects are smaller than those found in the main results in Fig. 2.[11]

5. Discussion

A better understanding of the relationship among climate change, urban mobility and sociodemographic characteristics is critical for policymakers, planners and transit agencies as they consider the future of public transit, which is often the only form of affordable transportation among lower-income households (American Public Transportation Association, 2017), in the U.S. This study helps further knowledge in the field by examining this relationship among U.S. cities with the greatest public transit usage over a near two-decade period. We examine how public transit ridership changes during extreme weather events, specifically on very hot and cold days, as well as days with heavy precipitation.

Our findings show a consistent reduction in public transit ridership for each additional very hot or cold day and day with heavy precipitation, which is in line with many other studies (Arana et al., 2014; Li et al., 2018; Liu et al., 2015; Ngo, 2019; Stover & McCormack, 2012). While the impacts are small relative to mean UPT per capita, it implies these weather events could be one of many factors affecting future trends in public transit ridership. For example, results in Fig. 2 imply that three days of heavy precipitation in a given month-year and city could be associated with a decline in ridership equivalent to 1 % of mean UPT per capita.

We explore possible reasons for this decline and their implications. First, public transit infrastructure exposed to certain extreme weather events, such as extreme heat, could limit how public transit operates. For example, in Portland, Oregon, when temperatures reach 100°F or higher, the trains must lower their speed or stop operating due to the overhead wires or steel rails expanding in the heat, making the trains unsafe to operate (Ionescu, 2024). Second, people may switch to using their own private vehicles or forego trips unless it is necessary (Liu et al., 2015; Wu & Liao, 2020). Yet, there are social costs associated with using private vehicles during extreme weather events. A growing literature shows extreme temperatures could affect road safety, how people drive and vehicle performance (Zare Sakhvidi et al., 2022), leading to a higher rate of traffic accidents and injuries as temperatures increase (Liang et al., 2022), including during the summer (Hsu, 2024a) and during periods of adverse weather (Hsu, 2024b). In which case, public transit, if it is operational, may be a safer alternative during an extreme weather event.

[10] We also explore heterogenous effects over time by bus and rail separately, which we discuss further in the supplementary material in section A and in Figures S1 and S2.

[11] We also observed differences in impacts based on population and income in bus versus rail. Results are discussed in section B of the supplementary material and in Figure S3 and S4.

Table 3
Results of independent variables of interest using equation (1) within a given season.

	1	2	3	4
	UPT	UPT	UPT	UPT
	per capita	per capita	per capita	per capita
	Winter	*Spring*	*Summer*	*Fall*
Daily maximum temperature < p10	−0.0073*	−0.0028	0.022	−0.0031
	[0.0035]	[0.0039]	[0.050]	[0.0066]
Daily maximum temperature ≥ p90	0.0064	0.0066	−0.0035*	0.0029
	[0.014]	[0.0038]	[0.0016]	[0.0038]
Daily precipitation ≥ p90	−0.0024	−0.0047	−0.0041	−0.0061
	[0.0030]	[0.0030]	[0.0032]	[0.0035]
Observations	2,530	2,527	2,526	2,526
R-squared	0.993	0.995	0.995	0.993
Number of clusters	48	48	48	48

Notes: **p < 0.01, *p < 0.05. This table shows alternative specifications of equation (1). See section 3.2.2. for more information. Coefficients on all the independent variables are in Table S5 in the supplementary material. Each column represents a separate regression.

