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DISCUSSION PAPER SERIES

IZA DP No. 15661

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ISSN: 2365-9793

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ABSTRACT

Weather Conditions and Daily Commuting*

Climate change and global warming are problems that currently affect the daily lives of the world population and, to the extent that climate projections are less than optimistic, understanding how individuals respond to extreme weather conditions is essential for the correct design of public policies. One of the human behaviors that can be most affected by extreme weather conditions is that of personal travel, including commuting, an activity that is done daily by millions of workers worldwide. Within this framework, we estimate the effects of weather conditions on daily commuting and travel choices, by examining daily variations in weather conditions within counties in the US. To that end, we use time-use diary information from the American Time Use Survey 2003-2019 and daily weather information at the county level for a sample of US workers, finding significant relationships between daily weather conditions, commuting time, and travel choices. Rainy days, high temperatures, and snowfall are associated with a statistically significant lower proportion of commuting time done by public transit and walking, whereas the relationship is found to be positive for the proportion of commuting time by car. With additional analysis, we find that the greatest substitution from greener modes of transport towards the private car is concentrated on days with greater precipitation and higher temperatures. Finally, our results suggest adaptation to higher temperatures in warmer places.

JEL Classification: R4, J22

Keywords: weather, commuting, green mobility, workers, American Time Use Survey

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* This paper has benefitted from funding from the Government of Aragón [Project S32_20R, funded by Program FSE Aragón 2014–2020], and the Spanish Ministry of Science and Innovation [Project PID2019- 108348RA-I00, funded by MCIN/AEI/10.13039/501100011033]. I. Belloc acknowledges support from the Spanish Ministry of Science, Innovation and Universities [FPU research fellowship Ref. FPU20/03564].Declarations of interest: None.

1. Introduction

In this paper we analyze the daily commuting of workers in the United States, with a focus on the relationship between daily weather conditions, on the one hand, and the time devoted to commuting and the mode choice for these travels, on the other. Millions of individuals travel every day, and commuting to and from work is one of the most important activities (Prakash et al., 2020). For instance, in the US, approximately 20% of all daily journeys are commuting trips, and more than 45% of workers travel to their work places, according to the American Time Use Survey (ATUS). The time devoted to commuting has increased considerably in recent decades in the US, from an average of 39 minutes per day in 2003 to 45 minutes per day in 2019. The percentage of commutes of less than 10 minutes has also declined, from 10% in 2003 to 6% in 2019, while the percentage of workers who commute more than 30 minutes has risen from 42% to 51%, over the period 2003-2019.[1] Hence, the time devoted to commuting represents a significant part of everyday life of workers worldwide, and thus the analysis of the factors affecting commuting behavior of workers is relevant to policy issues.

How workers travel to their workplaces (mode of transport) has important consequences for the environment, including pollution, congestion, and traffic accidents (Chapman, 2007; Buehler, 2011; Morris and Zhou, 2018). In the US, the car is the most common mode of transport chosen by workers to travel to/from work (Gimenez-Nadal and Molina, 2019b; Molina et al., 2020), which leads to an unsustainable transport system, and which could explain why the transport sector produces the largest share of greenhouse gas (GHG) emissions among all industrial sectors in the US, contributing around 27% of the nation's GHG emissions (EPA, 2022).[2] The most prominent GHG from transportation is carbon dioxide (CO_2), and mainly comes from burning fossil fuels, specifically petroleum, by passenger light or light-duty vehicles (Bleviss, 2021; EPA, 2022). Consequently, the analysis of the commuting behavior of workers in the US, including the mode choice for these travels, is important for policy makers to design policies aimed at mitigating the negative consequences of commuting on the environment.

[1] Own calculations using a sample of employed workers (no telecommuters) from the ATUS 2003-2019.

[2] Overall, net emissions decreased 10.6 percent from 2019 to 2020 due to the impacts of the coronavirus pandemic on travel and economic activity (EPA, 2022). Transportation sector emissions decreased by 13.3 percent.

One factor that may affect the commuting behavior of workers is that of weather conditions. Transportation and weather conditions are instrinsically linked (Koetse and Rietveld, 2009; Böcker et al., 2013a; Dist et al., 2013; Liu et al., 2017), and weather is an important determinant of travel behavior, influencing practically every aspect of travel (Miranda-Moreno and Nosal, 2011). Prior studies have found reductions in active and public transport use on rainy days (Richardson, 2000; Guo et al., 2007; Tucker and Gilliland, 2007; Winters et al., 2007; Böcker and Thorsson, 2014; Creemers et al., 2015; Liu et al., 2015), hotter conditions negatively influence activities such as walking, cycling and bus ridership (Richardson, 2000; Phung and Rose, 2008; Aultman-Hall et al., 2009; Heinen et al., 2011; Böcker et al., 2013b; Liu et al., 2015), and air wind speed negatively affects public transit use and cycling (Rietveld and Daniel, 2004; Aaheim and Hauge, 2005; Guo et al., 2007; Flynn et al., 2012; Gimenez-Nadal et al., 2022b). Adverse weather conditions, such as snowfall, have an impact on traffic speed (Martin et al., 2000; Stern et al., 2003; Keay and Simmonds, 2005; Hranac et al., 2006; Maze et al., 2006; Unrau and Andrey, 2006; Rakha et al., 2008; Call, 2011; Sabir et al., 2011; Zhao et al., 2012; Hooper et al., 2014), and rain and snow have a negative impact on road accidents (Edwards, 1999; Andrey et al., 2003; Eisenberg, 2004; Shankar et al., 2004; Chung et al., 2005; Eisenberg and Warner, 2005).

The impact of weather conditions on the commuting behavior of workers has been analyzed in Aaheim and Hauge (2005), Cools et al. (2010) and Liu et al. (2015). Aaheim and Hauge (2005) use data for the Bergen area of Norway, in 2000, and show that walking and cycling for commuting increase with higher temperatures, while higher precipitation decreases walking and cycling to work, and increases private transport. Cools et al. (2010) conduct an adaptation study in Flanders, a region of Belgium, and show that snow has the largest impact on commuting, whereas extreme temperatures, hot or cold, appear to have the least impact on commuting behavior. Liu et al. (2015) collect travel data from the Swedish National Transport Survey (SNTS) and show that the share of cycling increases substantially in warm months, in contrast to the share of walking. In addition, their results suggest that commuters tend to cycle more in months of high relative humidity.

Considering the predicted increase in the number and magnitude of extreme events, in terms of conditions and temperatures due to climate change in the near future (Brönnimann et al., 2012; Stott, 2016; IPCC, 2021), there is a compelling need to increase our understanding of the effect of weather on workers' daily travel behavior. Within this framework, this paper addresses the question of how the commuting behavior of workers relates to weather conditions. To that end, we use nationally representative time diary data from the American Time Use Survey (ATUS) 2003-2019, which contains information on daily activities of respondents, together with data on weather conditions at the county level in the US.[3] Our analysis covers a broad geographical region, with variations in weather across the country, and in different seasons, for a 17-year period. This allows for an analysis of daily weather conditions on the commuting behavior of US workers for the first time in the literature.

Our results suggest broad associations between daily commuting behavior and weather conditions. Unfavourable conditions, as measured by high temperatures, snowfall, or rain, are related to a reduction in the proportion of commuting done by sustainable modes of transport (e.g., walking and public transit; see Echeverría et al. 2022, 2022b) and an increase in the proportion of commuting done by private car.[4] The results suggest that extreme weather conditions make workers less likely to increase physical activity while commuting since the car seems to be an ideal travel choice for protection against heat, snowfall, and rainy days. We experiment with alternative specifications, finding robust results with respect to these factors. US workers adjust their daily commute in response to temperature, snow, and rain, seeking greater commuting comfort via their choice of transportation mode. We find that the relation between commuting time and weather conditions is heterogeneous across climatic regions, and that workers in warmer places appear to adapt more readily to high temperatures.

This paper contributes to the literature by exploring the relationship between weather conditions and commuting time, offering a novel analysis of how weather affects the daily commuting behavior of US workers. We use a nationally representative sample of time use behavior, merged with high-quality meteorological information collected at the county level, making our results of general interest since we are not focusing on a specific geographic region or case study area, in comparison to the prior literature. Only two studies using time use diaries for the US have examined the impact of weather, focusing

[3] The weather information obtained was daily maximum temperature, daily precipitation and daily snowfall for over 402 distinct counties covering a 17-year period, from thousands of meteorological stations located throughout the US.

[4] Sustainable mobility includes both public transit and active transport (walking and cycling), which may contribute significantly to reduce greenhouse gas emissions, especially walking and cycling (Chapman, 2007; Gössling and Choi, 2015; Holian and Kahn, 2015).

both on work, home production, and leisure activities (Connolly, 2008; Graff Zivin and Neidell, 2014), and on only one element of weather; rainfall in Connolly (2008) and temperature in Graff Zivin and Neidell (2014).[5] Thus, we complement prior analyses by focusing on commuting time by US workers and gathering information for several weather characteristics of the county of worker residence at the same time. Additional analysis reveals that the relationships we find between commuting time and weather conditions differ by climatic regions. Our results have significant implications for current climate change and transportation planning policy, since understanding how weather affects travel behaviour is crucial for policymakers to achieve a sustainable transport system in the current context, where governments around the world are attempting to implement policies to reduce emissions and encourage people to switch from cars and toward more environmentally friendly modes of travel, especially walking and cycling.

The remainder of the paper is organized as follows. Section 2 describes the data, sample selection, and variables used in our analysis, together with some first descriptive analyses. Section 3 details our econometric strategy, and Section 4 discusses the main results. Section 5 presents heterogeneous weather impacts, paying special attention to the estimates according to climate regions. Section 6 concludes the paper with final remarks and suggests future lines of research of our work.

