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Understanding how extreme heat impacts human activity-mobility and time use patterns

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ABSTRACT

There is growing interest in understanding the interaction between weather and transportation and the ability of communities and the nation's infrastructure to withstand extreme conditions and events. This study aims to provide detailed insights on how people adjust and change their activity-travel and time use behaviors in the face of extreme heat conditions. By leveraging time use records integrated with weather data, the study compares activity-mobility patterns between extreme heat days and non-extreme days. A series of models are estimated to understand the impact of extreme heat even after controlling for other variables. The findings reveal that heat significantly impacts time use and activity-mobility patterns, with some groups exhibiting potentially greater vulnerability arising from the inability to adapt sufficiently to extreme heat. Designing dense, shaded urban environments, declaring heat days to facilitate indoor stays, and providing transportation vouchers for vulnerable populations can help mitigate the ill-effects of extreme heat.

1. Introduction

This paper is being written in the midst of a worldwide heat wave, with extreme heat records being broken or set in cities around the world (Thomson, 2023). The effects are especially being felt in Phoenix, Arizona, which is experiencing multiple extreme heat records despite its reputation as a very hot place in the summer. As of July 26, 2023, the city has experienced a continuous stretch of 27 days with high temperatures at or above 110°F (43.3°C), which is a new record breaking the previous record of 18 days set in 1974. The city has tied the record for the most days at or above 115°F (46.1°C) within a single year. Not only are the daytime high temperatures shattering records, but the nighttime lows are also at all-time highs with the city recording 17 consecutive days (nights) with a low of 90°F (32.2°C) or higher. These new records, set in 2023, are beating previous records by a considerable margin, suggesting that humanity is grappling with an increasingly warmer environment that impacts daily activities and lives. As of July 15, 2023, at least 18 deaths had been attributed in Phoenix to the heat with an additional 69 deaths under investigation as possibly caused by extreme heat

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(Boehm, 2023). However, Phoenix is not alone; in city after city around the world, temperatures are at all-time highs – shattering records, straining electric grids, and leading to the appointment of "chief heat officers" in Phoenix, Los Angeles, and Miami and a half-dozen global cities (Noor, 2023).

How do people adapt to extreme heat, in terms of their in-home and out-of-home activity patterns, time use, and travel choices? This is the key question that is central to this paper – motivating an in-depth comparison of activity-travel patterns between days that are extremely hot and those that are not. As transportation plans and policies are developed for a future of increasingly warm built environments, it would be of value to understand how activity-travel demand, mobility choices, and use of different modes of transportation are impacted by extreme heat. There are multiple dimensions worthy of consideration when it comes to understanding adaptation to extreme heat.

People using alternative modes of transportation such as bus, rail, micromobility, bicycle, and walk are particularly vulnerable to extreme temperatures (Wei et al., 2019; Wu and Liao, 2020). As such, the design of the built environment may be critical to ensuring that those who do not have a car or are unable to drive/ride in a personal vehicle, are able to safely use alternative modes of transportation and access destinations. A variety of strategies may be employed to help mitigate the effects of heat. These include planting trees to provide dense tree cover/shade (Gunawardena et al., 2017; Ahmad et al., 2021; Patton and Pojani, 2022), to adopting cool pavement coatings (Santamouris 2013; Del Serrone et al., 2022), to providing free/subsidized first-mile/last-mile connectivity for transit systems – all of which can help ameliorate the adverse impacts of extreme heat. In some contexts, homeless individuals may seek shelter in bus and rail vehicles to escape the extreme heat; however, their presence creates a negative safety and security perception (whether fair or not), thus resulting in lower transit patronage (Ding et al., 2022). It is clear that the design of built environments and multimodal transportation systems of the future need to be increasingly sensitive to heat and how people adapt their activity-travel patterns in response to extremely hot conditions.

The other key consideration that motivates this paper is that the evidence on heat implications for activity-travel patterns, time use, and modal usage is rather limited. Under extreme heat, people are likely to make fewer trips, the percent of individuals staying home (all day) is likely to be higher, the use of alternative modes of transportation (including bus, rail, micromobility, walk, and bicycle) is likely to be lower, and the amount of time spent outside home is likely to be lower. Activities may be shifted in time so that they are undertaken during the cooler hours of the early morning or late evening, rather than the hotter hours of midday.

The resilience and adaptability of people to extreme weather conditions is of considerable interest to professionals in transportation, urban design and planning, public health, public policy, and the humanities. This interest is borne out through a number of recent studies that attempt to shed light on this topic (Gronlund et al., 2016; Liu et al., 2017; McElroy et al., 2020; Hatchett et al., 2021). Several studies have attempted to measure and assess urban heat exposure among different socioeconomic groups (e.g., Hoehne et al., 2018; Hondula et al., 2021) to identify the vulnerable populations. A few studies have focused on measuring heat stress and understanding coping mechanisms (e.g., Uejio et al., 2011; Harlan et al., 2013; Jenerette et al., 2016; Sandholz et al., 2021) among different demographic groups. Other studies have focused on time use and transportation and reported that travel behavior changes are made in response to extreme heat, with people reducing time outdoors and increasing use of motorized transportation modes (e.g., Cools et al., 2010; Böcker et al., 2019; Fan et al., 2023; Cosaert et al., 2023). Assessing the impacts of heat on transit ridership has been the focus of research by Wei et al. (2019), Ngo (2019), and Wu and Liao (2020). Mitigating heat impacts requires strategies and infrastructure assessments to ensure community resilience. This has been the focus of several studies including those by Markolf et al. (2019), Batur et al. (2022), and Li et al. (2023). Finally, Liu et al. (2020) explore how individuals' perception of the weather impacts their leisure activity participation and find considerable non-linearity in the nature of the effect. This study aims to contribute to the existing body of literature by providing detailed insights into the influence of extreme heat on activity-travel and time use patterns.

Adaptation to extreme heat raises critical questions related to equity. Certain socio-economic and demographic segments may not be able to adapt their activity travel patterns in a climate friendly way in response to extreme heat. Service workers, who may not enjoy flexible schedules or the flexibility of working from home, are likely to be disproportionately affected by extreme heat. Lower income individuals (who may be more likely to be employed in service jobs), those without access to an automobile, and those who cannot afford to pay for ridehailing services are also likely to be more adversely impacted by extreme heat. Other demographic segments that may be vulnerable to extreme heat include women, older adults, and minority groups such as Blacks and Hispanics. It is of interest to examine how activity-travel patterns differ between extremely hot and regular hot days for different socio-economic and demographic groups to better understand differential impacts of heat on a region's population.

The analysis in this paper aims to shed insights and unravel differences in activity-travel patterns, time use, and mobility choices between extremely hot and regular hot days. Data from the American Time Use Survey (ATUS) series are used to accomplish the study objectives. Data from 2006 through 2019 are pooled, and a dozen large metropolitan areas in the United States are chosen for analysis (to represent a diversity of geographic regions, modal contexts, and socio-economic conditions). The data from these specific years of ATUS are used to ensure that the study benefits from a sample size large enough to draw statistically valid conclusions, and yet is not impacted by COVID-era changes in activity-travel and time use behaviors. As the time use data records include the exact day on which the respondent provided time use diary data, it is possible to append temperature and humidity data from the National Oceanic and Atmospheric Administration (NOAA) weather database. Using the definitions of heat index, it is possible to distinguish extremely hot days that present a danger to humans from those that are regular hot days; humans need to exercise caution on regular hot days, but are not necessarily in danger (NWS, 2023). The paper includes a detailed comparison of activity-travel demand, time use patterns, and modal choices between extremely hot days and regular hot days to understand and quantify the differences arising from extremely hot weather. The paper includes a series of models of activity-trip engagement, activity-travel durations, and mode choice in order to determine the extent to which extreme temperatures are significant in shaping activity-mobility patterns even after controlling for socio-economic and demographic characteristics.

The rest of the paper is organized as follows. The next section presents a detailed description of the survey data series. The third section provides a comprehensive comparison of activity-travel and time use characteristics between day types for all of the metropolitan areas. The fourth section presents multivariate statistical models of activity-travel and time use behaviors. The fifth section offers a discussion of the implications of the study results while the sixth and final section presents concluding thoughts and directions for future research.

2. Data

This section presents a detailed overview of the data sources used for the analysis in this paper. Weather data is acquired from information gathered and archived by the National Oceanic and Atmospheric Administration (NOAA), which is a federal agency collecting, analyzing, and disseminating weather data through its network of weather stations. The data set used to evaluate the activity, time use, and mobility patterns of individuals in the face of extreme heat is derived from the American Time Use Survey (ATUS) data series for the years 2006 through 2019. Data is extracted for these years for 11 major metropolitan areas of the nation, with a view to ensure sufficient sample sizes to support robust statistical analyses and represent a diversity of geographical and multimodal transportation contexts in this study. The more time use data, corresponding to years 2020 through 2022, are not included in the analysis to avoid confounding effects attributable to COVID-19 era changes in activity and travel patterns. In addition, the early years of the ATUS (2003 through 2005) are not included because national weather data is not available at the desired level of detail to facilitate the type of analysis conducted in this research.

The following subsections provide more detailed descriptions, first of the weather data, and then of the time use data sets.