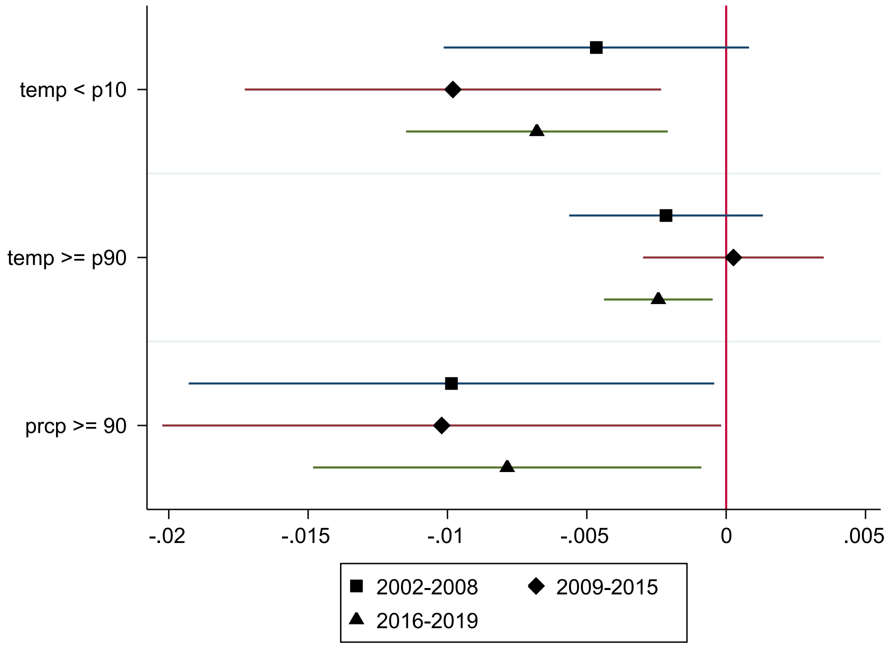

Fig. 3. This figure shows the heterogeneous impacts of different weather events on public transit ridership among the 48 cities in our sample using equation (1), but excluding sociodemographic characteristics, for different time periods. We separately observe impacts during 2002–2008 (square) (n = 3,948), 2009–2015 (diamond) (n = 3,889), and 2016–2019 (triangle) (n = 2,291). The vertical line represents zero. Each shape represents a separate regression. See the caption for Fig. 2 for more information. Coefficients on all the independent variables are in Table S7 in the supplementary material.

These results also have important implications for transportation systems in the future as incidences of extreme heat and heavy precipitation are expected to increase due to climate change. To further examine the implications of our results, we observe the effect of very high temperatures on public transit ridership in southwest Arizona, where 100-degree days are expected to increase based on various greenhouse gas emission scenarios (Kennedy, 2011). While the 90th percentile for daily maximum temperature varies by locale, a 100-degree day approximates the 90th percentile in Phoenix-Mesa, Arizona (104°F). We multiply the effect we find of an additional very hot day on UPT per capita (0.0023; see Fig. 2), by 90, the expected number of 100-degree days expected in a lower-emission scenario between 2080 and 2099 (Kennedy, 2011). This figure (0.21 UPT per capita) represents the total effect in a given year and city of 90 very hot days in these regions. To put this result in perspective, it represents 16 % of current mean UPT per capita in the Phoenix-Mesa metropolitan area, which is a sizeable effect on UPT. In fact, Phoenix-Mesa, Arizona currently experiences 111 100-degree days on average in a given year (Davis-Young, 2023), and in 2023 and 2020 they experienced a record number of 100-degree days (133 and 145 days respectively) (US Department of Commerce, 2024).

We also find differential effects based on transit mode, with bus ridership seeming more sensitive to extreme weather events