2. Data and variables

We use nationally representative time diary data from the American Time Use Survey (ATUS) for the years 2003-2019, with information on daily activities of respondents.[6]

[5] Shi and Skuterud (2015) gathered data on five weather elements (temperature, humidity, precipitation, wind speed, and cloud cover) and sickness absenteeism from Canada's monthly Labour Force Suvey (LFS) between 1997 and 2008, and found a positive correlation between good weather and short-term personal absences (this relationship is stronger when the weather of the previous weekend is of poorer quality), while weather does not afect other types of absenteeism. On the other hand, Krüger and Neugart (2018) match German time use data with regional weather information (temperature, precipitation, and cloud coverage) between April 2001 and March 2002 and find evidence of an interday labor supply substitution for women. Garg et al. (2020) use the China Health and Nutrition Survey and study work and childcare time, focusing on the causal effects of extreme temperatures, whereas Nguyen et al. (2021) use the Australian time use linked to weather data and focus on the time allocation of children.

[6] The ATUS is the largest source of time diary data collected anywhere and is considered the state-of-the-art in time use surveys (Aguiar et al., 2012). It is primarily conducted by computer-assisted telephone interviewing (CATI) software, once a household is contacted and the designated person agrees to participate, but special provision is made to reach those who arenot easily reached by phone. Interviews are conducted in English and Spanish, the two most frequently spoken languages in the US, and have a conversational structured format, rather than paper diaries as in many other countries.

The ATUS database is an annual, nationally representative time use survey, considered the official time use survey of the US, sponsored by the Bureau of Labor Statistics (BLS) and conducted continuously since January 2003 by the US Census Bureau. The respondents (a single individual from a unique household over age 15, previously interviewed in the Current Population Survey (CPS) randomly chosen to answer the questionnarie) fill in a time use diary, where they report their primary activities for each minute of the 24 hours of a single survey day (from 4:00 a.m. on the previous day to 3:59 a.m. on the interview day).[7] Consequently, the ATUS collects one detailed time diary day per household.[8] The advantage of self-reported time diary data over those from recall questions asking respondents about usual time spent or time spent over the last week, is that diary-based estimates of time use are more precise and reliable (Juster, 1985; Schober and Conrad, 1997; Bianchi et al., 2000, 2006; Robinson, 2002; Bonke, 2005; Klevmarken, 2005; Aguiar and Hurst, 2007; Guryan et al., 2008; Kan, 2008; Robinson and Godbey, 2010; Robinson et al., 2011; Gimenez-Nadal and Sevilla, 2012; Harms et al., 2019).

The ATUS collects the start and stop times of activities, allowing us to define the time devoted to any given activity such as commuting or market work, the main time use categories in our analysis. For most activities, the ATUS also collects information about where these activities occur, including travel mode, and who else was present during the activity, except for activities that are generally done alone, such as sleeping, grooming and certain other personal activities. Furthermore, the ATUS collects information about a range of respondent and household characteristics, both socio-demographic and geographic characteristics, via a personal and household interview.

Our sample is restricted to workers between 16 and 65 years old (inclusive), who completed their diaries on working days, defined as days when respondents report working for at least one hour, excluding commuting time (Gimenez-Nadal and Molina,

[7] Specifically, individuals are randomly selected from a subset of households that have completed their eighth and final month of interviews for the CPS, approximately 2-5 months after completion of the final CPS month. Days are selected to ensure proportional distribution across days of the week and weeks of the year and the diary day can be any day of the year, except for a few major holidays like Thanksgiving Day and Christmas Day. Approximately one half of the diaries come from Saturdays and Sundays, and 10 percent is allocated to each of the weekdays Monday through Friday.

[8] Time use data are collected initially in an episode file format comprised of a separate row of information for each activity performed by the respondent (see Gimenez-Nadal and Molina (2022) for a review of the typical instruments used in time use surveys).

2019a, 2019b; Gimenez-Nadal et al., 2018a, 2018b, 2020, 2021; Molina et al., 2020).[9] We omit workers who filled in their diaries during holidays in order to avoid atypical or unusual days that do not reflect the usual commuting behavior of workers, and we exclude self-employed workers, since they are more likely to work from home and generally have different commuting patterns than employees (van Ommeren and van der Straaten, 2008; Roberts et al., 2011; Künn-Nelen, 2016; Lorenz, 2018; Albert et al., 2019; Gimenez-Nadal et al., 2018a, 2018b, 2022a; Gimenez-Nadal and Molina, 2019a, 2019b).[10] We exclude zero-commuters and individuals with missing information for any explanatory variable used in the regressions. From these restrictions, our final sample is composed of 47,355 workers from the original 210,586 pooled diaries for the period between 2003 and 2019.

The dependent variables are the commuting of workers in minutes per day (activity code 180501 'travel to/from work'), and the proportion of commuting time by modes of transport. The ATUS gathers information about a number of transportation-related mode categories asking the question "Where were you?" (description "Location of activity"), which is especially useful for our approach regarding the use of sustainable modes of transport while commuting. There are twenty-six different locational coding categories, but we focus on the following answers: 'car, truck, or motorcycle (as driver or passenger)', 'walking', 'bus', 'subway/train', 'bicycle', 'boat/ferry', 'taxi/limousine service', and 'airplane'. The travel modes in this analysis are grouped, following Gimenez-Nadal and Molina (2019b), into private vehicle (car, truck, or motorcycle, both as driver or passenger), public transit (bus, subway/train, boat/ferry, taxi/limousine service, or airplane), walking, and cycling (bicycle). We calculate the total time devoted to commuting (in minutes) and the total commuting time using each mode of transport (in minutes) as the sum of all episodes reported by each worker throughout the diary day, obtaining then the proportion of commuting time by car, public transit, walking and cycling. Other modes of transportation are excluded from the analysis.[11]

[9] We explain with more detail in Appendix Table A1 the activity codes included in the market work category. We only use this category to restrict the sample to working days.

[10] The American Time Use Survey asks repondents to choose "class of worker code" (main job) from the following categories: 1 government, federal; 2 government, state; 3 government, local; 4 private, for profit; 5 private, nonprofit; 6 self-employed, incorporated; 7 self-employed, unincorporated; and 8 without pay. We exclude people who choose categories 6, 7 and 8.

[11] Other travel modes represent 3% of the total commuting time.

We merge the information from ATUS with daily weather records from over 16,000 meteorological stations gathered from the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA).[12] As the ATUS includes information on the day of month, month, and year in which respondents were interviewed, and the county of residence, for each respondent we can match weather information for the county of residence at the time of the interview. We merge those two data sets by the county of residence of the respondent and the survey date, leaving us with a final sample of just over 19,317 workers with valid weather data.[13] The measures used here are daily total precipitation (in inches), snowfall (in inches), and air maximum temperature (in degrees Fahrenheit, ºF).[14] From the information of precipitation, we define a dummy variable for rainy days (1 if precipitation was at least 0.10 inches of precipitation in 24 hours, 0 otherwise) following Connolly (2008).

Table 1 presents the weighted summary statistics of the minutes workers spend commuting and the proportion of commuting made by each mode of transport, after imposing the above restrictions and merging with the weather data. The average commuting time in the sample is 45.604 minutes per day, with a standard deviation of 39.358 minutes, and car mode is most preferred in commuting trips in the US, with an average 92.58% of commuting done by private vehicle, as either the driver or as a passenger. The proportion of time by public transit while commuting is on average 3.37%, while the proportion of commuting by walking and bicycle is 3.34% and 0.70%, respectively.

A first descriptive analysis shows that the correlation between total commuting time and weather conditions (rainy days, snowfall, and maximum temperature) are not statistically significant at standard confidence levels. On the other hand, the correlation

[12] Meteorological station level data are averaged in order to create county-level measures.

[13] Information on county of residence is the most detailed measure of location available for the ATUS respondents. The sample is limited to respondents living in an exact identifiable US county in the data, since county information is only available for individuals from locations with a population exceeding 100,000 inhabitants in general, in order to guarantee confidentiality. For this reason, there are many unidentified counties and this restricts our analysis to 402 counties, losing information for over 26,948 respondents from the original 47,355 individuals of the sample selection.

[14] Although a variety of weather variables are available, most stations only collect total amounts of precipitation, amount of snowfall, minimum and maximum temperature. Following Graff Zivin and Neidell (2014), we focus on maximum temperature, rather than daily average temperature, because most individuals are indoors for a significant period of time for routine activities, such as sleeping, when minimum temperatures often occur. Maximum temperature is also likely to be highly correlated with other relevant temperature measures throughout the day, so it is likely to be a reasonable proxy for individual exposure.

between rainy days and proportion of commuting time done by car is 0.0252, whereas between maximum temperature and the proportion of commuting time done by car is 0.0355; both correlation coefficients are statistically significant at the 99% confidence level. By contrast, the correlation between rainy days and proportion of commuting by public transit is -0.0161, while between maximum temperature and proportion of commuting time by public transit is -0.0380, both correlations being statistically significant at the 95% confidence level. When we compute the coefficient of correlation between the proportion of commuting done walking on the one hand and rainy days and daily maximum temperature on the other hand, the correlation coefficients are -0.0168 and -0.0210, respectively. Both coefficients are statistically significant at the 95% confidence level. When we calculate the correlations between weather conditions and the proportion of commuting time by bicycle we obtain no statistically significant coefficient at standard levels. Hence, this preliminary analysis suggests a possible negative relationship between rainy days and the proportion of commuting done by public transit and walking, while the relationship is positive for the proportion of commuting done by car. The same applies to daily maximum temperature, with all these correlations being statistically significant at the 99% confidence level.[15]

The ATUS also contains rich information that allows us to define several variables to control for the socio-demographic characteristics of respondents that have been found to affect the time spent commuting, aimed at accounting for the observed heterogeneity of individuals, both at the individual and the household level. We first consider gender, defined as a dummy that takes value 1 for males, and 0 for females. We also include age of respondent, measured in years. The native status is defined through a dummy variable that takes value 1 for native citizens (being a naturalized US citizen), 0 otherwise. The highest educational attainment is separated into three dummy variables indicating if the respondent has achieved the primary education, secondary education or University education. The full/part-time status is included through a dummy variable that takes value 1 if the employee is a full-time worker, 0 otherwise. We also include controls for the employment sector and include a dummy variable that takes value 1 for employees in the

[15] The correlations between weather variables are highly statistically significant too, as could be expected. Nevertheless, the correlations are not very strong: the highest is -0.2470 in the correlation between daily maximum temperature and snowfall, the correlation between rainy days and snowfall rises to 0.1362, and the correlation between rainy days and daily maximum temperature is -0.1183. All these are statistically significant at the 99% confidence level.

public sector, 0 otherwise. Hourly earnings are defined in dollars.[16] Household composition is defined by three variables: a control for the marital status of workers, and define a dummy variable for the presence of a partner (both married or cohabiting) in the household, the presence of children is measured by a continuous variable indicating the number of children (aged 17 or under) in the household, and we control for the total household size. Table A2 in the Appendix shows this set of variables.