2.1. Weather data

In this study, the outdoor environmental heat is measured by the apparent temperature (T_A), also known as the Heat Index, based on work by Steadman (1979). Various alternative approaches were explored to define a measure of heat. The effectiveness of using maximum, average, or minimum temperatures to identify extremely hot days was tested, along with categorizing days into extremely

NWS Heat Index — **Temperature (°F)**

Relative Humidity (%)	80	82	84	86	88	90	92	94	96	98	100	102	104	106	108	110
40	80	81	83	85	88	91	94	97	101	105	109	114	119	124	130	136
45	80	82	84	87	89	93	96	100	104	109	114	119	124	130	137	
50	81	83	85	88	91	95	99	103	108	113	118	124	131	137		
55	81	84	86	89	93	97	101	106	112	117	124	130	137			
60	82	84	88	91	95	100	105	110	116	123	129	137				
65	82	85	89	93	98	103	108	114	121	128	136					
70	83	86	90	95	100	105	112	119	126	134						
75	84	88	92	97	103	109	116	124	132							
80	84	89	94	100	106	113	121	129								
85	85	90	96	102	110	117	126	135								
90	86	91	98	105	113	122	131									
95	86	93	100	108	117	127										
100	87	95	103	112	121	132										

Likelihood of Heat Disorders with Prolonged Exposure or Strenuous Activity

Caution Extreme Caution Danger Extreme Danger

Classification	Heat Index	Effect on the body
Caution	80°F - 90°F	Fatigue possible with prolonged exposure and/or physical activity
Extreme Caution	90°F - 103°F	Heat stroke, heat cramps, or heat exhaustion possible with prolonged exposure and/or physical activity
Danger	103°F - 124°F	Heat cramps or heat exhaustion likely, and heat stroke possible with prolonged exposure and/or physical activity
Extreme Danger	125°F or higher	Heat stroke highly likely

Fig. 1. NWS Heat Index Look-up Figure and Classification (Reproduced from NWS, 2023).

hot versus non-extremely hot by sorting them within a metro area based on temperature and selecting the top five percent, ten percent, or fifteen percent of days as hot days. Another approach considered was selecting the top five, ten, or fifteen hottest days directly. However, these methods did not yield significant insights, primarily due to the absence of humidity data. Temperature alone does not adequately reflect how people experience heat, which is why the Heat Index was ultimately used. While these alternative methods did not produce significant findings, their exploration was valuable in understanding the challenges of measuring the true effects of extreme weather conditions on human behaviors. To support further investigation, the data analysis script used in this study, including different methods for defining extremely hot days, as well as the datasets used in the analysis, are provided in a GitHub repository (Batur, 2024). Interested readers can use these resources to experiment with different methods for defining extremely hot days.

The Heat Index combines measures of temperature and humidity to represent the thermal stress experienced by the human body due to environmental heat (Hoehne et al., 2018). The selection of the Heat Index as a measure of thermal stress is further justified considering the variation in the weather contexts across the United States. For example, consider the examples of Miami and Phoenix, which differ in their temperature and humidity characteristics, and yet residents of these two locales are susceptible to similar dangers of extreme heat during the summer months. In Miami, summer air temperatures have historically rarely exceeded 90°F (32°C), but the high humidity levels intensify the heat experience and thermal stress on the human body. The humidity hampers the body's ability to cool itself through sweating, resulting in a higher Heat Index than the actual air temperature. Consequently, it feels much hotter than it actually is, presenting risks of heat-related illnesses if proper precautions for staying hydrated and cool are not taken. On the other hand, Phoenix regularly registers air temperatures of more than 105°F (40.6°C) in the summer months. However, despite the air temperature reaching such extreme levels, the low humidity allows sweat to evaporate efficiently, providing some relief to the body's cooling mechanism. As a result, the Heat Index in Phoenix aligns more closely with the actual air temperature and is not necessarily all that different from the Heat Index of a region with a relatively lower temperature but high humidity levels.

Based on Steadman's work, the National Weather Service (NWS, 2023) provides a lookup figure to determine Heat Index values based on a combination of air temperature and humidity levels. Additionally, the NWS classifies the Heat Index values into four categories based on the likelihood of heat-related disorders with prolonged exposure or strenuous activity. These classes are described at the bottom of Fig. 1 and serve as indicators of the Heat Index range and the possible impacts on the human body. They provide a measure of the level of danger that different levels of Heat Index present to humans.

To calculate the Heat Index values without using the lookup figure, Rothfusz (1990) proposed a Heat Index (HI) equation that estimates values within an error of ∓ 1.3°F. For this study, the equation was adopted to compute Heat Index values for any given day by the combination of the Daily Maximum Dry Bulb Temperature and Daily Average Relative Humidity. This was done to facilitate the calculation and merger of secondary weather data to time use records in the ATUS data.

The analysis is performed for 11 metropolitan areas in the United States. These areas were chosen for their geographic diversity,

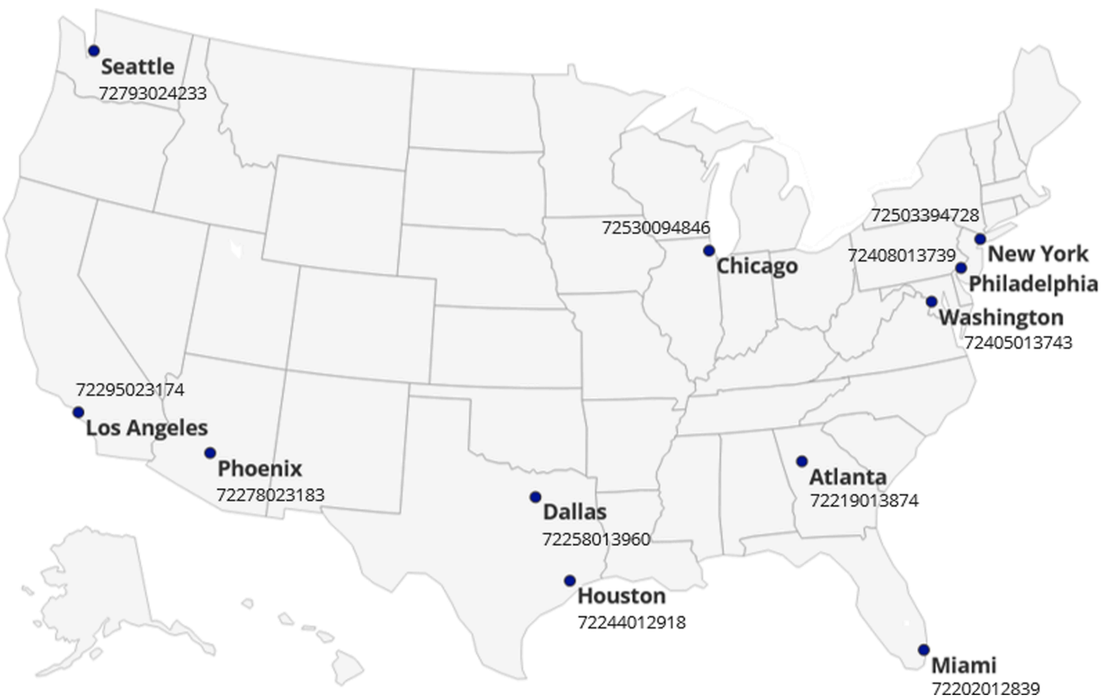

Fig. 2. MSAs and Selected NOAA Weather Stations.

differences in weather patterns (temperature versus humidity), and variations in transportation contexts (car-centric, transit-rich, street configurations). Fig. 2 shows the 11 metropolitan areas selected for analysis in this study and the specific NOAA weather station from which temperature and humidity data were derived. As extreme heat conditions are generally experienced in the south, one half of the selected areas are in the south. Three areas are in the Northeast region, one metro area is in the Midwest region, and one metro area is in the Pacific Northwest region. Overall, the selected metropolitan areas cover the variety of contexts that one may encounter in the United States.

As previously mentioned, weather data for each metropolitan area is acquired from information gathered and archived by NOAA. For each metropolitan area, NOAA maintains and records data through multiple weather stations. However, the ATUS records are geocoded only to the metropolitan area level. Therefore, it became necessary to select a representative station for each metropolitan area from which weather data would be extracted. It should be recognized that microclimates can vary considerably within some metropolitan areas. Therefore, following the best practices adopted in other multi-city scale assessments of temperature-health risks, the locations of the weather stations in each metropolitan area were carefully examined, and the stations that had the most comprehensive and complete data and were located closest to the population centroids of the metropolitan areas were chosen as the source of weather information. One such representative station was selected for each metropolitan area.

The ATUS records corresponding to the hottest months of the year, namely, July and August, were selected and extracted for the 11 metropolitan areas. Heat index (HI) was calculated for each of the time use records and appended to the ATUS data. Based on the HI values, the days corresponding to the time use records were labeled as Extreme and Non-Extreme days. In this binary classification scheme, the Extreme days refer to those corresponding to Danger or Extreme Danger levels (as depicted in Fig. 1) and Non-Extreme days are more regular hot days that correspond to levels of Extreme Caution and Caution (or less) depicted in Fig. 1.

Fig. 3 shows the share of extreme heat days for each metropolitan area, as defined by the Metropolitan Statistical Area (MSA), during the selected periods. It also provides the total number of days (in parentheses) for which data are available. Among the 11 metro areas, the Phoenix region experienced the highest number of extreme heat days, with 808 extreme days (of 867 total days), while Los Angeles experienced the lowest number with only three extreme days (of 867 total days). It can be seen that metro areas in the south – Dallas, Houston, Miami, and Atlanta – experience a larger share of extreme heat days when compared to other cities. Both Seattle and Los Angeles register very few extreme heat days.

Fig. 4 depicts the number of extreme heat days in all metropolitan areas by year between 2006 and 2019, along with the total number of days (in parentheses) for each year. The figure reveals that, overall, the number of extreme days is quite high in the July-August period; and in recent years, the fraction of extreme heat days is consistently well over 50 percent, suggesting that these regions are showing signs of a warming trend.