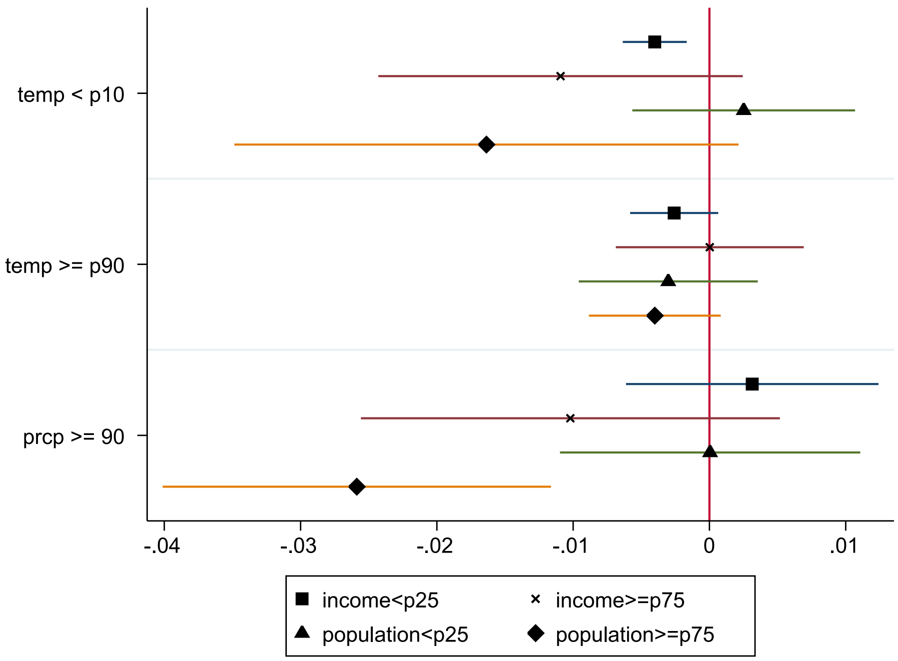

Fig. 4. This figure shows the heterogeneous impacts of different weather events based on median income and population of a city using equation (1). Each shape represents a separate regression. We observe cities where income is < the 25th percentile (based on all cities and years in our study) (square) (n = 2,447) and in a separate regression observe cities only where median income is ≥ the 75th percentile ("X") (n = 2,556). We perform the same analysis based on if the population in a city is < 25th percentile (triangle) (n = 2,522) or ≥ the 75th percentile (diamond) (n = 2,592). The vertical red line represents zero. See the caption for Fig. 2 for more information. Coefficients on all independent variables are in Table S7 and S8 in the supplementary material.

relative to rail ridership. These differences have also been found in other studies (Wu & Liao, 2020), and may relate to the types of trips taken on each transit mode, where buses could be used for both commuting and leisure trips, while rail transit is primarily used for commuting. For example, several studies find inclement weather has greater impacts on weekend trips relative to weekday trips (Guo et al., 2007; Jiang & Cai, 2023; Kalkstein et al., 2009; Tao et al., 2018). However, since we are unable to separate leisure trips from commuting trips based on these data, this reasoning is only speculative.

Our findings also highlight the importance of cold and heat events. We find an additional day of a cold or heat event is associated with declines in UPT per capita, which aligns with another study examining the impact of a heat wave in Shenzhen, China (Wang et al., 2024). These consecutive days of heat are important given heat waves are an important indicator of climate change and expected to increase in the U.S. (U.S. Global Change Research Program, 2023). In fact, there have been 12 instances of four consecutive 100-degree days, and since 2003, there have been five instances of nine consecutive 100-degree days in the U.S.. Public transit agencies should consider how to make public transit more accessible during such events (e.g., ensure buses have air conditioning, provide more bus shelters or shade at stops, ensure public transit systems can withstand heat) which could help reduce future decline in ridership (Fraser & Chester, 2017; Lanza & Durand, 2021).

Next, we observe how the impacts of extreme weather events on UPT per capita varied over time. Very few studies have observed the long-term impacts of weather on public transit ridership, so there are less studies to compare our analysis to. We find days with heavy precipitation are consistently associated with reductions in UPT per capita across all three time periods, while very cold days are associated with declines in public transit after 2008, and very hot days are associated with reductions in the last time period only. The greater sensitivity of public transit ridership to extreme weather events in the later time periods could be due to the growth of alternative transportation modes, such as ride-hailing or micromobility (e.g., bike sharing, e-scooters), though it is beyond the scope of the study to explicitly show this.