Table 1 presents summary statistics of the set of socio-demographic characteristics for our sample. Around 53.8% of the sample are males, and workers are, on average, 39 years old. Further, 77% of workers are native citizens born in the US. In terms of the maximum level of education achieved, 9.7% of workers have primary education, 25.4% secondary education, and 64.8% of the sampled workers have attained at least some college; 84% of respondents are full-time workers, and 16% are public sector employees. The average wage rate of workers in the sample is 21.48 dollars per hour. Regarding family composition, 60% of workers have a spouse or partner in the household, the number of children under 17 in households is 0.811 and the average family size is 3 members. In terms of weather conditions, the average daily precipitation is 10.83 inches per day, the percentage of rainy days is 48.6% (it does not rain on 51% of our county-day observations), the average daily snowfall is 0.506 inches, and the average daily maximum temperature is 69.34ºF, respectively.

3. Econometric strategy

We use two models to analyze the daily commuting of US workers. We estimate the following linear econometric models by Ordinary Least Squares (OLS) to investigate the impact of weather conditions on the time devoted to commuting, total, and by mode of transport:[17]

[16] Information on hourly earnings is given directly by most respondents in the ATUS, and for those who do not report hourly earnings we compute them as weekly earnings divided by the hours usually worked per week.

[17] OLS may produce inefficient and inconsistent estimates because not all workers commute by every mode of transportation on a given day (Cameron and Trivedi, 2005). This problem can be addressed by using the Tobit model. However, prior studies comparing OLS and Tobit models of time allocation conclude that the results are qualitatively similar and conclusions are equivalent (Frazis and Stewart, 2012; Gershuny, 2012; Foster and Kalenkoski, 2013; Stewart, 2013). As a consequence, we will rely on OLS models for the sake of simplicity.

$$C_{i,jt} = \alpha + Weather'_{jt}\beta_W + X'_{i,jt}\beta_X + FE_t + FE_i + \varepsilon_{ijt} \quad (1)$$

$$p_{i,jt} = \alpha + Weather'_{jt}\beta_W + X'_{i,jt}\beta_X + FE_t + FE_i + \varepsilon_{ijt} \quad (2)$$

where i refers to individual "i", j refers to county "j", and t refers to survey day "t". The dependent variables, $C_{i,jt}$ and $p_{i,jt}$, represent the daily time spent on commuting measured in minutes per day and the proportion of commuting done by car, public transit, walking, and cycling for individual i in county j at time t, respectively. $Weather'_{jt}$ is a vector of weather conditions of county j at time t, including the dummy variable for rainy days, daily snowfall (in inches), and maximum air temperature (ºF).

$X'_{i,jt}$ represents a number of observable demographic and household controls of individual i correlated with commuting time, including gender; age, and age squared to allow for non-linear effects; native status (1 if native citizen, 0 otherwise); education level (indicators for secondary and University education, ref.: primary education); full-time status (1 if full-time worker, 0 otherwise); type of worker (1 if public sector worker, 0 otherwise); the hourly wage ($ per hour); cohabitation status (1 if living with a married/unmarried partner, 0 otherwise); the number of children aged 0-17 years old in the household; and the family size. FE_t are dummies for year of interview (2019 is the reference survey year), month (December is the reference month), and day of the week (Sunday is the reference weekday), to capture possible changes in commuting time throughout the week (workdays Monday through Saturday), months (any seasonality in commuting) and years, and FE_i is a vector of variables that includes occupation fixed effects, to control for the characteristics of workers.[18] ε_{ijt} is the error term capturing unmeasured factors in the model.

This econometric strategy permits us to examine the relationship between the weather conditions of each county, on the one hand, and the total time spent commuting and the proportion of commuting done by several modes of transport, on the other. Consequently, we estimate five different models, separately including as dependent variables the total

[18] The ATUS codes occupations into 22 general categories: Management; Business and financial operations; Computer and mathematical science; Architecture and engineering; Life, physical, and social science; Community and social service; Legal; Education, training, and library; Arts, design, entertainment, sports; Healthcare practitioner and technical; Healthcare support; Protective service; Food preparation and serving related; Building and grounds cleaning; Personal care and service; Sales and related; Office and administrative support; Farming, fishing, and forestry; Construction and extraction; Installation, maintenance, and repair; Production; Transportation and material moving. We include the first 21 occupations in the regressions (with the last occupation, Transportation and material moving, as the reference or omitted occupation).

commuting time, and the percentage of commuting done by car, public transit, walking, and cycling. We include in all regressions robust standard errors to account for potential heteroskedasticity and all estimates are weighted at the individual level using survey demographic weights provided by the ATUS. Our parameters of interest that relate weather conditions to commuting time are identified from cross-county and daily variations in weather.

Multicollinearity is investigated and the Variance Inflation Factors (VIFs) are not close to 5 in all models, indicating a very low level of intercorrelation between the independent variables and no serious problem of multicollinearity (except for age and its quadratic, as expected), so we retain all variables in subsequent analyses.

4. Results

Table 2 shows the results of estimating Equation (1) in Column (1), and Equation (2) in Columns (2-5) for the proportion of commuting time by car, public transit, walking and cycling, respectively. We find that the coefficients for weather conditions display statistically insignificant effects on the daily time devoted to commuting by US workers, but we do obtain significant relationships between weather conditions and choice of transport during the commute to work.[19] Specifically, results suggest that at higher temperatures, and during snowfall and rainy days, workers appear to substitute their travel choices, from greener alternatives, such as public transit and walking, to more polluting modes of transport, such as private cars.

The first row of Table 2 shows that rainy days are related to the proportion of commuting done by car, public transit, and walking. A rainy day is associated with an increase of 2.092% in the proportion of commuting done by private car, along with reductions of 1.128% and 0.731% in the proportion of commuting done by public transit and walking, respectively. Consequently, on rainy days American workers adjust their travel choices, shifting from public transit and walking to the private car. All these coefficients are estimated to be statistically significant at the 5% level. Results from row 2 of Table 2 suggest that daily snowfall is positively correlated with the proportion of

[19] The statistical insignificance of the coefficients for weather conditions confirm the claim made by Connolly (2008). Connolly (2008) run regressions with and without consider commuting time in the total time at work, and her results were similar, suggesting that there does not appear to be an effect of rain (the main weather condition in her study) on overall commuting time.

commuting by car, along with a statistically significant negative coefficient with the proportion of commuting done by public transit and walking. The coefficients displayed suggest that each additional inch of snowfall is correlated with a increase of 0.146 percent in the daily proportion of commuting by car, and reductions of 0.072 and 0.071 percent, respectively, in the proportion of commuting done by public transit and walking.

Row 3 of Table 2 suggests that daily maximum temperature also has a statistically significant relationship with daily travel choices to commute, positive for the proportion of commuting by car, and negative for the proportion of commuting done by public modes and walking. We find that the percentage of commuting done by public transit and walking decreases by 0.096% and 0.069%, respectively, for every degree Fahrenheit increase in daily maximum temperature, while producing an increase of 0.170% in the proportion of commuting done by car. These results suggest that workers substitute their travel choices, from more eco-friendly alternatives (public transit and walking) to more polluting modes (the car), as maximum temperatures rise.

The findings that rain, snow and high temperatures are negatively correlated with the proportion of commuting done by public transit and walking, and positively associated with the proportion of commuting done by car is consistent with the hypothesis that the car seems to be an ideal travel choice for protection against inclement weather, offering a preferred microclimate while travelling and providing privacy and security (Böcker et al., 2013b; Gatersleben, 2014; Graff Zivin and Neidell, 2014); in short, a private bubble (Böcker et al., 2015). Consequently, these results show unfavorable weather leads workers to shift from public modes and walking to private vehicle usage.

Additional results

We now dig deeper into the relationship between daily commuting and high temperatures, replicating Graff Zivin and Neidell (2014), by modifying prior models by including a series of indicators for every 5-degree temperature increment, rather than a daily maximum air temperature. Specifically, we define the following maximum temperature brackets: ≤ 30ºF, 31-35ºF, 36-40ºF, 41-45ºF, …, 96-100ºF, and 100+ºF.[20] We establish

[20] The hottest band covering temperatures above 100ºF and the coldest covering temperatures below 30ºF, and 5ºF increments in-between. We omit the 76ºF-80ºF indicator variable, as do Graff Zivin and Neidell (2014), Krüger and Neugart (2018) and Jiao et al. (2021), and interpret all other temperature estimates as the change in commuting time/proportion of commuting by mode of transport associated with a particular

16 dummy variables that take value 1 if daily maximum temperature in county j at time t is within this range and 0 otherwise, including these explanatory variables in the models previously estimated, plus the snowfall and precipitation variables. The results are displayed in Table 3 and suggest that the greatest substitution from greener modes of transport (public modes, and walking) to more polluting modes of transport (private car usage) are concentrated at the extreme of the distribution of daily maximum temperature.