2.2. ATUS data samples

The activity-mobility and time use patterns are derived from the American Time Use Survey data series. The ATUS is a federally administered continuous time use survey in the United States, with data collection commencing in 2003 and continuing through today. The survey data is collected by the Bureau of Labor Statistics (BLS) and anonymized data sets are made available online. The survey aims to measure how people spend their time through a 24-hour period for a comprehensive set of activities including personal care, household maintenance, work, education, shopping, travel, volunteering, religious, child and elder care, and social and recreational. Data is collected in the form of a time use diary to ensure that there is no gap in reporting, thus accounting for the entire 24-hour period. The survey data includes a detailed set of socio-economic and demographic characteristics, information about the

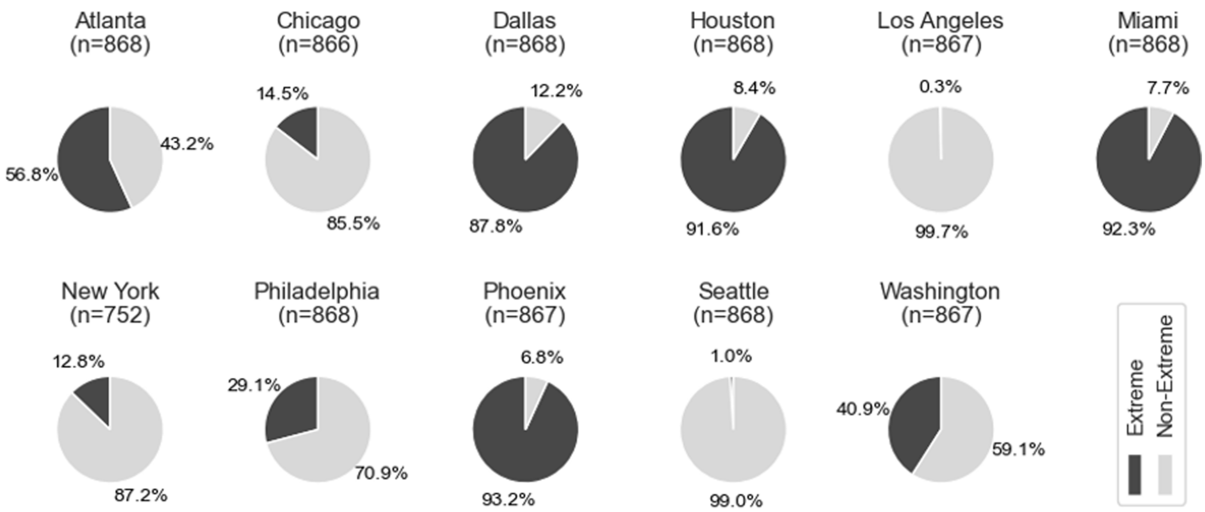

Fig. 3. The Share of Extreme Days in Selected MSAs During August and July (2006–2019).

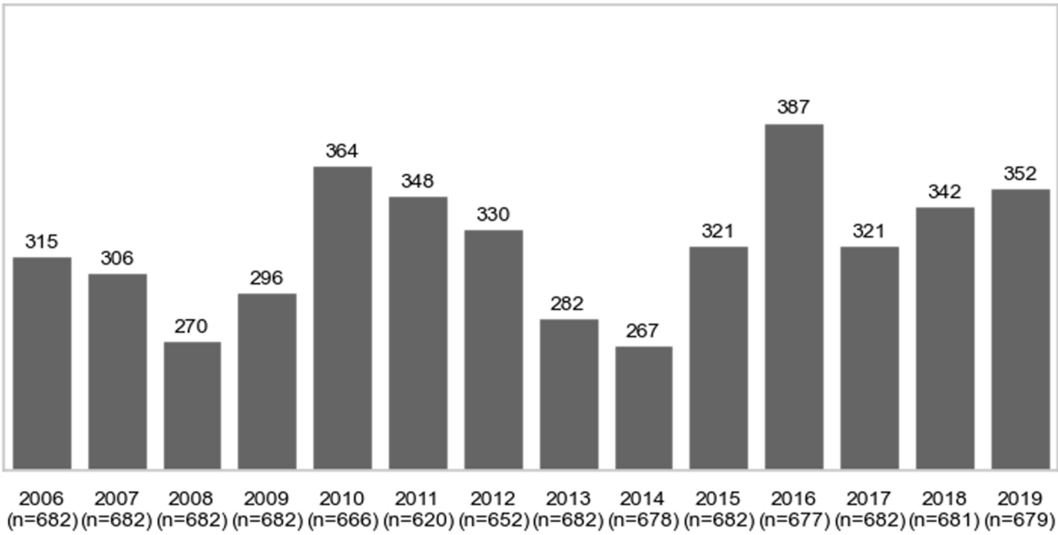

Fig. 4. Total Number of Extreme Days by Year During August and July (2006–2019).

metropolitan area of residence of the respondent, the exact date on which the time use survey was completed, and a number of attributes associated with the time use (activity) records. For each activity record, information is known about the start time and end time, presence of other individuals, location (in-home or out-of-home), and purpose. Each travel episode is recorded as a separate activity as well; travel records include data about the mode of transportation used, thus enabling an analysis of mode use patterns under different weather conditions.

The records for July and August for the selected 11 metropolitan areas were extracted and the weather data was merged to compile a comprehensive activity-weather profile for each respondent in the survey data set. This exercise resulted in the creation of a data set with 3,278 individuals for Non-Extreme days and 2,481 individuals for Extreme heat days. Since each individual records time use for one day, the number of individuals is equal to the number of days.

The socio-economic and demographic attributes of the final samples are shown in Table 1. For both non-extreme and extreme samples, females represent a slightly larger fraction. Nearly 20 percent of the samples comprise older individuals 65 years of age or more, while under four percent are aged 15–18 years. Just over 30 percent of the samples are aged 36–50 years. There are some modest differences in educational attainment levels between the two samples. While 12 percent of non-extreme day respondents have less than a high school diploma, the corresponding percent for extreme heat day respondents is higher at 16.7 percent. At the other extreme, the percent of non-extreme day sample respondents with a graduate or professional degree is 18.2 percent; the corresponding percent for the extreme heat subsample is considerably lower at 13.4 percent. About one quarter of the respondents in either sample have some college or associate degree. Just over 70 percent of the samples are White and 20 percent are Black. The percent of Asian respondents is slightly higher in the non-extreme day sample (7.6 % vs 4.2 %). In both samples, just about 63 percent of respondents are employed while about five percent are unemployed, and 32–33 percent are not in the labor force. In terms of household income, the percent residing in households making less than $35,000 per year differs slightly with one-third of the extreme day sample falling in this low income category; the corresponding percentage for the non-extreme sample is 27 percent. The household size distribution shows that nearly one-half of the samples reside in households with three or more persons. About 60 percent of the respondents in both samples report having no children in the household.

As expected, the samples differ substantially with respect to their geographical location. While non-extreme sample records are largely drawn from the cooler areas of Chicago, New York, Seattle, and Los Angeles, the extreme sample records show larger presence in the hot areas of Dallas, Houston, Miami, and Phoenix. In other words, the two samples differ with respect to location, but are largely similar with respect to socio-economic and demographic characteristics. This suggests that differences in behaviors may be largely attributable to differences in climates.

To assess whether and to what extent the two samples are statistically significantly different in their composition across the attributes in Table 1, a Chi-square test of independence was conducted. The results of this test are presented in the last column of Table 1. Among the tested attributes, the two samples exhibited differences in certain attributes such as educational attainment, race, and household income, while other attributes, including gender, age, employment, and household size did not show statistically significant differences. Nevertheless, there is no considerable reason to believe that the sample characteristics do differ in any substantial way between the two groups. Statistical tests, especially ones like the Chi-square test, can be sensitive to sample size (Saris et al., 2009). Additionally, since the respondents for the extreme and non-extreme samples in this study were selected based solely on the weather on the day of the survey, and the Census Bureau (which conducts the American Time Use Survey) does not account for temperature when choosing its respondent pool for any given survey day, there is no basis to assume that there would be any systematic biases in the characteristics of respondents between extremely hot days and non-extremely hot days. Any slight variations observed between the

Table 1
Socioeconomic and Demographic Characteristics of the Samples.