Further, we investigate how effects on public transit ridership vary based on two important sociodemographic indicators: income and population. We find when and where median income is low (i.e., < the 25th percentile), public transit ridership is more sensitive to very cold days, showing small reductions in UPT per capita, suggesting public transit ridership in lower-income cities is more sensitive to extreme weather events relative to higher income cities. This is surprising since we might expect higher-income cities to be more sensitive to inclement weather, assuming they have more alternatives (e.g., a private vehicle, ride-hailing services), and suggest possible inequities in how people access public transit during these events. Very few studies have explored this relationship among extreme weather events, public transit ridership and income, but one of the few studies to do so found greater declines in bus ridership in lower-income neighborhoods on very hot days, but not on very cold days and a positive relationship on days with heavy precipitation (Ngo, 2019).

Finally, we assess differences based on population since access to public transit likely varies between large and smaller cities. For example, in smaller cities, public transit runs less frequently and is more sparse outside the urban core relative to the largest cities (Neog & Brown, 2022; Rasca & Saeed, 2022; Sidloski & Diab, 2020) due to lower population density and demand. We observe impacts based on population and only find impacts in cities with populations ≥ the 75th percentile on days with heavy precipitation. These results suggest that in the most populated cities, public transit ridership is more sensitive to extreme weather events. These reductions in more populated cities or urban areas have been found in other studies (Zhou et al., 2017) and may relate to having greater access to alternative transportation modes (e.g., micromobility, ride hailing services) relative to smaller, less populated cities (Mcleod, 2023).

6. Limitations, future work, and conclusion

We note a couple of limitations to our study. First, ideally, we would use daily public transit ridership data to more directly observe the relationship between public transit ridership and daily weather. However, there are no daily level public transit ridership data that cover the study period, nor geographic scale of interest. Another limitation is that our main- and sub-analyses focused on correlations among extreme weather, mild weather and public transit ridership since we were unable to explore possible causal mechanisms using these datasets.

Future work should focus on the relationship between extreme weather events, as well as heat waves and precipitation waves, which are important indicators of climate change (U.S. Global Change Research Program, 2023), and public transit ridership. This includes further exploring how this relationship may vary based on different sociodemographic characteristics. Further research on travel behavior using survey data could help address why these reductions occur during extreme weather events and policies to address them. More work exploring impacts across a range of cities and over an extended period of time will help inform transit agencies how extreme weather events could differentially affect cities. This includes how the influence of other travel modes, such as micromobility or ride hailing services, could affect future public transit ridership in the context of climate change.

CRediT authorship contribution statement

By Nicole S. Ngo: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Shahinur Bashar:** Writing – review & editing, Writing – original draft, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We would like to thank Krishna Anand for helping to collect data for this project, as well as Wren Ganey for reviewing this manuscript. We also want to thank the editor and two anonymous reviewers for their very helpful feedback.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2024.104504.

Data availability

Data will be made available on request.

References

AlQuhtani, S., Anjomani, A., 2021. Do Rail Transit Stations Affect the Population Density Changes around Them? The Case of Dallas-Fort Worth Metropolitan Area. Sustainability 13 (6), Article 6. https://doi.org/10.3390/su13063355.
Arana, P., Cabezudo, S., Peñalba, M., 2014. Influence of weather conditions on transit ridership: A statistical study using data from Smartcards. Transp. Res. A Policy Pract. 59, 1–12. https://doi.org/10.1016/j.tra.2013.10.019.
American Public Transportation Association. (2017). Who Rides Public Transportation. *American Public Transportation Association*.
Bhuiyan, J., & Milmo, D. (2022, July 15). 'Embrace the chaos': A history of Uber's rapid expansion and fall from favour. *The Guardian*. https://www.theguardian.com/news/2022/jul/15/embrace-the-chaos-a-history-of-ubers-rapid-expansion-and-fall-from-favour.
Böcker, L., Dijst, M., Prillwitz, J., 2013. Impact of Everyday Weather on Individual Daily Travel Behaviours in Perspective: A Literature Review. Transp. Rev. 33 (1), 71–91. https://doi.org/10.1080/01441647.2012.747114.
Changnon, S.A., 1996. Effects of summer precipitation on urban transportation. Clim. Change 32 (4), 481–494. https://doi.org/10.1007/BF00140357.
Davis-Young, K. (2023, October 25). *Phoenix had 22 more 100-degree days than normal in 2023*. KJZZ. https://www.kjzz.org/2023-10-25/content-1861125-phoenix-had-22-more-100-degree-days-normal-year.
Fraser, A.M., Chester, M.V., 2017. Transit system design and vulnerability of riders to heat. J. Transp. Health 4, 216–225. https://doi.org/10.1016/j.jth.2016.07.005.