In Table 4, we show the results of including additional regressors in the main specifications (Eqs. (1) and (2)), by focusing here on the relationship between daily commuting and precipitation. We conduct additional analyses of the effects of precipitation, using a precipitation-band approach that allows for a more flexible function of precipitation. Specifically, we include indicators for no rain (reference or omitted category), 0-0.1 inches (considered as light rainfall), 0.1-0.2 inches, …, 0.8-0.9 inches and > 0.9 inches (considered as heavy rainfall).[21] The results suggest that rainy days are associated with a negative relationship with the proportion of commuting done by public modes, independently of the precipitation intensity (note that although we do not obtain a statistically significant relationship for the rainy days between 0.3 and 0.4 inches, and between 0.8 and 0.9 inches, the rest of the estimates suggest a negative relationship with the proportion of commuting done by public modes, indicating that workers respond by decreasing their proportion of commuting by public modes on rainy days). Surprisingly, the negative relationship between rainy days and the proportion of commuting done walking, previously identified, is only present on days with more than 0.9 inches of precipitation. Workers increase the proportion of commuting done by car on days with a total precipitation between 0.4 and 0.5 inches. Light rain (precipitation from 0 to 0.1 inches), days with 0.4-0.5 inches of precipitation, and days with 0.8-0.9 inches of precipitation are all negatively associated with the proportion of commuting done cycling.

We measure the effect of snowfall by creating 11 snowfall bands (of width 0.1 inches) as for rain, rather than the actual amount of snow, and we set the reference to no snowfall days. The results are displayed in Table 5 and suggest that there is a substitution from public transport and walking to private car on days with more than 0.9 inches of snowfall.

temperature range relative to a day with a maximum temperature of 76-80ºF. The bars in Appendix Figure A1 depict the distribution of daily maximum temperatures across these temperature-day bands over the 2003-2019 period.

[21] See Appendix Figure A2 for the distribution of daily amounts of precipitation, 2003-2019.

Days with amount of snowfall between 0.2-0.3 inches, 0.5-0.6 inches and 0.8-0.9 inches are associated with lower commuting times.

We test the sensitivity of our estimation results by a wide range of estimation methods, sample constraints, and model specifications. Table A3 shows the results of excluding public workers and the effects of weather conditions are still valid. Table A4 omits part-time workers and the results are analogous to those reported in Table 2. Table A5 drops hourly earnings from the econometric specification and maintains the rest of the regressors (prior research has indicated that education level can be considered a suitable proxy for earnings (Gimenez-Nadal and Molina, 2016; Gimenez-Nadal et al., 2018b)). Note that the results are little changed when we exclude hourly earnings from the econometric model, mainly due to the statistical significance of snowfall in the total time devoted to commuting. We also use average daily temperature (calculated as the average of the daily minimum and maximum) instead of daily maximum temperature and find similar results (reported in Table A6). As our analysis so far has focused only on the effects of weather on the day of interview, Table A7 includes additional lagged effects and the coefficients on lagged weather conditions are insignificant, while the coefficients on contemporaneous weather conditions are practically unchanged, suggesting that workers do not plan their commute to work.

Other results

For the remaining regressors included in Table 2, we find that being male is related to increases in commuting time and the proportion of commuting done by bicycle, but with a decrease in the proportion of commuting by car. Specifically, men commute about 5.7 more minutes per day than women, and their percentage of commuting by car and bicycle is 1.8 percent lower and 0.744 greater, respectively. Age has a linear positive relationship with commuting time, statistically significant at the 10% level. Native workers commute 6.6 fewer minutes per day than their non-native counterparts, and being a native US citizen is related to a lower proportion of commuting done by public transit and walking, and a higher proportion of commuting done by car. Thus, for native workers there is a greater use of private transport in detriment to the use of public and physical modes of transport while travelling to work.

Secondary and University education all have a positive significant relationship with the proportion of commuting by car, compared to those with primary education. Being a full-time worker is associated with longer commuting times, and a greater (lower) proportion of commuting done by car (walking), in comparison to their part-time counterparts. Against this, public sector workers devote less time to commuting, around 4.25 fewer minutes per day. Hourly earnings have a positive relationship to total commuting, and the proportion of commuting done by public transit, whereas the coefficient displays a negative coefficient for the proportion of commuting done by car. Workers cohabiting in a couple tend to commute more by private vehicle, against public modes and walking, which are negatively related to living with a married/unmarried partner. The number of children is negatively related to the total time devoted to commuting, consistent with the Household Responsibilities Hypothesis, since parents choose jobs closer to home to fulfill their childcare responsibilities (see Gimenez-Nadal and Molina (2016)). Finally, family size is related to an increase in the daily time devoted to commuting, and to a greater proportion of commuting done by car, while it is negatively related to the proportion of commuting done walking.

5. Heterogeneity and adaptation: Comparison across climatic regions

Table 6 shows the estimates by subgroups of the population as it seems reasonable to think that weather conditions will impact workers differentially according to their climatic regions (for example, workers in more temperate regions may be more tolerant of heat, whereas workers in colder regions could be more sensitive to warmer temperatures). We run separate regressions for the commuting-weather conditions relationship for warmer and colder areas respectively.[22] This approach allows us to document any heterogeneity in the estimates across climate areas. The results show that very hot places seem to be better adapted to greater temperatures, due to the greater frequency of these events, since we observe that extreme maximum temperatures (days

[22] The colder places are counties in the Northeast and Midwest, whereas warmer places are counties in the South and West. States in the Northeast and Midwest are Connecticut, Illinois, Indiana, Iowa, Kansas, Maine, Massachusetts, Michigan, Minnesota, Missouri, Nebraska, New Hampshire, New Jersey, New York, North Dakota, Ohio, Pennsylvania, South Dakota, and Wisconsin; states in the South and West are Alabama, Alaska, Arizona, Arkansas, California, Colorado, Delaware, District of Columbia, Florida, Georgia, Hawaii, Idaho, Kentucky, Louisiana, Maryland, Montana, Nevada, New Mexico, North Carolina, Oklahoma, Oregon, South Carolina, Tennessee, Texas, Utah, Virginia, Washington D.C., and West Virginia. Weather conditions summary statistics by climate region are reported in Appendix Table A8.

when the maximum temperature exceeds 95ºF) have a greater statistical significant impact in colder regions. Thus, workers living in colder regions are more sensitive to warmer temperatures, in contrast to those residing in warmer regions. This finding is in line with that obtained in Graff Zivin and Neidell (2014), Barreca et al. (2016), Behrer and Park (2017), Alberto et al. (2021), Heutel et al. (2021), Jiao et al. (2021), Johnston et al. (2021) and Nguyen et al. (2021), and suggests that workers in warmer areas have adapted better to temperature extremes and their commuting behavior is less elastic. Rainy days have a greater impact in colder places, whereas snow has more dramatic effects in warmer regions as estimates are more statistically significant and of a greater magnitude in absolute terms.

6. Conclusions and discussion

In this paper, we investigate how weather conditions relate to the daily commuting and mode choice of US workers, using weather and national time use data for 17 consecutive years (for the years 2003 to 2019) throughout the country. To the best of our knowledge, our study is the first investigation of the relationship between commuting, means of travel and weather conditions using time use surveys and daily data of weather conditions, on a nationally representative sample. Our findings suggest that time spent commuting is not responsive to changes in weather conditions but travel mode choices do change with precipitation, snowfall and high temperature. More specifically, results show that high temperatures, snowfall, and rain are related to a shift in commuting by public transit and walking, to using a private car. Weather aspects do not reduce the total time devoted to daily commuting as there are statistically insignificant effects of weather conditions on commuting time. Workers in hotter regions seem to be better adapted to higher temperatures.

Based on the effects of temperature and precipitation on travel choices, and given the increase in global temperatures and heavier rain (IPCC, 2021), we can expect that a warmer future (materialised in summer being unpleasantly hot and winters more pleasantly temperate), due to climate change, will increase the car share of commuting trips in the US, ultimately having a negative impact on air quality due to increased fossil fuel consumption, and leading to more congestion on roads. This may be especially harmful to the current unsustainable transportation sector of the US (Bleviss, 2021; EPA, 2022) and can also have an effect on traffic. Policymakers can use these findings to develop targeted policies to help workers avoid traffic congestion and accidents. Appropriate congestion mitigation policies must be adjusted to cope with these changes in travel behavior and the results of this study could help in designing suitable transport policy to anticipate and mitigate the effects of weather on travel behavior and better meet the travel needs of workers under different weather conditions.

We must acknowledge certain data limitations of this study. First, our data is a cross-section of individuals which limits conclusions of causality and our analysis of conditional correlations, subject to permanent unobserved individual heterogeneity in preferences. The R-squared of our regressions suggests that individual unobserved heterogeneity may influence decisions about how much time is spent in commuting trips, and what mode of travel workers use to get to their workplaces. An ideal source of data would be to follow the same respondents over time to enable us to control for individual-specific characteristics and more fully explore the dynamics of commuting. Nevertheless, weather is an external variable that cannot be influenced by individual travel habits, or any other third variable, and we can expect that our findings would be consistent in a causal analysis. The ATUS is a nationally representative time use survey in the US and results from this study may be generalizable to countries with high levels of car dependency. In fact, individuals who live in different regions develop different behaviours in different local climates (Liu et al., 2014). Hence, the importance of geographical context with regard to weather conditions should not be overlooked by policymakers.