Attribute	Category	Sample				Chi-square Test of Independence (p value)
		Non-Extreme		Extreme		
		Percent	N	Percent	N	
Sample size		100	3,278	100	2,481	
Gender	Female	54.4	1782	55.7	1383	0.31
	Male	45.6	1496	44.3	1098	
Age	15 to 18 years	3.2	106	3.6	89	0.51
	19 to 25 years	5.6	185	5.7	141	
	26 to 35 years	15.2	498	16.6	411	
	36 to 50 years	31.8	1043	30.8	763	
	51 to 64 years	24.3	797	24.9	619	
	65 years or older	19.8	649	18.5	458	
Educational attainment	Less than high school	12.1	395	16.7	415	0.00*
	High school	21.2	696	21.4	532	
	Some college	23.3	764	25.5	632	
	Bachelor's degree	25.2	825	22.9	569	
	Graduate degree	18.2	598	13.4	333	
Race	White	70.7	2317	73.9	1834	0.00*
	Black	20.0	654	20.2	502	
	Asian	7.6	249	4.2	104	
	Some other race	1.8	58	1.7	41	
Employment	Employed	62.4	2045	62.5	1551	0.69
	Unemployed	4.8	158	5.3	131	
	Not in labor force	32.8	1075	32.2	799	
Household income	< $35 K	27.2	843	33.2	798	0.00*
	≥ $35 K, < $50 K	12.5	387	14.4	347	
	≥ $50 K, < $75 K	16.8	521	16.8	404	
	≥ $75 K, < $100 K	14.1	438	12.1	290	
	≥ $100 K, <150 K	13.8	426	12.0	289	
	≥ $150 K	15.6	482	11.5	277	
Household size	One	27.0	885	26.8	665	0.11
	Two	24.4	801	26.8	664	
	Three or more	48.6	1592	46.4	1152	
Child presence in household	Child present	41.0	1164	37.7	842	0.02*
	No child present	59.0	1677	62.3	1389	
Metropolitan area of household	Atlanta, GA	5.7	187	9.5	236	na
	Chicago, IL	20.4	670	5.1	127	
	Dallas, TX	2.0	67	19.3	479	
	Houston, TX	1.0	34	16.9	420	
	Los Angeles, CA	6.1	200	0.0	1	
	Miami, FL	1.0	32	17.1	424	
	New York, NY	30.4	997	4.8	119	
	Philadelphia, PA	11.6	380	6.2	153	
	Phoenix, AZ	0.9	30	11.6	288	
	Seattle, WA	10.6	348	0.2	5	
	Washington, DC	10.2	333	9.2	229	

Note: Percent distributions exclude missing values and/or categories with a small share for each attribute.
(*) There is a statistically significant association between the samples and the corresponding attribute.
(na) Not applicable.

two samples in terms of socio-economic and demographic attributes are likely random.

For the purpose of this study, what is paramount is ensuring that neither sample is disproportionately skewed towards specific demographics and that both samples include a diverse range of respondents from a broad spectrum of backgrounds. In this study, neither the extreme nor the non-extreme sample is substantially skewed in any socio-demographic or household attributes. Therefore, any differences in activity and mobility patterns between the two subsamples may be largely attributed to differences in Heat Index as opposed to any other extraneous variables. Nevertheless, an additional analysis was conducted to match the non-extreme and extreme samples in terms of their socio-demographic composition using a weighting technique. This analysis helps to determine the extent to which the study findings presented in the upcoming sections remain consistent after ensuring similarity between the two samples. While the detailed results of this additional analysis are not presented here for the sake of brevity, it was found that the study findings have remained virtually consistent. Interested readers are referred to the online supplementary material for further details.

3. Analysis of activity-travel behavior trends

This section presents a detailed analysis of travel behavior trends between extreme and non-extreme heat days. The analysis focuses both on activity and time use patterns as well as trip rates and mobility choices. The analysis in this paper is conducted entirely on

Table 2
Activity and Time Use Patterns (Average Minutes Per Day).

Activity type	Location	Worker				Non-Worker			
		Weekday		Weekend		Weekday		Weekend	
		Non-Extreme	Extreme	Non-Extreme	Extreme	Non-Extreme	Extreme	Non-Extreme	Extreme
Sample size		***1,027***	***779***	***1,018***	***772***	***589***	***480***	***644***	***450***
Sleeping	In-home	478.4	480.7	542.0	552.6	545.4	557.7	551.6	572.9
	Out-home	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Personal care activities	In-home	47.4	49.7	42.3	47.3	46.5	45.6	49.2	45.7
	Out-home	0.1	0.2	0.0	0.1	0.1	0.3	0.1	0.0
Household activities	In-home	70.1	66.4	122.9	107.8	124.0	135.1	121.1	124.0
	Out-home	4.9	6.2	11.8	7.8	8.7	8.3	8.2	10.7
Caring for & helping household members	In-home	23.2	23.3	25.9	25.8	26.5	22.3	17.5	21.9
	Out-home	7.4	6.9	11.0	7.9	7.0	5.9	4.5	4.7
Caring for & helping non-household members	In-home	1.2	1.4	1.5	2.7	3.5	5.2	3.2	4.3
	Out-home	4.0	2.1	6.3	5.3	7.7	11.6	5.9	4.8
Work & work-related activities	In-home	37.4	39.0	16.9	23.7	9.4	8.6	4.7	1.6
	Out-home	353.5	366.9	81.0	95.1	5.0	1.6	1.0	0.9
Education	In-home	2.1	2.6	2.8	2.8	7.3	7.9	9.9	5.3
	Out-home	3.9	2.5	1.8	0.0	11.2	11.5	1.1	1.8
Consumer purchases	In-home	0.6	0.8	0.8	1.0	0.3	0.9	1.4	0.6
	Out-home	16.8	15.1	35.6	33.3	25.9	23.0	26.3	27.9
Professional & personal care services	In-home	0.1	0.1	0.7	0.3	0.7	0.4	0.0	0.1
	Out-home	4.8	6.2	4.1	3.0	10.3	7.5	1.9	1.7
Household services	In-home	0.2	0.1	0.5	0.1	1.3	1.6	0.6	0.4
	Out-home	0.9	0.7	0.3	1.5	0.3	1.3	0.2	0.6
Government services & civic obligations	In-home	0.0	0.0	0.0	0.0	0.2	0.4	0.0	0.0
	Out-home	0.4	0.6	0.3	0.0	1.1	1.6	0.2	0.0
Eating and drinking	In-home	33.4	33.5	40.9	39.9	52.5	49.5	53.4	51.9
	Out-home	31.6	30.7	32.1	31.8	16.8	16.7	21.1	20.8
Socializing, relaxing, and leisure	In-home	143.2	147.0	209.5	216.1	335.7	344.4	342.2	333.5
	Out-home	39.8	29.3	79.9	74.3	54.7	47.6	68.1	61.3
Sports, exercise, & recreation	In-home	2.7	3.4	4.4	5.3	3.8	3.8	4.5	5.3
	Out-home	14.0	16.3	29.8	22.9	24.8	20.7	17.7	17.4
Religious and spiritual activities	In-home	1.2	1.4	1.1	2.1	4.4	4.9	4.9	3.2
	Out-home	1.5	1.2	12.8	15.4	4.0	3.8	22.3	22.0
Volunteer activities	In-home	1.0	1.5	1.8	2.0	2.3	4.7	1.6	1.9
	Out-home	3.4	3.5	5.9	6.4	9.3	3.9	7.0	10.0
Telephone calls	In-home	3.7	4.2	5.8	5.2	11.1	10.4	10.3	7.8
	Out-home	0.6	0.6	0.4	0.4	0.2	0.4	0.2	0.1
Traveling	In-home	1.0	0.9	0.8	0.5	0.6	0.7	0.4	1.0
	Out-home	95.8	87.8	93.8	87.9	61.6	53.7	61.1	56.2
Other (data codes)	In-home	7.3	4.2	9.2	7.6	12.3	12.0	13.1	13.6
	Out-home	2.7	2.8	3.3	3.8	3.6	4.7	3.6	4.4
Total	In-home	854.1	860.2	1029.7	1043.0	1187.8	1216.0	1189.8	1194.9
	Out-home	585.9	579.8	410.3	397.0	252.2	224.0	250.2	245.1

unweighted samples to account for the fact that the sample is comprised of respondents from 14 years of the ATUS. Utilizing year-specific weights (provided in the year-specific ATUS data sets) is challenging in the context of an integrated multi-year data set spanning 14 years. As the focus of the analysis is on studying and inferring differences between extreme and non-extreme day samples, rather than inferring behaviors of the general population, the use of unweighted data in the context of this study is reasonable and appropriate. Moreover, in order to account for any limitations associated with a descriptive analysis of unweighted data sets, the paper does present multivariate statistical models of activity and mobility behaviors to understand the influence of extreme heat after controlling for socio-economic and demographic variables. This section is dedicated to presenting results of the descriptive analysis and comparisons.

3.1. Activity and time use patterns

Table 2 offers a detailed description of activity-based time use patterns for different segments in the overall sample. The sample is sliced by heat day type (extreme versus non-extreme), employment status (worker versus non-worker), and day of week (weekday versus weekend). The table is a complete and comprehensive documentation of time use/expenditures for various activities, both in-home and out of home. For the sake of brevity, a detailed presentation of all of the numbers and patterns in the table is not provided in the text. There are, however, some noteworthy patterns discernible in the table. At the very bottom of the table, the total time spent in-home and out-of-home is documented. It can be seen that, regardless of employment status and day type, the amount of time spent in-home is higher on extreme heat days and conversely, the amount of time spent out-of-home is less on such extremely hot days. This suggests that, broadly speaking, people adapt to extreme heat by engaging in less activities out of home and spending more time indoors at home.

A note is due here regarding the nature of activity engagement inside and outside home. Even when there is extreme heat, it is entirely possible for people to escape the heat by largely confining themselves to the comfort of an air-conditioned vehicle, air-conditioned office, air-conditioned stores and recreational facilities (gyms), air-conditioned dining establishments, and so on. In other words, even though people are spending time out-of-home, it does not necessarily mean that they are outdoors in the heat. Unfortunately, the ATUS does not afford the ability to determine whether an individual is indoors or outdoors when out of home. It is entirely reasonable to expect that, on extremely hot days, individuals would confine themselves to the indoors (even when out-of-home) more so than on non-extreme heat days. Thus, the comparisons seen in Table 1 may not be capturing the full extent of the adaptation to extreme heat. If it were possible to compute time spent outdoors versus indoors, it is entirely plausible to expect that such differences would be larger than what is observed in the table (in terms of differences between time spent in-home and out-of-home). Nevertheless, the trends seen in the table, i.e., less time spent out-of-home, are indicative of an adaptation whereby individuals are more prone to staying indoors at home on extreme heat days.