Gössling, S., Neger, C., Steiger, R., Bell, R., 2023. Weather, climate change, and transport: A review. Nat. Hazards 118 (2), 1341–1360. https://doi.org/10.1007/s11069-023-06054-2.

Guo, Z., Wilson, N.H.M., Rahbee, A., 2007. Impact of Weather on Transit Ridership in Chicago Illinois. Transport. Res. Record 2034 (1), 3–10. https://doi.org/10.3141/2034-01.

Hall, J.D., Palsson, C., Price, J., 2018. Is Uber a substitute or complement for public transit? J. Urban Econ. 108, 36–50. https://doi.org/10.1016/j.jue.2018.09.003.

Herring, D. (2020, October 29). *What is an "extreme event"? Is there evidence that global warming has caused or contributed to any particular extreme event? | NOAA Climate.gov*. http://www.climate.gov/news-features/climate-qa/what-extreme-event-there-evidence-global-warming-has-caused-or-contributed.

Hsu, C.-K., 2024a. Heat-induced risks of road crashes among older motorcyclists: Evidence from three motorcycle-dominant cities in Taiwan. J. Transp. Health 35, 101754. https://doi.org/10.1016/j.jth.2023.101754.

Hsu, C.-K., 2024b. Reconsidering Seasonality, Weather, and Road Safety in Non-temperate Areas: The Case of Kaohsiung Taiwan. Travel Behav. Soc. 34, 100710. https://doi.org/10.1016/j.tbs.2023.100710.

The Urban Institute. (2020, October 6). *The Unequal Commute | Urban Institute*. https://www.urban.org/features/unequal-commute.

Ionescu, D. (2024, July 8). *Portland Train Speed Limited by Extreme Heat*. https://www.planetizen.com/news/2024/07/130138-portland-train-speed-limited-extreme-heat.

Jasim, I.A., Al-Jaberi, A.A., Al-Maliki, L.A., Al-Ansari, N., Al-Mamoori, S.K., 2022. Do the population density and coverage rate of transit affect the public transport contribution? Cogent Eng. 9 (1), 2143059. https://doi.org/10.1080/23311916.2022.2143059.

Jiang, S., Cai, C., 2023. The impacts of weather conditions on metro ridership: An empirical study from three mega cities in China. Travel Behav. Soc. 31, 166–177. https://doi.org/10.1016/j.tbs.2022.12.003.

Kalkstein, A.J., Kuby, M., Gerrity, D., Clancy, J.J., 2009. An analysis of air mass effects on rail ridership in three US cities. J. Transp. Geogr. 17 (3), 198–207. https://doi.org/10.1016/j.jtrangeo.2008.07.003.

Kashfi, S.A., Bunker, J., 2015. Adverse weather effects on bus ridership. Road Transport Res. 24 (1), 44–57. https://doi.org/10.3316/informit.339776361309008.

Kennedy, C. (2011, May 24). *100° Days, Past and Future | NOAA Climate.gov*. http://www.climate.gov/news-features/featured-images/100%C2%B0-days-past-and-future.