In addition, although time use surveys are a powerful source for the analysis of daily behaviors, most time use surveys only collect one day's worth of time use per person, so it is not possible to construct an individual time use panel. (One exception to this is the United Kingdom Time Use Survey (UKTUS) 2014-2015, which collects two time diaries per respondent, and future studies using panel data have the potential to implement more sophisticated methodologies that will allow more precise estimates and disentangle the complex relationships between weather conditions, commuting time and transport mode choices.) At this point, the Panel Study of Income Dynamics (PSID), a dataset with a panel data structure, also has information on commuting in the US. However, some activities, such as commuting, have a large degree of persistence and occur frequently, so day-to-day variation is minimal (Wojan and Hamrick, 2015) and one-day diaries continue to provide reliable estimates.

Several directions emerge from the work presented here, taking advantage of the wealth of our daily climate data at the county level, which motivates our future avenues of research. First, we could further extend the analysis presented here to other travels or other countries, to test whether our results are generalizable, since changes in travel behavior in response to weather conditions are highly dependent on the trip purpose. Analytical results on the impact of weather conditions on mode choices in the US do not automatically apply to other geographical locations characterised by other climates, weather, and means of transport (e.g., the Netherlands or Denmark and cycling, Romania or Bulgaria and walking). One very promising extension would be to test the impact of weather conditions on the subjective well-being reported by workers during their commuting episodes, using the American Time Use Survey Well Being Module (2010-2012-2013-2021). According to Kahneman et al. (2004) commuting ranks as one of the least enjoyable activities and Böcker et al (2015, 2016) point out that we know very little about the role of weather on travel satisfaction and wellbeing. Connolly (2013) explores the relationship between weather (temperature and precipitation) and subjective well-being in the US, using affective data from the Princeton Affect and Time Survey (PATS), from May to August 2006, and her results reveal that temperature and rain have significant effects on feelings.

Furthermore, exploring the potentially different exposures and vulnerabilities to weather of different occupations and sub-populations (women or older workers) could generate a more precise and detailed view of our results (for more details, we refer to Graff Zivin and Neidell, 2014; Böcker et al., 2015, 2017; Noelke et al., 2016; Jiao et al., 2021; Nguyen et al., 2021; Abou-Ali et al., 2022).

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Table 1. Summary statistics

VARIABLES	Mean	Std. Dev.
Dependent variables		
Total commuting	45.604	(39.358)
% car	92.583	(25.086)
% public	3.372	(16.594)
% walking	3.345	(15.871)
% bicycle	0.700	(8.170)
Independent variables		
Precipitation (inches)	10.833	(29.500)
Rainy day (Precipitation ≥ 0.1 inches)	0.486	(0.500)
Snowfall (inches)	0.506	(4.117)
Maximum temperature (ºF)	69.339	(18.570)
Being male	0.538	(0.499)
Age	39.428	(12.699)
Native citizen	0.772	(0.419)
Primary education	0.097	(0.296)
Secondary education	0.254	(0.436)
University education	0.648	(0.478)
Full time worker	0.844	(0.363)
Public sector worker	0.160	(0.367)
Hourly earnings	21.484	(15.331)
Live in couple	0.600	(0.490)
Number of children	0.811	(1.116)
Family size	3.156	(1.547)

Notes: Sample is restricted to workers aged 16-65 on their working days, defined as days workers spend 60 minutes working excluding commuting. Self-employed workers are excluded. Statistics computed using ATUS 2003-2019 sampling demographic weights.

Table 2. Baseline results

VARIABLES	(1) Total commuting	(2) % car	(3) % public	(4) % walking	(5) % bicycle
Rainy day	-0.329	2.092***	-1.128***	-0.731**	-0.233
	(0.731)	(0.483)	(0.312)	(0.313)	(0.173)
Snowfall	-0.068	0.146***	-0.072***	-0.071***	-0.004
	(0.060)	(0.030)	(0.020)	(0.016)	(0.010)
Maximum temperature	-0.001	0.170***	-0.096***	-0.069***	-0.005
	(0.027)	(0.019)	(0.012)	(0.012)	(0.006)
Being male	5.681***	-1.798***	0.402	0.652*	0.744***
	(0.825)	(0.593)	(0.377)	(0.391)	(0.217)
Age	0.378*	-0.099	0.107	-0.016	0.007
	(0.228)	(0.145)	(0.100)	(0.090)	(0.052)
Age squared	-0.336	0.180	-0.136	-0.013	-0.032
	(0.271)	(0.169)	(0.117)	(0.105)	(0.059)
Native citizen	-6.650***	5.283***	-2.935***	-2.619***	0.272*
	(0.926)	(0.672)	(0.462)	(0.433)	(0.147)
Secondary education	-0.489	2.343**	-1.421*	-0.628	-0.294
	(1.408)	(1.033)	(0.733)	(0.659)	(0.290)
University education	1.609	2.106**	-1.108	-0.864	-0.134
	(1.372)	(1.015)	(0.727)	(0.639)	(0.287)
Full time worker	5.314***	2.191**	0.322	-2.294***	-0.219
	(0.974)	(0.852)	(0.501)	(0.637)	(0.265)
Public sector worker	-4.249***	-0.275	-0.535	0.581	0.229
	(0.958)	(0.725)	(0.474)	(0.444)	(0.273)
Hourly earnings	0.221***	-0.029*	0.029**	0.002	-0.002
	(0.034)	(0.017)	(0.012)	(0.010)	(0.006)
Live in couple	1.394	4.020***	-2.283***	-1.816***	0.078
	(0.898)	(0.595)	(0.416)	(0.346)	(0.213)
Number of children	-2.100***	-0.098	0.080	0.131	-0.113
	(0.622)	(0.394)	(0.276)	(0.219)	(0.149)
Family size	1.619***	0.723**	-0.056	-0.596***	-0.071
	(0.490)	(0.333)	(0.242)	(0.174)	(0.132)
Constant	16.751***	73.821***	11.753***	13.442***	0.983
	(5.394)	(3.886)	(2.927)	(2.130)	(1.208)
Occupation F.E.	Yes	Yes	Yes	Yes	Yes
Weekday F.E.	Yes	Yes	Yes	Yes	Yes
Month F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations (workers)	19,317	19,317	19,317	19,317	19,317
R-squared	0.068	0.042	0.028	0.024	0.013

Notes: ATUS data observation period from 2003 to 2019. Sample is restricted to workers aged 16-65 on their working days, defined as days workers spend 60 minutes working excluding commuting. Self-employed workers are excluded. Estimates computed using ATUS sampling demographic weights. Robust standard errors are shown in parentheses. Dependent variables are the total commuting time (in minutes), and the proportion of commuting by car, public, walking, and cycling mode of transport (in percentages), respectively. Y determines whether the specifications include or not controls for fixed effects. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Table 3. Additional results: maximum temperature

VARIABLES	(1) Total commuting	(2) % car	(3) % public	(4) % walking	(5) % bicycle
Rainy day	-0.374	2.283***	-1.209***	-0.791**	-0.283
	(0.735)	(0.489)	(0.323)	(0.310)	(0.175)
Snowfall	-0.044	0.093***	-0.058**	-0.045***	0.011
	(0.063)	(0.033)	(0.023)	(0.016)	(0.011)
Maximum temperature (≤ 30ºF)	-2.146	-5.330***	4.289***	1.514*	-0.473
	(2.131)	(1.401)	(0.978)	(0.812)	(0.337)
Maximum temperature (31-35ºF)	0.921	-6.792***	5.496***	1.819	-0.523
	(3.213)	(2.185)	(1.681)	(1.204)	(0.330)
Maximum temperature (36-40ºF)	-2.880	-5.259***	3.287***	1.748	0.224
	(2.373)	(1.565)	(0.947)	(1.064)	(0.545)
Maximum temperature (41-45ºF)	0.012	-7.430***	5.395***	2.285**	-0.249
	(2.192)	(1.495)	(1.129)	(0.921)	(0.426)
Maximum temperature (46-50ºF)	-0.164	-7.111***	4.353***	2.413**	0.345
	(2.064)	(1.589)	(0.963)	(0.970)	(0.688)
Maximum temperature (51-55ºF)	1.279	-2.829***	2.326***	0.529	-0.025
	(2.121)	(1.097)	(0.697)	(0.730)	(0.370)
Maximum temperature (56-60ºF)	-0.244	-3.649***	2.344***	1.042	0.263
	(1.881)	(1.129)	(0.680)	(0.764)	(0.434)
Maximum temperature (61-65ºF)	-1.690	-3.644***	2.547***	0.744	0.353
	(1.627)	(1.135)	(0.694)	(0.720)	(0.456)
Maximum temperature (66-70ºF)	1.179	-2.955***	1.455**	0.773	0.726
	(1.691)	(1.085)	(0.609)	(0.734)	(0.480)
Maximum temperature (71-75ºF)	-1.262	0.066	-0.013	-0.132	0.080
	(1.543)	(0.950)	(0.492)	(0.712)	(0.378)
Maximum temperature (81-85ºF)	-1.540	1.651	0.320	-1.333*	-0.638**
	(1.483)	(1.008)	(0.635)	(0.692)	(0.321)
Maximum temperature (86-90ºF)	-0.293	3.289***	-0.635	-2.112***	-0.542
	(1.612)	(0.998)	(0.663)	(0.642)	(0.330)
Maximum temperature (91-95ºF)	-1.735	3.936***	-0.922	-2.687***	-0.327
	(1.950)	(1.187)	(0.783)	(0.726)	(0.494)
Maximum temperature (96-100ºF)	-4.773*	5.331***	-2.838***	-2.093*	-0.401
	(2.707)	(1.640)	(0.808)	(1.255)	(0.727)
Maximum temperature (> 100ºF)	4.112	6.974***	-2.737***	-3.727***	-0.510
	(3.262)	(1.565)	(0.804)	(1.020)	(0.843)
Constant	16.895***	86.843***	3.762	8.711***	0.684
	(5.541)	(3.654)	(2.632)	(2.082)	(1.259)
Socio-demographics	Y	Y	Y	Y	Y
Occupation F.E.	Y	Y	Y	Y	Y
Weekday F.E.	Y	Y	Y	Y	Y
Month F.E.	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y
Observations (workers)	19,317	19,317	19,317	19,317	19,317
R-squared	0.069	0.044	0.030	0.026	0.015