In terms of actual activity engagement, it is found that sleep duration is higher on extremely hot days (it is known that extremely

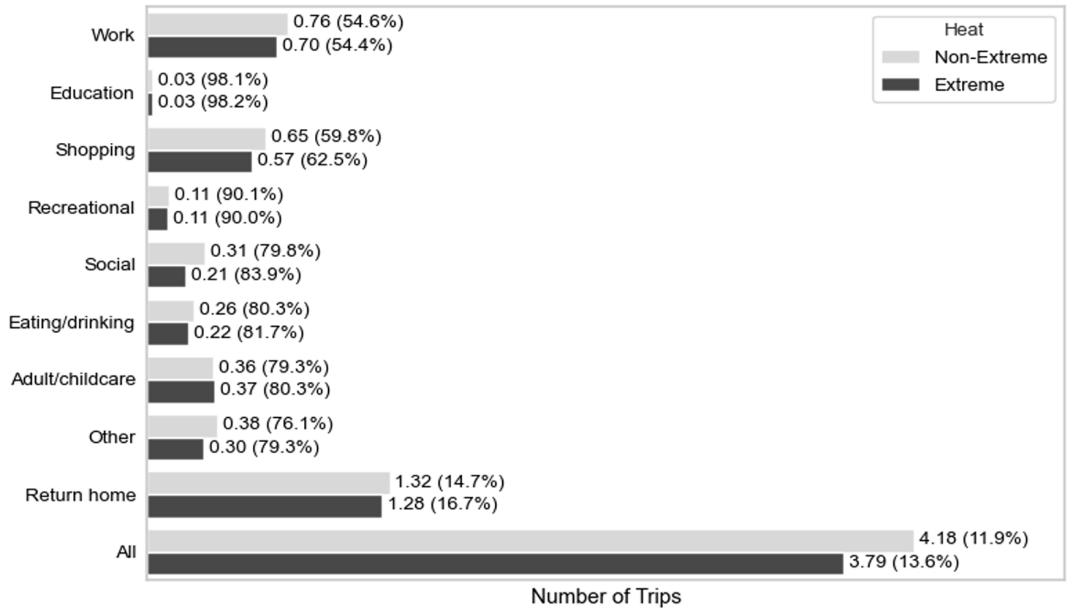

Fig. 5. Daily Individual Trip Rates by Trip Purpose (Zero Participation Rates in Parentheses).

hot days are associated with a higher degree of lethargy as noted by González-Alonso et al., 1999). Workers report spending more time on work, both in-home and out-of-home, on extreme heat days (this is seen for weekdays and weekends). This again suggests that individuals are more likely to stay within the confines of indoor air-conditioned spaces on extreme heat days. Indeed, the time spent socializing, relaxing, and leisure out-of-home is considerably lower on extreme heat days; this reduction is seen on both weekdays and weekends and for both workers and non-workers. With respect to sports, exercise, and recreation, it is found that workers spend (on average) more time out-of-home on weekdays and less time out-of-home on weekends. The pattern is different for non-workers. While these patterns merit further investigation, it is likely that workers spend more time at the gym for sports, exercise and recreation on weekdays, but forgo weekend activities on extreme heat days (because weekend activities may be more outdoor oriented – e.g., hiking, bicycling, walking, running). In most cases, the time spent shopping (consumer purchases) out-of-home is less on extreme heat days (the only exception is non-workers on weekend days).

The activity of particular interest and focus for this study is "traveling". It is found that the time spent traveling on extreme heat days is consistently lower for all situations of employment status and day type. Both workers and non-workers report lower average daily travel time expenditures on weekdays or weekend days when there are extreme heat conditions. Because travel generally entails exposure to the heat (even driving a car would require walking outdoors to and from the car and experiencing a hot car until the air-conditioning cools down the inside), it is not surprising that individuals report lower travel durations on extreme heat days. In general, the patterns seen in the table are consistent with expectations and provide a first glimpse into the broad impacts of extreme heat on activity and time use patterns.

3.2. Travel characteristics

The next set of comparisons focuses on travel characteristics. Fig. 5 shows daily average trip rates by purpose (some consolidation of activity purposes shown in Table 2 was performed to ease of interpretation and presentation), together with the percent of individuals not participating in the activity (outside home). That is, the percentages reflect the percent of individuals reporting zero trips for each activity purpose. The figure reveals a statistically significant decline in daily average trip rates between non-extreme days and extreme heat days. The overall trip rate declines from 4.18 to 3.79 with the percent zero trip makers increasing from 11.9 percent to 13.6 percent. There is a decline in trip rates for all purposes, except adult/childcare – suggesting that this purpose is not amenable to compromise even under extreme heat conditions. Likewise, education – which was not adaptable to virtual modality prior to the COVID-19 pandemic – shows very similar rates between non-extreme and extreme heat days. With online education tools becoming more in vogue following the pandemic, it is likely that education-related trips will also drop under extreme heat conditions. It is interesting to note that recreational trip rates do not show a drop on extreme heat days, suggesting that 10 percent of people will engage in recreational activities no matter what.

Next, Fig. 6 shows the average daily trip rates by mode of transportation. Because of missing travel mode information for some records, the trip rates in this figure do not necessarily align perfectly with trip rates shown in Fig. 5. Nevertheless, the trends are clear and show a strong adaptation pattern in response to extreme heat. Under extreme heat conditions, the car trip rate increases, while the trip rates by all other modes decrease substantially (except for bicycle, which has a very low trip rate overall). The average trip rate for public transportation on extreme heat days is nearly one-half of that seen on non-extreme days. Also, the walking trip rate drops to one-half on extreme heat days. In other words, under extreme heat conditions, people use transit and walk much less than they normally would and use the personal car more than they would otherwise. The modal trip frequencies reveal an important relationship between extreme heat and mode use. What is important to consider in this context is that 5.1 percent and 12.1 percent of the extreme heat

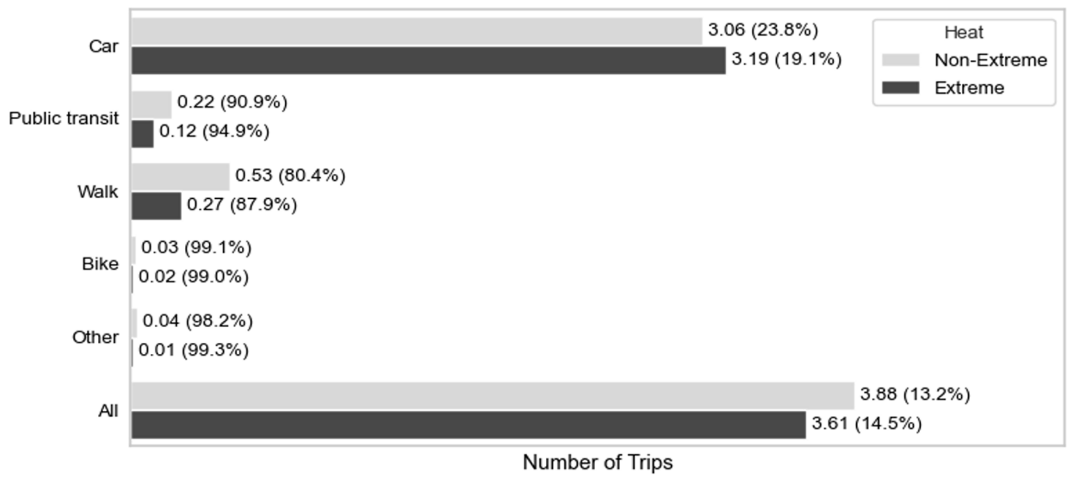

Fig. 6. Daily Individual Trip Rates by Travel Mode (Zero Participation Rates in Parentheses).

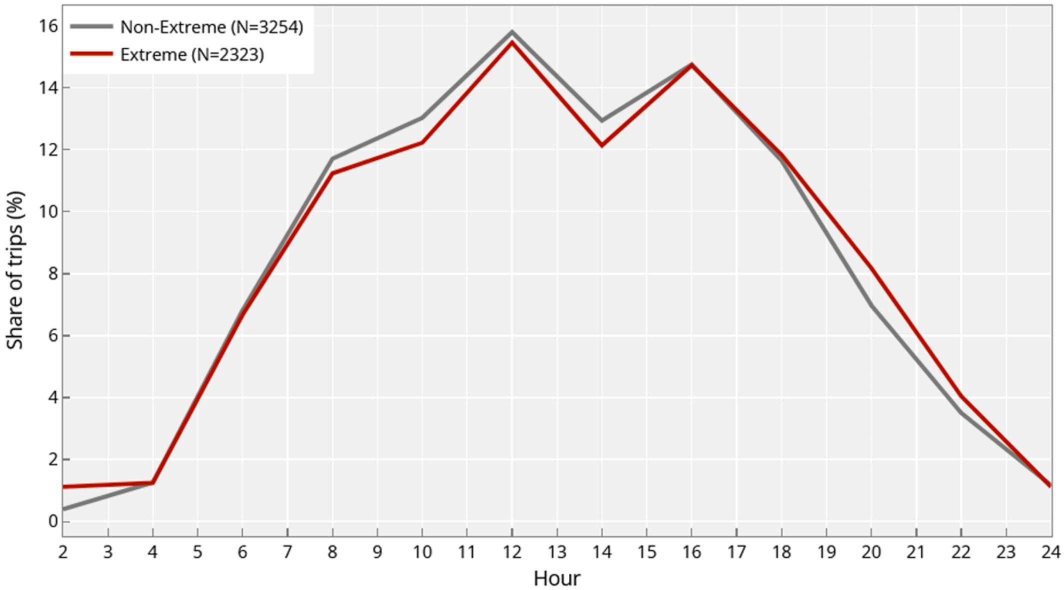

Fig. 7. Temporal Distribution of Travel Activities by Start Time (in 2-hour Bins).

sample use public transit and walk respectively on extreme heat days. These individuals are susceptible to adverse heat-related health effects, and it is necessary to formulate mobility policies and interventions that would reduce their vulnerability to extreme heat.