Lanza, K., Durand, C.P., 2021. Heat-Moderating Effects of Bus Stop Shelters and Tree Shade on Public Transport Ridership. Int. J. Environ. Res. Public Health 18 (2), Article 2. https://doi.org/10.3390/ijerph18020463.

Li, J., Li, X., Chen, D., Godding, L., 2018. Assessment of metro ridership fluctuation caused by weather conditions in Asian context: Using archived weather and ridership data in Nanjing. J. Transp. Geogr. 66, 356–368. https://doi.org/10.1016/j.jtrangeo.2017.10.023.

Liang, M., Min, M., Guo, X., Song, Q., Wang, H., Li, N., Su, W., Liang, Q., Ding, X., Ye, P., Duan, L., Sun, Y., 2022. The relationship between ambient temperatures and road traffic injuries: A systematic review and meta-analysis. Environ. Sci. Pollut. Res. Int. 29 (33), 50647–50660. https://doi.org/10.1007/s11356-022-19437-y.

Liu, C., Susilo, Y.O., Karlström, A., 2015. Investigating the impacts of weather variability on individual's daily activity–travel patterns: A comparison between commuters and non-commuters in Sweden. Transp. Res. A Policy Pract. 82, 47–64. https://doi.org/10.1016/j.tra.2015.09.005.

Lyft. (2023, May 4). *Lyft Announces Results for First Quarter 2023*. https://investor.lyft.com/news-and-events/news/news-details/2023/Lyft-Announces-Results-for-First-Quarter-2023/default.aspx.

Mcleod, K. (2023, August 14). *New Data On Shared Micromobility Shows Growth Of E-Scooters, Success Of Large Cities*. Benchmarking Report By the League of American Bicyclists. https://data.bikeleague.org/new-data-on-shared-micromobility-shows-growth-of-e-scooters-success-of-large-cities/.

NATCO. (2023, October 23). *Shared Micromobility in 2022*. National Association of City Transportation Officials. https://nacto.org/publication/shared-micromobility-in-2022/%20.

Neog, D., Brown, J., 2022. Transit Ridership Growth in Small Urbanized Areas: Lessons from Seven US Transit Systems. J. Urban Plann. Dev. 148 (1), 05021051. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000771.

Ngo, N.S., 2019. Urban bus ridership, income, and extreme weather events. Transp. Res. Part D: Transp. Environ. 77, 464–475. https://doi.org/10.1016/j.trd.2019.03.009.

NOAA. (2024). *Climate Data Online (CDO)—The National Climatic Data Center's (NCDC) Climate Data Online (CDO) provides free access to NCDC's archive of historical weather and climate data in addition to station history information. | National Climatic Data Center (NCDC)*. https://www.ncdc.noaa.gov/cdo-web/#t=secondTabLink.

Perkins-Kirkpatrick, S.E., Lewis, S.C., 2020. Increasing trends in regional heatwaves. Nat. Commun. 11 (1), 3357. https://doi.org/10.1038/s41467-020-16970-7.

Rasca, S., Saeed, N., 2022. Exploring the factors influencing the use of public transport by commuters living in networks of small cities and towns. Travel Behav. Soc. 28, 249–263. https://doi.org/10.1016/j.tbs.2022.03.007.

Sabir, M., van Ommeren, J., Rietveld, P., 2013. Weather to travel to the beach. Transp. Res. A Policy Pract. 58, 79–86. https://doi.org/10.1016/j.tra.2013.10.003.

Sidloski, M., Diab, E., 2020. Understanding the Effectiveness of Bus Rapid Transit Systems in Small and Medium-Sized Cities in North America. Transp. Res. Rec. 2674 (10), 831–845. https://doi.org/10.1177/0361198120940993.

Singhal, A., Kamga, C., Yazici, A., 2014. Impact of weather on urban transit ridership. Transp. Res. A Policy Pract. 69, 379–391. https://doi.org/10.1016/j.tra.2014.09.008.