Notes: ATUS data observation period from 2003 to 2019. Sample is restricted to workers aged 16-65 on their working days, defined as days workers spend 60 minutes working excluding commuting. Self-employed workers are excluded. Estimates computed using ATUS sampling demographic weights. Robust standard errors are shown in parentheses. Dependent variables are the total commuting time (in minutes), and the proportion of commuting by car, public, walking and cycling mode of transport (in percentages), respectively. Y determines whether the specifications include or not controls for socio-demographics and fixed effects. Full model results including socio-demographics are available from the authors on request. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Table 4. Additional results: rainy days

VARIABLES	(1) Total commuting	(2) % car	(3) % public	(4) % walking	(5) % bicycle
Rainy day (0-0.1 inches)	-1.501	1.352	-1.797***	1.007	-0.562**
	(1.864)	(1.775)	(0.674)	(1.737)	(0.250)
Rainy day (0.1-0.2 inches)	-1.580	2.761**	-2.833***	0.450	-0.378
	(1.881)	(1.232)	(0.455)	(1.106)	(0.333)
Rainy day (0.2-0.3 inches)	-0.220	1.707	-2.014***	0.619	-0.313
	(2.436)	(1.827)	(0.763)	(1.556)	(0.475)
Rainy day (0.3-0.4 inches)	-2.113	3.050*	-1.478	-1.437	-0.135
	(2.721)	(1.635)	(0.913)	(1.154)	(0.445)
Rainy day (0.4-0.5 inches)	1.003	4.674***	-2.817***	-1.122	-0.736***
	(3.031)	(1.084)	(0.607)	(0.864)	(0.168)
Rainy day (0.5-0.6 inches)	0.832	2.213	-2.244**	0.412	-0.381
	(5.406)	(2.455)	(1.103)	(1.857)	(0.530)
Rainy day (0.6-0.7 inches)	-3.604	2.039	-1.999*	-0.712	0.673
	(2.906)	(2.931)	(1.101)	(2.235)	(1.612)
Rainy day (0.7-0.8 inches)	-4.759	0.094	-3.101***	1.705	1.302
	(3.028)	(3.156)	(0.649)	(2.725)	(1.555)
Rainy day (0.8-0.9 inches)	-1.625	2.209	-0.638	-1.025	-0.546***
	(4.471)	(2.471)	(2.060)	(1.355)	(0.181)
Rainy day (more than 0.9 inches)	-0.181	2.069***	-0.971***	-0.806***	-0.292
	(0.805)	(0.514)	(0.347)	(0.304)	(0.190)
Snowfall	-0.074	0.149***	-0.079***	-0.068***	-0.003
	(0.060)	(0.030)	(0.021)	(0.016)	(0.010)
Maximum temperature	-0.001	0.170***	-0.095***	-0.070***	-0.005
	(0.027)	(0.019)	(0.012)	(0.012)	(0.006)
Constant	16.864***	73.656***	11.911***	13.369***	1.064
	(5.396)	(3.890)	(2.926)	(2.132)	(1.212)
Socio-demographics	Y	Y	Y	Y	Y
Occupation F.E.	Y	Y	Y	Y	Y
Weekday F.E.	Y	Y	Y	Y	Y
Month F.E.	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y
Observations (workers)	19,317	19,317	19,317	19,317	19,317
R-squared	0.068	0.042	0.029	0.025	0.013

Notes: ATUS data observation period from 2003 to 2019. Sample is restricted to workers aged 16-65 on their working days, defined as days workers spend 60 minutes working excluding commuting. Self-employed workers are excluded. Estimates computed using ATUS sampling demographic weights. Robust standard errors are shown in parentheses. Dependent variables are the total commuting time (in minutes), and the proportion of commuting by car, public, walking and cycling mode of transport (in percentages), respectively. Y determines whether the specifications include or not controls for socio-demographics and fixed effects. Full model results including socio-demographics are available from the authors on request. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Table 5. Additional results: snowfall

VARIABLES	(1) Total commuting	(2) % car	(3) % public	(4) % walking	(5) % bicycle
Rainy day	-0.231	1.992***	-1.023***	-0.699**	-0.271
	(0.739)	(0.487)	(0.314)	(0.319)	(0.170)
Snowfall (0-0.1 inches)	-3.934	-2.926	1.646	2.066	-0.786***
	(10.377)	(6.612)	(5.572)	(3.810)	(0.287)
Snowfall (0.1-0.2 inches)	-3.533	0.551	-4.935***	4.739	-0.355
	(6.436)	(6.037)	(0.630)	(6.311)	(0.235)
Snowfall (0.2-0.3 inches)	-11.684***	-6.986	-1.473	6.467	1.992
	(4.369)	(6.500)	(2.984)	(5.836)	(2.228)
Snowfall (0.3-0.4 inches)	17.748	0.701	-4.718***	-2.783***	6.799
	(21.559)	(7.186)	(0.704)	(0.841)	(6.992)
Snowfall (0.4-0.5 inches)	0.662	-1.633	4.353	-2.466**	-0.254
	(6.754)	(5.170)	(5.283)	(0.986)	(0.316)
Snowfall (0.5-0.6 inches)	-20.508***	2.160	-3.338***	0.465	0.713
	(3.869)	(3.801)	(0.831)	(3.459)	(1.184)
Snowfall (0.6-0.7 inches)	-1.028	1.193	-3.431**	2.726	-0.487*
	(7.672)	(5.635)	(1.369)	(5.478)	(0.276)
Snowfall (0.7-0.8 inches)	1.362	-1.518	3.857	-2.078	-0.260
	(6.043)	(8.372)	(8.293)	(2.168)	(0.277)
Snowfall (0.8-0.9 inches)	-10.023**	-13.057	-3.623***	17.409	-0.729**
	(4.673)	(16.738)	(0.663)	(16.705)	(0.301)
Snowfall (more than 0.9 inches)	-2.505	3.745***	-2.189***	-1.864***	0.308
	(1.705)	(1.205)	(0.753)	(0.579)	(0.670)
Maximum temperature	-0.011	0.176***	-0.103***	-0.070***	-0.003
	(0.028)	(0.020)	(0.014)	(0.012)	(0.006)
Constant	17.416***	73.264***	12.212***	13.729***	0.795
	(5.462)	(3.972)	(2.969)	(2.155)	(1.303)
Socio-demographics	Y	Y	Y	Y	Y
Occupation F.E.	Y	Y	Y	Y	Y
Weekday F.E.	Y	Y	Y	Y	Y
Month F.E.	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y
Observations (workers)	19,317	19,317	19,317	19,317	19,317
R-squared	0.069	0.042	0.028	0.026	0.014

Notes: ATUS data observation period from 2003 to 2019. Sample is restricted to workers aged 16-65 on their working days, defined as days workers spend 60 minutes working excluding commuting. Self-employed workers are excluded. Estimates computed using ATUS sampling demographic weights. Robust standard errors are shown in parentheses. Dependent variables are the total commuting time (in minutes), and the proportion of commuting by car, public, walking and cycling mode of transport (in percentages), respectively. Y determines whether the specifications include or not controls for socio-demographics and fixed effects. Full model results including socio-demographics are available from the authors on request. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Table 6. Heterogeneity results by climatic regions