Fig. 7 presents an analysis of the temporal distribution of travel on extreme and non-extreme heat days. Although the curves generally depict a similar distribution, differences are discernible. The percent of trips undertaken in the later evening hours is higher on extreme heat days (when compared with non-extreme days). In other words, it appears that individuals seek to shift trips temporally to the late evening (cooler) hours of the day when extreme heat conditions prevail. There is no discernible difference in the percent of trips undertaken in the morning hours; however, it is clearly seen that the percent of trips undertaken in the midday is greater on non-extreme days than on extreme heat days. Overall, it appears that extreme heat brings about a small, but noticeable, temporal shift in trip making.

4. Models of activity-travel behavior

The descriptive trends presented in the previous section suggest that patterns of activity and travel engagement are different on extreme heat days than on non-extreme days. Although preliminary inferences can be drawn from such descriptive comparisons, more conclusive evidence regarding the influence of extreme heat on activity-travel characteristics can be obtained through the specification and estimation of multivariate statistical/econometric models that control for the influence of a host of exogenous variables (so that the effect of extreme heat can be better isolated and understood).

In this study, six different models are estimated as follows:

- Model 1: A binary logit model of zero trip-making
- Model 2: A linear regression model of the (natural log of) daily travel time expenditure (excluding zero-trip-makers)
- Models 3 through 5: Count models of the total number of daily trips, total number of transit trips, and total number of bike and walk trips (combined), respectively
- Model 6: Multinomial logit model of mode choice, estimated on a random subset of trips (to avoid inflated test statistics that may result from using a very large sample size)

The count models (Models 3 through 5) take the form of negative binomial regression models to account for the possibility that the variance and mean are not equal (thus, violating the assumption of the Poisson regression model). The remainder of this section is devoted to a discussion and presentation of the model estimation results, with a view to deciphering the significance of the influence of extreme heat in shaping these activity-travel choices.

Model estimation results are shown in Table 3. The variables included in the final model specification for each of these six individual models are determined based on insights from previous research, intuitive understanding, and considerations for parsimony. For variables presented in brackets (e.g., age) and those that are naturally discrete (e.g., gender, race, employment), dummy variables were generated in the most disaggregated form. These variables were then progressively consolidated based on statistical tests and intuitive reasoning. Throughout this process, different functional forms and combinations of explanatory variables, and their interactions were systematically tested. This approach ensures that the model specifications remain parsimonious without omitting

Table 3
Model Estimation Results.

Variable (base)	Attribute	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6					
		Binary logit		Linear regression		Negative binomial regression						Multinomial logit					
		Outcome variables															
		Zero-trip-maker (base: Trip maker)		In (Daily travel duration)		Daily total trip count		Daily transit trip count		Daily walk-bike trip count		Mode choice (base: other)					
												Car		Transit		Walk or bike	
		Coef	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*
Constant		−2.63	−24.57	4.20	77.38	1.08	23.09	−2.83	−20.28	−1.65	−21.73	2.58	31.76	−1.35	−7.13	0.33	2.63
Heat (non-extreme)	Extreme	0.35	3.41	−0.06	−2.38	−0.61	−9.08	−0.24	−2.21	−0.26	−3.76	0.21	2.21	–	–	–	–
Individual Characteristics																	
Gender (male)	Female	–	–	−0.10	−2.29	–	–	–	–	–	–	–	–	–	–	–	
Age (*)	15 to 19 years	–	–	–	–	–	–	–	–	–	–	−0.88	−5.79	–	–	–	–
	20 to 29 years	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.69	4.98
	50 to 64 years	0.34	3.45	–	–	−0.12	−3.39	–	–	−0.30	−4.66	–	–	–	–	–	–
	65 or older	0.48	4.68	−0.07	−1.87	−0.23	−5.12	−0.29	−2.22	−0.53	−5.92	–	–	–	–	–	–
Education (*)	Less than high school	–	–	–	–	–	–	0.31	2.69	–	–	–	–	–	–	–	–
	Bachelor's degree	–	–	0.07	2.45	–	–	–	–	–	–	–	–	−0.50	−2.53	–	–
	Graduate degree	−0.34	−2.54	0.18	5.25	0.17	4.22	0.30	2.49	0.48	7.24	–	–	–	–	0.32	2.52
Race (*)	Black	0.18	1.96	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	White	–	–	–	–	–	–	−0.62	−6.18	–	–	–	–	–	–	−0.43	−4.10
Employment (*)	Non-worker	1.18	13.07	–	–	−0.11	−2.71	−0.55	−5.46	–	–	–	–	–	–	–	–
	Worker	–	–	0.12	2.34	–	–	–	–	–	–	–	–	–	–	–	–
Household Characteristics																	
Income (*)	Up to $35,000	0.54	4.69	–	–	–	–	0.63	6.82	0.37	6.16	–	–	–	–	0.46	4.06
	$100,000 or more	−0.25	−2.17	–	–	–	–	–	–	–	–	0.20	2.11	–	–	–	–
Location (*)	Atlanta	–	–	–	–	–	–	–	–	–	–	0.88	4.65	–	–	–	–
	Chicago	–	–	–	–	–	–	0.70	5.12	0.49	5.57	–	–	–	–	–	–
	Dallas	–	–	–	–	–	–	–	–	–	–	0.67	3.91	–	–	–	–
	Houston	–	–	–	–	–	–	–	–	–	–	1.06	4.88	–	–	–	–
	New York	–	–	–	–	–	–	1.65	15.47	1.15	15.74	–	–	1.15	6.78	0.88	8.18
	Philadelphia	–	–	–	–	–	–	–	–	0.56	5.84	–	–	–	–	–	–
	Phoenix	–	–	–	–	–	–	–	–	–	–	0.64	2.69	–	–	–	–
	Washington	–	–	–	–	–	–	1.01	7.50	0.49	5.12	–	–	0.70	3.03	–	–
Household size (2+)	One	–	–	–	–	–	–	–	–	0.33	5.50	−0.54	−6.40	–	–	–	–
Other Characteristics		–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Afternoon (not afternoon)		–	–	–	–	–	–	–	–	–	–	–	–	−0.34	−1.85	–	–
Weekday (weekend)		−0.35	−4.44	0.06	2.62	0.11	3.59	0.68	8.24	0.27	5.15	–	–	0.77	4.75	–	–
Car user (not car user)		–	–	–	–	0.44	9.67	–	–	–	–	–	–	–	–	–	–
Interaction Terms (*)		–	–	–	–												
Extreme × Age 65 or older		–	–	–	–	–	–	–	–	−0.56	−3.16	–	–	–	–	–	–
Extreme × Car user		–	–	–	–	0.58	7.69	–	–	–	–	–	–	–	–	–	–
Extreme × Graduate degree		–	–	–	–	–	–	0.42	1.92	–	–	–	–	–	–	–	–
Extreme × Income up to $35,000		−0.41	−2.50	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Extreme × Washington		–	–	–	–	0.24	3.08	–	–	–	–	–	–	–	–	–	–
Female × Black		–	–	–	–	–	–	0.41	3.37	–	–	–	–	–	–	–	–
Male × Student		–	–	–	–	–	–	–	–	0.69	5.01	–	–	–	–	–	–
Male × Washington		–	–	0.21	3.52	–	–	–	–	–	–	–	–	–	–	–	–
Male × Worker		–	–	−0.10	−1.94	–	–	–	–	–	–	–	–	–	–	–	–

(*continued on next page*)

Table 3 (*continued*)

Variable (base)	Attribute	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6					
		Binary logit		Linear regression		Negative binomial regression						Multinomial logit					
		Outcome variables															
		Zero-trip-maker (base: Trip maker)		ln (Daily travel duration)		Daily total trip count		Daily transit trip count		Daily walk-bike trip count		Mode choice (base: other)					
												Car		Transit		Walk or bike	
		Coef	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*
White × Non-worker		–	–	−0.16	−3.42	–	–	–	–	–	–	–	–	–	–	–	–
Non-worker × Philadelphia		–	–	−0.18	−2.43	–	–	–	–	–	–	–	–	–	–	–	–
Income up to $35,000 × Phoenix		0.51	2.12	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Income up to $35,000 × Non-worker		–	–	–	–	−0.17	−3.21	–	–	–	–	–	–	–	–	–	–
Household size 2 × Dallas		0.54	2.52	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Household child present × Houston		−0.80	−2.37	–	–	–	–	–	–	–	–	–	–	–	–	–	–

Sample Sizes	**Goodness-of-Fit Statistics**
Model 1: 5,759 persons	Model 1: Log-likelihood = −2147.4; LL-Null = −2405.0; Pseudo R-sq. = 0.11
Model 2: 4,904 persons (trip-maker only)	Model 2: R-squared = 0.038; Log-Likelihood = −6135.1; AIC = 1.229e+04; BIC = 1.237e+04
Model 3: 5,759 persons	Model 3: Log-likelihood = −13913.0; Pearson chi2 = 3.53e+03; Pseudo R-sq. = 0.0917
Modal 4: 5,759 persons	Modal 4: Log-likelihood = −2116.5; Pearson chi2 = 1.29e+04; Pseudo R-sq. = 0.1052
Model 5: 5,759 persons	Model 5: Log-likelihood = −4415.5; Pearson chi2 = 1.20e+04; Pseudo R-sq. = 0.1143
Model 6: 5,000 trips (random sample)	Model 6: Log-likelihood = −3162.4; LL-Null = −6931.4; LL ratio test = 0.11; AIC = 6368; BIC = 6512

Note: Coef = coefficient; t-stat = *t*-statistic; "–" = not applicable. *Base category corresponds to all omitted categories in each individual model.

crucial information.