Stover, V.W., McCormack, E.D., 2012. The Impact of Weather on Bus Ridership in Pierce County Washington. J. Public Transport. 15 (1), 16.

Tao, S., Corcoran, J., Rowe, F., Hickman, M., 2018. To travel or not to travel: 'Weather' is the question. Modelling the effect of local weather conditions on bus ridership. Transp. Res. Part C Emerging Technol. 86, 147–167. https://doi.org/10.1016/j.trc.2017.11.005.

Taylor, B.D., Morris, E.A., 2015. Public transportation objectives and rider demographics: Are transit's priorities poor public policy? Transportation 42 (2), 347–367. https://doi.org/10.1007/s11116-014-9547-0.

Taylor, B.D., Miller, D., Iseki, H., Fink, C., 2009. Nature and/or nurture? Analyzing the determinants of transit ridership across US urbanized areas. Transp. Res. A Policy Pract. 43 (1), 60–77. https://doi.org/10.1016/j.tra.2008.06.007.

U.S. Global Change Research Program. (2023). *Fifth National Climate Assessment: Report-in-Brief*. U.S. Global Change Research Program. doi: 10.7930/NCA5.2023.RiB.

US Department of Commerce, N. (2024). *Historical Extreme Temperatures in Phoenix and Yuma*. NOAA's National Weather Service. https://www.weather.gov/psr/ExtremeTemps.

US EPA, O. (2021b, April 16). *Impacts of Climate Change* [Overviews and Factsheets]. https://www.epa.gov/climatechange-science/impacts-climate-change.

Wang, K., Woo, M., 2017. The relationship between transit rich neighborhoods and transit ridership: Evidence from the decentralization of poverty. Appl. Geogr. 86, 183–196. https://doi.org/10.1016/j.apgeog.2017.07.004.

Wang, B., Zhang, F., Liu, J., Tan, Z., 2024. The impacts of extreme hot weather on metro ridership: A case study of Shenzhen China. J. Transport Geography 117, 103899. https://doi.org/10.1016/j.jtrangeo.2024.103899.

Wei, M., 2022. How does the weather affect public transit ridership? A model with weather-passenger variations. J. Transp. Geogr. 98, 103242. https://doi.org/10.1016/j.jtrangeo.2021.103242.

Wei, M., Corcoran, J., Sigler, T., Liu, Y., 2018. Modeling the influence of weather on transit ridership: a case study from Brisbane Australia. Transport. Res. Record 2672 (8), 505–510. https://doi.org/10.1177/0361198118777078.

Welle, B., Kustar, A., Tun, T. H., & Albuquerque, C. (2023). *Post-pandemic, Public Transport Needs to Get Back on Track to Meet Global Climate Goals*. https://www.wri.org/insights/current-state-of-public-transport-climate-goals.

Wooldridge, J. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT Press. https://mitpress.mit.edu/9780262232586/econometric-analysis-of-cross-section-and-panel-data/.

Wu, J., Liao, H., 2020. Weather, travel mode choice, and impacts on subway ridership in Beijing. Transp. Res. A Policy Pract. 135, 264–279. https://doi.org/10.1016/j.tra.2020.03.020.

Zare Sakhvidi, M.J., Yang, J., Mohammadi, D., FallahZadeh, H., Mehrparvar, A., Stevenson, M., Basagaña, X., Gasparrini, A., Dadvand, P., 2022. Extreme environmental temperatures and motorcycle crashes: A time-series analysis. Environ. Sci. Pollut. Res. 29 (50), 76251–76262. https://doi.org/10.1007/s11356-022-21151-8.

Zhou, M., Wang, D., Li, Q., Yue, Y., Tu, W., Cao, R., 2017. Impacts of weather on public transport ridership: Results from mining data from different sources. Transp. Res. Part C Emerging Technol. 75, 17–29. https://doi.org/10.1016/j.trc.2016.12.001.