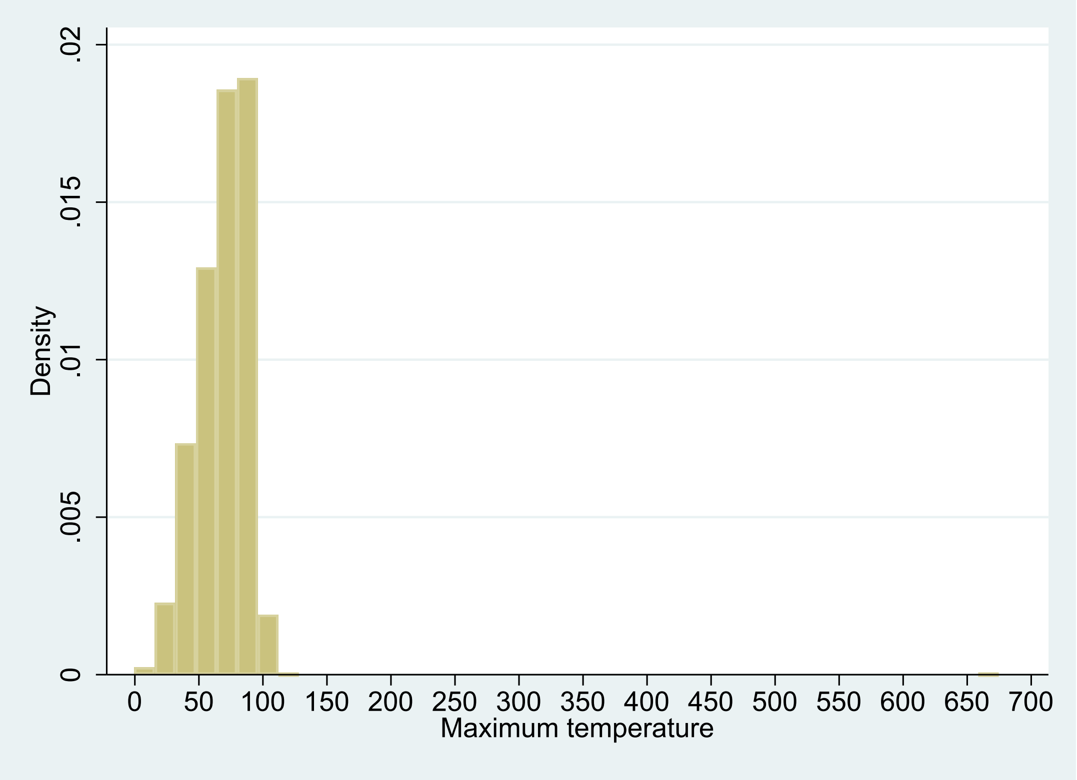
	Warmer region					Colder region				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
VARIABLES	Total commuting	% car	% public	% walking	% bicycle	Total commuting	% car	% public	% walking	% bicycle
Rainy day	0.220	1.286**	-0.642**	-0.455	-0.189	-1.063	3.722***	-2.324***	-1.170**	-0.228
	(0.879)	(0.538)	(0.295)	(0.379)	(0.240)	(1.281)	(0.887)	(0.662)	(0.494)	(0.202)
Snowfall	0.050	0.151***	-0.070***	-0.066**	-0.015	-0.049	0.051	-0.030	-0.034	0.013
	(0.097)	(0.041)	(0.021)	(0.026)	(0.013)	(0.081)	(0.047)	(0.035)	(0.021)	(0.013)
Maximum temperature (≤ 30ºF)	-7.919*	-2.555	3.180**	0.017	-0.641	-0.472	2.857	-1.649	-0.307	-0.902
	(4.641)	(2.211)	(1.599)	(1.176)	(0.423)	(3.751)	(2.634)	(1.850)	(1.478)	(0.923)
Maximum temperature (31-35ºF)	-6.916	-3.903	3.930**	0.276	-0.303	2.937	0.741	-0.136	0.372	-0.977
	(4.246)	(2.453)	(1.873)	(1.123)	(0.422)	(4.557)	(3.154)	(2.330)	(1.817)	(0.901)
Maximum temperature (36-40ºF)	-10.108***	-5.196**	0.451	2.764*	1.980	0.142	2.652	-1.448	-0.379	-0.825
	(3.082)	(2.374)	(0.560)	(1.553)	(1.734)	(3.961)	(2.743)	(1.885)	(1.698)	(0.921)
Maximum temperature (41-45ºF)	-9.751***	-4.942***	2.644***	2.775**	-0.477	6.268	-0.852	1.595	0.043	-0.785
	(2.631)	(1.769)	(0.982)	(1.374)	(0.388)	(3.948)	(2.802)	(2.154)	(1.516)	(1.029)
Maximum temperature (46-50ºF)	-6.244**	-3.452**	2.634**	0.904	-0.086	4.766	-3.019	0.682	2.121	0.216
	(2.532)	(1.699)	(1.150)	(1.210)	(0.428)	(3.806)	(2.907)	(1.815)	(1.668)	(1.341)
Maximum temperature (51-55ºF)	-4.544*	-2.821**	2.150***	0.140	0.531	8.200**	3.405	-1.884	-0.501	-1.020
	(2.612)	(1.317)	(0.791)	(0.895)	(0.544)	(3.809)	(2.385)	(1.688)	(1.382)	(0.805)
Maximum temperature (56-60ºF)	-3.618*	-4.633***	2.036***	1.978*	0.619	4.963	3.017	-0.874	-1.388	-0.755
	(2.157)	(1.410)	(0.632)	(1.081)	(0.595)	(3.555)	(2.372)	(1.794)	(1.224)	(0.825)
Maximum temperature (61-65ºF)	-4.417**	-2.825**	1.624**	0.356	0.845	3.340	-1.070	1.272	0.794	-0.995
	(1.802)	(1.317)	(0.641)	(0.900)	(0.639)	(3.251)	(2.265)	(1.679)	(1.265)	(0.704)
Maximum temperature (66-70ºF)	-0.743	-2.716**	1.065**	0.519	1.133*	4.616	-0.830	0.201	1.037	-0.408
	(1.997)	(1.190)	(0.520)	(0.873)	(0.630)	(3.088)	(2.300)	(1.527)	(1.442)	(0.703)
Maximum temperature (71-75ºF)	-3.355*	-0.476	0.354	0.256	-0.135	3.136	1.825	-1.498	-0.753	0.426
	(1.719)	(1.077)	(0.394)	(0.923)	(0.425)	(3.073)	(1.807)	(1.242)	(1.080)	(0.715)
Maximum temperature (81-85ºF)	-2.455	2.128**	0.100	-1.513*	-0.716	1.459	-0.501	1.896	-0.780	-0.616
	(1.686)	(1.025)	(0.414)	(0.833)	(0.439)	(2.845)	(2.122)	(1.632)	(1.209)	(0.410)
Maximum temperature (86-90ºF)	0.379	2.988***	0.665	-2.750***	-0.903*	0.411	0.729	-0.470	0.204	-0.463

	(1.828)	(1.157)	(0.698)	(0.769)	(0.471)	(3.136)	(2.006)	(1.405)	(1.336)	(0.429)
Maximum temperature (91-95ºF)	-2.175	4.079***	-0.037	-2.917***	-1.125*	4.580	-5.789	5.445	-0.538	0.882
	(2.199)	(1.295)	(0.633)	(0.919)	(0.632)	(4.102)	(4.079)	(3.542)	(1.638)	(1.461)
Maximum temperature (96-100ºF)	-2.043	3.005	-0.196	-1.784	-1.025	-21.323***	11.111***	-6.956***	-3.381*	-0.774
	(2.921)	(1.897)	(0.871)	(1.462)	(0.891)	(5.655)	(3.330)	(2.108)	(1.906)	(0.485)
Maximum temperature (> 100ºF)	4.682	5.049***	-0.390	-3.372***	-1.286	-5.826	19.617***	-10.399***	-7.793**	-1.425
	(3.403)	(1.712)	(0.773)	(1.171)	(0.954)	(11.892)	(7.237)	(3.870)	(3.420)	(1.381)
Constant	23.963***	91.747***	0.512	6.698***	1.043	7.691	69.466***	16.795***	13.735***	0.003
	(6.945)	(4.012)	(2.502)	(2.547)	(1.663)	(8.811)	(6.977)	(5.246)	(3.805)	(2.152)
Socio-demographics	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Occupation F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Weekday F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations (workers)	11,876	11,876	11,876	11,876	11,876	7,441	7,441	7,441	7,441	7,441
R-squared	0.073	0.040	0.024	0.027	0.021	0.086	0.083	0.066	0.046	0.034

Notes: ATUS data observation period from 2003 to 2019. Sample is restricted to workers aged 16-65 on their working days, defined as days workers spend 60 minutes working excluding commuting. Self-employed workers are excluded. Estimates computed using ATUS sampling demographic weights. Robust standard errors are shown in parentheses. Dependent variables are the total commuting time (in minutes), and the proportion of commuting by car, public, walking and cycling mode of transport (in percentages), respectively. Y determines whether the specifications include or not controls for socio-demographics and fixed effects. Full model results including socio-demographics are available from the authors on request. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