It is immediately apparent from the model estimations results that extreme heat is a statistically significant determinant of activity-travel patterns even after controlling for a host of other socio-economic, demographic, and contextual variables. Extreme heat increases the probability of zero trip-making (Model 1), reduces time devoted to travel (Model 2), reduces trip frequencies or counts in total and by transit and bicycle/walk (Models 3–5), and increases the propensity to use a car for trip making (Model 6). The coefficients on the extreme heat variable are statistically significant and have signs that are behaviorally intuitive. Although this finding is entirely consistent with expectations, it is of value to document empirical evidence of this impact of extreme heat so that appropriate policy interventions and transport service adjustments can be made to mitigate the effects of extreme heat.

Virtually all of the socio-economic and demographic variables influence activity-travel variables in expected ways. Females devote less time to travel when compared with males as evidenced by the negative coefficient associated with females on the linear regression model of ln (daily travel duration). Those 15–19 years of age are less likely to use the car for trip-making, largely because they may not yet have access to a car (or acquired their driving license). Those 20–29 years of age are more amenable to walking or bicycling mode choice, as expected. Those who are older are more likely to make no trips (higher probability of zero trip-making), spend less time traveling, and make fewer daily trips overall and fewer daily trips by transit and bicycle and walk. Those who have a lower education level (less than high school) make more transit trips. Those with a Bachelor's degree are less likely to choose transit as a mode and spend more time traveling in the day (higher daily travel time expenditure). Those with a graduate degree are less likely to be zero trip-makers and engage in more travel – both in terms of duration and trip frequencies by mode. It is interesting to see that those with a graduate degree exhibit a higher propensity to bicycle and walk, suggesting that the higher education level may be associated with a greater awareness of the benefits using active travel modes. It is found that Blacks exhibit a higher propensity for zero trip-making, while Whites exhibit a lower transit trip frequency and a lower propensity to choose active travel modes for trip-making. Non-workers are more likely to be zero trip-makers and make fewer trips overall and by transit. Workers are more likely to report transit trips as transit is often used for commuting purposes. Workers, as expected, devote more time to travel.

In terms of household characteristics, it is found that low income individuals have a higher probability of reporting zero trips, make more trips by transit and bike/walk, and are more likely to choose bike/walk as a mode of transportation (compared to other income groups). This clearly indicates that low income individuals are vulnerable to extreme heat conditions. They use transit and bicycle/walk on a more frequent basis, and hence they are most susceptible to experiencing the deleterious effects of extreme heat due to the exposure to the environment that the use of these modes entails. Higher income individuals residing in households with incomes greater than or equal to $100,000 exhibit a lower probability of zero trip-making and higher probability of car mode choice. Single persons report more bicycle/walk trips and are less likely to choose the car for travel when compared with persons living in multi-person households. This is largely because single persons do not have the household obligation and other constraints that multi-person households often have.

As expected, there are differences in trip-making characteristics across geographic regions. The car-centric regions of Atlanta, Dallas, Houston, and Phoenix are associated with a higher probability of choosing the car for trip making (Model 6). Residents of New York make more trips by transit and bike/walk and are more likely to choose such modes of transportation for trip-making. The same can be said of residents of Chicago and Washington, D.C. who are also more likely to choose transit for their trip-making. Those in Philadelphia make more bicycle/walk trips. In general, these findings are entirely consistent with expectations.

Among other characteristics, weekdays are associated with a higher propensity for trip-making, greater frequencies of trips by all modes, and higher propensity to use transit (presumably because of the larger prevalence of commute trips on weekdays). A car user is defined as an individual who reported at least one car on the time use survey day. As expected, car users report making more daily trips overall, in part because of the flexibility and superior travel times afforded by the automobile.

The model specifications included a number of interaction terms to explore how extreme heat may differentially affect various socio-economic groups. There are also a number of other interaction terms to account for the complex interactions among variables influencing activity-travel characteristics. What is important to note is that, even after including all of these interaction variables, extreme heat (by itself) turned out to be a statistically significant variable in shaping all aspects of activity-travel choices considered in this study. The interaction terms reflect heterogeneity in the effects of extreme heat on activity-travel choices. For example, it can be seen that, under extreme heat conditions, those aged 65 years or older depict a greater reduction in bike and walk trips than other age groups (in other words, extreme heat impacts biking and walking of older people more than it impacts biking and walking of younger people). Similar interaction effects are discernible in other socio-demographic attributes. Although extreme heat contributes to lower overall trip making, the interaction term for car users is associated with a positive coefficient suggesting that car users do not experience the same level of decline in overall trip rates. The interaction term corresponding to a graduate degree has a positive coefficient for transit trip count, suggesting that extreme heat does not impact transit trip rates for those with the highest education level as much as it affects transit trip rates for other education groups. Lower income individuals are less likely to be zero trip makers on extreme heat days (compared to other income groups), suggesting that their ability to adapt is not quite identical to that of other income groups. This finding is further explored in the next section. The remainder of the interaction terms capture some geographic nuances and key interactions among socio-economic attributes. For example, Black females make more transit trips while male students make more bike/walk trips; these interaction effects are above and beyond any sole effects that these variables may individually have on travel characteristics. Individuals residing in Houston with a child in the household are less likely to report making zero trips when compared with their observationally similar counterparts in other metropolitan areas. On the other hand, lower income individuals in Phoenix are more likely to report making zero trips (compared to lower income individuals in other jurisdictions). This could be because residents of Phoenix, including those from lower income households, are better equipped to deal with the heat, potentially due to a greater familiarity with its effects (Chuang et al., 2013). They may have access to more information about the impacts of extreme heat through emergency heat plans enacted in the region (City of Phoenix, 2023), which might encourage them to stay indoors. Also, they are possibly more likely to live in houses equipped with air conditioning (compared to residents of other regions).

Overall, the models provide behaviorally intuitive interpretations and results. Most importantly, the multivariate statistical model estimation results show that extreme heat is a significant predictor of activity-travel choices under hot weather conditions and that the influence of extreme heat is not necessarily homogeneous across socio-economic groups. The goodness-of-fit statistics documented at the end of Table 3 suggests that all of the model specifications fit the data and explain the behavioral phenomena of interest in a manner consistent with what is typically seen in travel behavior research.

5. Focus on zero trip-making

In the face of extreme heat, it would appear that individuals are more prone to staying indoors at home (see patterns in Table 2). This is a natural adaptation mechanism; unless there is a serious deficiency in amenities, the home represents a comfortable location to shelter from the heat and avoid any adverse impacts of extreme heat conditions. In general, it is often considered troublesome when people report making no trips. Zero trip-making is often viewed as an indicator of social isolation, social exclusion, and lower levels of well-being (Delbosc and Currie, 2011; Stanley et al., 2011; Batur et al., 2019). Being able to travel affords people the opportunity to access destinations, engage in activities, interact with others, and accomplish tasks necessary to earn a living and maintain a household. When people do not make trips and are home-bound, it may signal the loss of social interaction capabilities, leading to lower well-being (Stanley et al., 2011; Batur et al., 2019).

However, in the face of extreme heat, the exact opposite may hold true. As seen in Table 2, the natural adaptation mechanism is to spend more time at home on extremely hot days. In other words, on extremely hot days, reduced trip making (and zero trip-making) may actually be a healthy and desirable adaptation mechanism as people should minimize exposure to the heat. In order to better understand how zero trip-making manifests itself for different socio-economic groups on extreme heat and non-extreme heat days, this section presents an analysis that exclusively focuses on this behavioral choice/phenomenon.

Fig. 8 shows the percent of individuals in various socio-economic groups reporting zero trips on extreme heat days and non-extreme days (with the sample size indicated in square brackets for each bar). In general, it is seen that the percent of individuals reporting zero trips is higher on extreme heat days for all socio-economic and demographic groups. For example, on non-extreme days, 6.4 percent of workers report making zero trips; on extreme heat days, 9.4 percent of workers report making zero trips. For non-workers, the percent

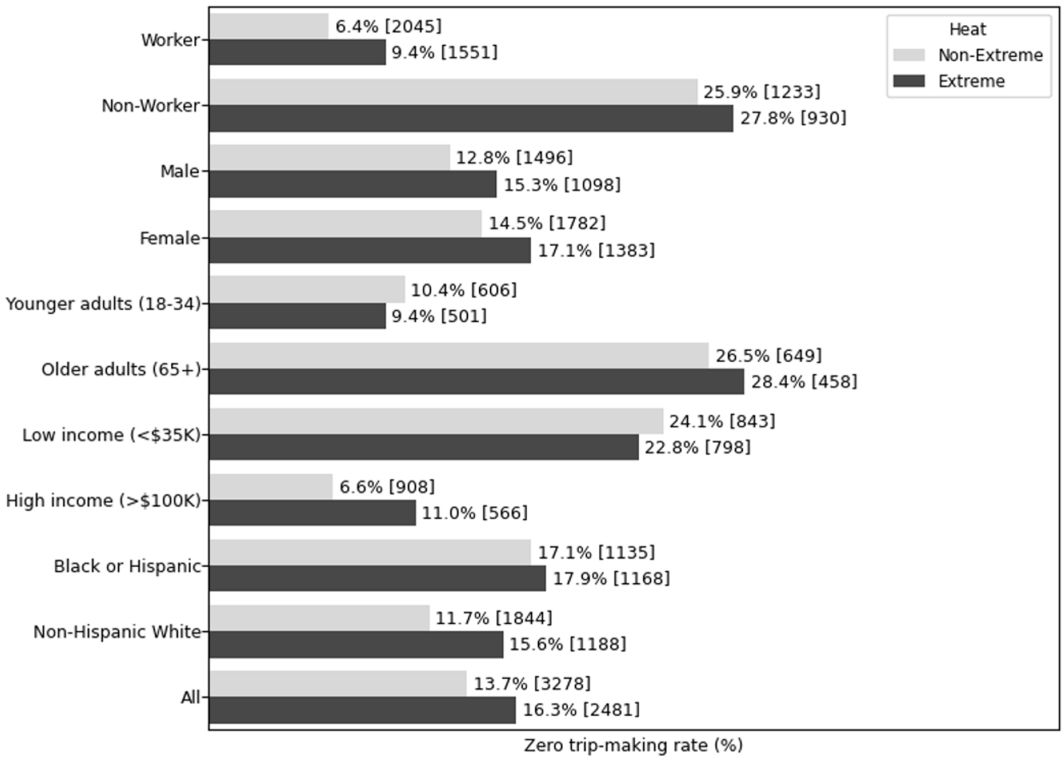

Fig. 8. Zero Trip-Making (%) by Select Segments During Extreme and Non-Extreme Heat.

of zero trip-makers increases from 25.9 percent to 27.8 percent on extreme heat days. One group that shows a decrease in zero trip-making on extreme heat days is the 18–34 year old segment. It is entirely possible that those in the younger age group are in school at a greater rate than their counterparts in other age groups. In addition, they may be in lower paying service jobs that require human presence. Moreover, the younger age individuals may not be as susceptible or vulnerable to the heat as the older age groups. As such, it is not entirely unexpected that this group depicts no increase in zero trip-making on extreme heat days.

The other group that depicts a lower zero trip-making rate on extreme heat days is that reporting household incomes less than $35,000 per year. This low income group is likely to enjoy the least amount of flexibility with respect to employment protocols, child care, and other household obligations. In general, they depict the highest rate of zero trip-making (after the group that is 65 years or older). This high rate of zero trip-making is not necessarily a desirable trait as it may be reflective of a diminished level of access to opportunities and destinations, participation in society, and level of mobility and social interactions. However, the fact that this group does not depict a higher rate of zero trip-making under extreme heat conditions suggests that this group is not able to adapt to the heat. They do not have flexibility or the amenities to adjust their activity-travel and time use patterns. It is also possible that their home is not necessarily the best place to shelter during extreme heat (especially if their residences lack fully functioning air conditioning units); and hence the percent making zero trips on extremely hot days actually decreases as these individuals seek shelter in other cooler locations to escape the heat.

Differences between racial groups are also particularly notable. Minority groups (Blacks and Hispanics) and non-Hispanic Whites show a higher level of zero trip-making on extremely hot days. However, the magnitude of difference is not at all similar. While the percent of Blacks and Hispanics reporting zero trips on non-extreme days is 17.1 percent, the corresponding percent on extremely hot days is quite similar at 17.9 percent. For non-Hispanic Whites, the percentages are 11.7 percent and 15.6 percent, suggesting that non-Hispanic Whites are able to adapt to extreme heat conditions and stay indoors at home to a greater degree than their Hispanic and Black counterparts. Once again, this points to potential adaptability constraints (due to less flexibility) or home constraints (not ideal location to shelter from heat) that render it difficult for minority groups to exhibit resilience to extreme heat conditions. It would be of value to identify the reasons for these differences between socio-demographic groups, and craft interventions that help enhance comfort and adaptability for groups that seem less able to adjust their activity-travel behaviors under extreme heat.

6. Conclusions

Extreme heat conditions in the recent past are motivating a closer look at the adaptability and resilience of communities. As extreme heat conditions are expected to become more frequent in the years ahead, it is essential to ensure that people are able to adapt their lifestyles to reduce vulnerability to extreme heat. This paper presents a detailed analysis of the differences in human activity-travel choices and time use patterns between extremely hot days and non-extreme days. Extreme heat days present conditions that are dangerous to people as indicated by the National Weather Service heat index categorization. The study utilizes 14 years of American Time Use Survey (ATUS) data for 11 diverse large metropolitan areas to analyze the impact of extreme heat on activity and mobility patterns. The analysis focuses on time spent on various activities both in-home and out-of-home, mode choice, trip rates by purpose, percent zero trip-making (staying home all day), and temporal distribution of travel episodes. A detailed descriptive analysis is followed by the presentation of a series of multivariate statistical models that help understand the impact of extreme heat on activity-mobility choices and patterns, even after controlling for a host of socio-economic, demographic, and contextual factors.

The study shows that extreme heat has a significant impact on activity-mobility choices and time use patterns. On days that are extremely hot, people stay indoors at home more, essentially spending less time out-of-home. They make fewer trips overall, with even greater reductions in trips by active modes of travel and transit. The percent of zero trip makers (i.e., percent of individuals staying home all day) increases considerably on extremely hot days. Both the descriptive analysis and the multivariate statistical models showed these patterns of differences between extremely hot days and non-extreme days. In other words, people do adapt, and activity-travel choices and time use patterns are indeed impacted by extreme heat.

However, the analysis also reveals the vulnerable socio-economic and demographic groups. In particular, it is found that individuals in low income households, Blacks, and Hispanics are unable to adapt their activity-mobility choices and time use patterns as much as other groups. These groups do not show an increase in the percent of zero trip-makers on extreme heat days, suggesting that they do not enjoy the same level of flexibility and resources necessary to adapt and stay home. They also depict a higher usage of transit and bike/walk modes of transportation when compared with other socio-demographic groups.

The implications of these findings for urban design and transport policy are worthy of consideration. From an urban design perspective, the landscape should be enhanced with tree cover so that individuals using alternative modes of transportation can navigate the urban spaces in shade. A more dense, bike and walk friendly design, with mixed land use will help reduce distances that need to be covered (thus reducing exposure to extreme heat) and enhance accessibility to transit (thus reducing the length of access and egress legs of a transit journey). Transit services can be made more frequent on extremely hot days to reduce wait times and transit stops should be sheltered and provided tree cover. It would be beneficial to offer vouchers to mobility disadvantaged individuals including those in lower income segments and/or do not own a car so that they can use ridehailing or other shared mobility services for accessing transit and fulfilling their travel needs on extremely hot days. The bottom line is that efforts need to be made to reduce exposure to the extreme heat through a combination of urban design strategies and provision of curb-to-curb mobility services on-demand.

It is also important to view zero trip-making in a new light in the context of extreme heat and heat vulnerability of disadvantaged groups. While zero trip-making has historically been viewed as a signal of social exclusion and lower well-being, the opposite is true on extremely hot days. Again, groups that are vulnerable (e.g., low income households) should be provided with the flexibility and resources needed to be able to shelter in the comfort of home. Workers who can telework should be provided the resources and connectivity to be able to do so. In extremely cold climates, snow days are declared to avoid exposure to cold and enhance public safety; these are days that school classes are canceled or delayed, outdoor activities are curtailed, and workers are told to stay at home. Although some locales are implementing heat days (along similar lines), the practice is yet to be fully embraced – largely because schools and related activities are already closed for the summer. However, this places front line workers, low income individuals, and those without a car in a vulnerable position as they struggle to shelter themselves from the heat. In Phoenix this year, despite heat records being obliterated, not a single day was declared as a heat day with a provision for workers to stay home. By recognizing the potential deleterious effects of heat and understanding the ways in which people adapt, appropriate strategies and policies to mitigate heat impacts can be implemented.

Finally, the interpretation and generalizability of this study's findings are subject to certain limitations that future research could address. While this study incorporates a host of socioeconomic, demographic, weather, and activity-travel attributes, other confounding factors may still be at play. For example, this study did not account for the potential influence of health-related variables on activity and travel patterns during extreme heat conditions. While the use of proxy variables such as age may capture some effects of underlying health conditions, the absence of specific health-related data limits our ability to fully understand the variations in activity-mobility and time use patterns. Similarly, this study also did not account for the potentially confounding effects of detailed built environment characteristics, due to the unavailability of such data. More importantly, this study did not investigate the complex interplay between heat and other environmental factors, such as air pollution (Jacob and Winner, 2009; Hertig, 2020) and rainfall (Brum-Bastos et al., 2018), and their combined effects on human activity-mobility behaviors, due to the scope and data limitations, which may confound the findings. Additionally, the diversity of heat emergency plans and interventions across the studied cities also adds a layer of complexity (Benmarhnia et al., 2019). These interventions, which are activated based on varying temperatures and thresholds, could significantly influence the observed activity and mobility patterns – a factor not controlled for in this analysis. Lastly, this study employed a binary classification (extreme vs. non-extreme days) based on heat index to assess the impact of extreme heat on human activity-travel and time-use patterns. It is possible that there may be other measures, methods, or classifications that could be more effective in disentangling the true impacts of extreme heat.

CRediT authorship contribution statement

Irfan Batur: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Victor O. Alhassan:** Writing – original draft, Validation. **Mikhail V. Chester:** Supervision, Methodology, Formal analysis, Conceptualization. **Steven E. Polzin:** Writing – review & editing, Formal analysis, Conceptualization. **Cynthia Chen:** Writing – review & editing, Funding acquisition. **Chandra R. Bhat:** Writing – review & editing, Validation, Methodology, Formal analysis. **Ram M. Pendyala:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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.

Data availability

Data is available at the following GitHub repository: https://github.com/ibatur/atus_heat_paper.

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Appendix A. Supplementary data

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