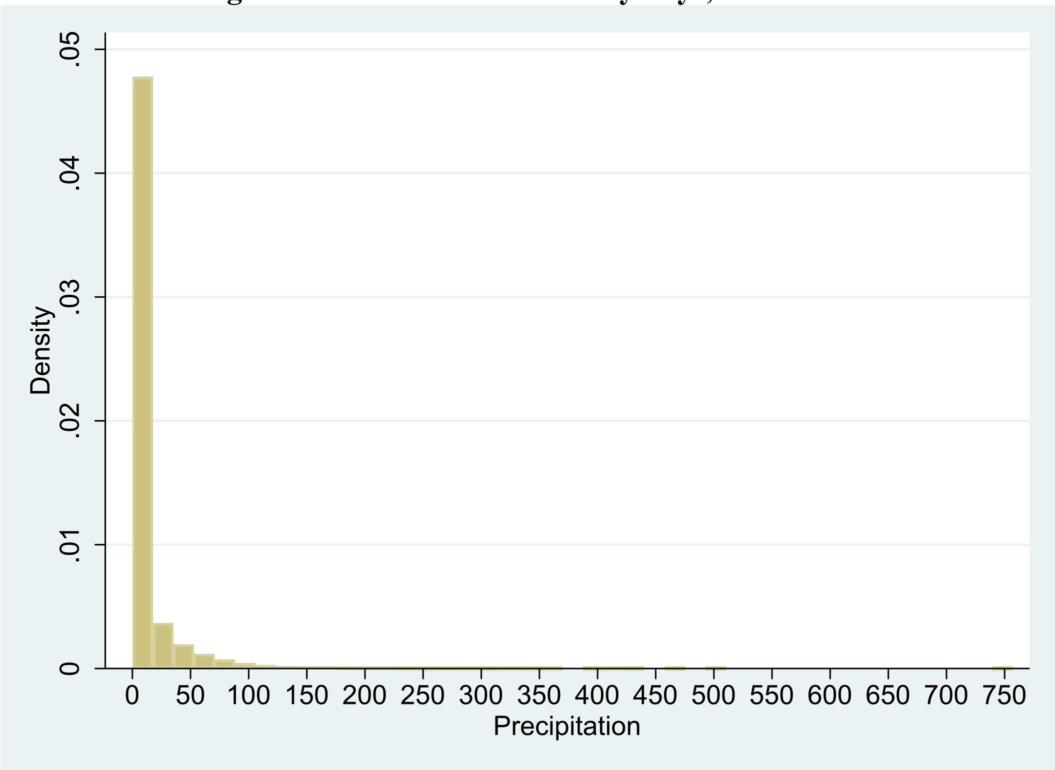
APPENDIX

Figure A1. Distribution of daily maximum temperature, 2003-2019



Source: Authors' calculation

Figure A2. Distribution of rainy days, 2003-2019



Source: Authors' calculation

Table A1. Description of Time Use categories

Category	Activity description (Code in parenthesis)
Commuting	Travel to/from work (180501)
Market work	Work/main job (50101); Work, other job(s) (50102); Security procedures related to work (50103); Waiting associated with working (50104); Working, n.e.c. (50199); Socializing, relaxing, and leisure as part of job (50201); Eating and drinking as part of job (50202); Sports and exercise as part of job (50203); Security procedures as part of job (50204); Waiting associated with work-related activities (50205); Work-related activities, n.e.c. (50299); Income-generating hobbies, craft, and food (50301); Income-generating performances (50302); Income-generating services (50303); Income-generating rental property activities (50304); Waiting associated with other income-generating activities (2004+) (50305); Other income-generating activities, n.e.c. (50399); Job search activities (50401); Job interviewing (50403); Waiting associated with job search or interview (50404); Security procedures related to job search or interviewing (50405); Job search and interviewing, n.e.c. (50499); Work and work-related activities, n.e.c. (59999); Taking class for degree, certification, or licensure (60101); Taking class for personal interest (60102); Waiting associated with taking classes (60103); Security procedures related to taking classes (60104); Taking class, n.e.c. (60199); Extracurricular club activities (60201); Extracurricular music and performance activities (60202); Extracurricular student government activities (60203); Waiting associated with extracurricular activities (2004+) (60204); Education-related extracurricular activities, n.e.c. (60299); Research or homework for class (for degree, certification, or licensure) (60301); Research or homework for class (for personal interest) (60302); Waiting associated with research or homework (60303); Research or homework, n.e.c. (60399); Administrative activities: class for degree, certification, or licensure (60401); Administrative activities: class for personal interest (60402); Waiting associated with administrative activities (education) (60403); Administrative for education, n.e.c. (60499); Education, n.e.c. (69999); Teaching, leading, counseling, mentoring (150204); Travel related to work-related activities (180502); Travel related to income-generating activities (2004+) (180503); Travel related to job search and interviewing (2004+) (180504); Travel related to work, n.e.c. (180599); Travel related to taking class (180601); Travel related to extracurricular activities (ex. sports) (2005+) (180602); Travel related to research or homework (2005+) (180603); Travel related to registration or administrative activities (2005+) (180604); Education-related travel, not commuting (2003, 2004) (180605); Travel related to education, n.e.c. (180699)

Source: Author's own elaboration

Table A2. Description of socio-demographics set from 2003-2019 ATUS

Variable	Details and measurements
Being male	Coded from sex, 1 if male. Value 0 otherwise
Age	Coded from age, measured in years
Native citizen	Coded from citizen, 1 if citizen equal to "Native, born in United States". Value 0 otherwise
Primary education	Coded from educ, 1 if educ equal to "Less than 1st grade", "1st, 2nd, 3rd, or 4th grade", "5th or 6th grade", "7th or 8th grade", "9th grade", "10 th grade", "11th grade", "12 th grade, no diploma". Value 0 otherwise
Secondary education	Coded from educ, 1 if educ equal to "High school graduate – GED", "High school graduate – diploma". Value 0 otherwise
University education	Coded from educ, 1 if educ equal to "Some college but no degree", "Associate degree - occupational vocational", "Associate degree - academic program", "Bachelor's degree (BA, AB, BS, etc.)", "Master's degree (MA, MS, MEng, MEd, MSW, etc.)", "Professional school degree (MD, DDS, DVM, etc.)", "Doctoral degree (PhD, EdD, etc.)". Value 0 otherwise
Full time worker	Coded from fullpart, 1 if fullpart equal to "Full time". Value 0 otherwise
Public sector worker	Coded from clwkr, 1 if clwkr qual to "Government, federal", "Government, state", "Government, local". Value 0 otherwise
Hourly earnings	Coded from hourwage, earnweek and uhrsworkt
Live in couple	Coded from spousepres, 1 if spousepres equal to "Spouse present", "Unmarried partner present". Value 0 otherwise
Number of children	Coded from hh_numkids: Number of children under 18 in household
Family size	Coded from hh_size: Number of people in household

Source: Author's own elaboration

Table A3. Baseline estimates excluding public sector workers

VARIABLES	(1) Total commuting	(2) % car	(3) % public	(4) % walking	(5) % bicycle
Rainy day	0.014	2.001***	-1.225***	-0.621*	-0.155
	(0.822)	(0.537)	(0.355)	(0.348)	(0.183)
Snowfall	-0.119*	0.143***	-0.077***	-0.064***	-0.001
	(0.067)	(0.033)	(0.022)	(0.017)	(0.011)
Maximum temperature	-0.004	0.177***	-0.098***	-0.072***	-0.007
	(0.030)	(0.021)	(0.014)	(0.013)	(0.007)
Being male	6.088***	-1.853***	0.435	0.824*	0.594**
	(0.929)	(0.665)	(0.432)	(0.435)	(0.235)
Age	0.457*	-0.219	0.187*	0.034	-0.001
	(0.256)	(0.160)	(0.113)	(0.096)	(0.056)
Age squared	-0.428	0.328*	-0.233*	-0.083	-0.013
	(0.306)	(0.188)	(0.132)	(0.114)	(0.064)
Native citizen	-6.029***	4.964***	-2.590***	-2.615***	0.240
	(0.997)	(0.719)	(0.494)	(0.456)	(0.163)
Secondary education	-0.068	2.027*	-1.397*	-0.310	-0.320
	(1.487)	(1.058)	(0.759)	(0.659)	(0.303)
University education	1.797	2.087**	-1.126	-0.743	-0.218
	(1.448)	(1.044)	(0.757)	(0.642)	(0.293)
Full time worker	5.106***	2.137**	0.158	-2.296***	0.001
	(1.080)	(0.919)	(0.564)	(0.683)	(0.247)
Hourly earnings	0.239***	-0.046**	0.041***	0.007	-0.001
	(0.034)	(0.022)	(0.016)	(0.012)	(0.007)
Live in couple	1.440	3.913***	-2.401***	-1.693***	0.181
	(1.009)	(0.658)	(0.470)	(0.374)	(0.227)
Number of children	-2.200***	-0.157	0.089	0.144	-0.076
	(0.692)	(0.424)	(0.308)	(0.222)	(0.167)
Family size	1.834***	0.854**	-0.085	-0.716***	-0.053
	(0.546)	(0.368)	(0.273)	(0.185)	(0.151)
Constant	13.821**	75.925***	10.204***	12.986***	0.885
	(6.010)	(4.300)	(3.306)	(2.264)	(1.301)
Occupation F.E.	Y	Y	Y	Y	Y
Weekday F.E.	Y	Y	Y	Y	Y
Month F.E.	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y
Observations (workers)	15,979	15,979	15,979	15,979	15,979
R-squared	0.068	0.044	0.029	0.026	0.015

Notes: ATUS data observation period from 2003 to 2019. Sample is restricted to workers aged 16-65 on their working days, defined as days workers spend 60 minutes working excluding commuting. Self-employed and public sector workers are excluded. Estimates computed using ATUS 2003-2019 sampling demographic weights. Robust standard errors are shown in parentheses. Dependent variables are the total commuting time (in minutes), and the proportion of commuting by car, public, walking and cycling mode of transport (in percentages), respectively. Y determines whether the specifications include or not controls for fixed effects. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Table A4. Baseline estimates omitting part-time workers

VARIABLES	(1) Total commuting	(2) % car	(3) % public	(4) % walking	(5) % bicycle
Rainy day	-0.207	2.229***	-1.192***	-0.715**	-0.322*
	(0.818)	(0.506)	(0.337)	(0.313)	(0.186)
Snowfall	-0.035	0.131***	-0.073***	-0.060***	0.001
	(0.066)	(0.032)	(0.022)	(0.016)	(0.011)
Maximum temperature	0.009	0.181***	-0.101***	-0.069***	-0.010
	(0.030)	(0.020)	(0.013)	(0.012)	(0.007)
Being male	5.367***	-1.421**	0.334	0.279	0.808***
	(0.928)	(0.616)	(0.397)	(0.394)	(0.239)
Age	0.227	0.137	-0.052	-0.039	-0.047
	(0.283)	(0.162)	(0.116)	(0.094)	(0.062)
Age squared	-0.169	-0.087	0.044	0.011	0.032
	(0.332)	(0.188)	(0.136)	(0.107)	(0.070)
Native citizen	-6.675***	4.245***	-2.974***	-1.628***	0.356**
	(1.031)	(0.678)	(0.474)	(0.416)	(0.165)
Secondary education	-1.140	1.782	-0.748	-0.528	-0.507
	(1.749)	(1.091)	(0.738)	(0.695)	(0.361)
University education	1.262	1.331	-0.323	-0.683	-0.325
	(1.727)	(1.093)	(0.747)	(0.684)	(0.361)
Public sector worker	-4.036***	-0.037	-0.484	0.477	0.044
	(1.059)	(0.743)	(0.512)	(0.404)	(0.280)
Hourly earnings	0.274***	-0.062***	0.046***	0.017	-0.000
	(0.035)	(0.023)	(0.016)	(0.012)	(0.008)
Live in couple	1.274	3.896***	-2.311***	-1.673***	0.087
	(0.995)	(0.604)	(0.399)	(0.357)	(0.233)
Number of children	-2.140***	0.094	-0.002	0.025	-0.116
	(0.723)	(0.435)	(0.318)	(0.216)	(0.172)
Family size	1.746***	0.604*	-0.097	-0.478***	-0.029
	(0.567)	(0.335)	(0.233)	(0.167)	(0.153)
Constant	22.843***	72.204***	15.244***	11.066***	1.487
	(6.836)	(4.302)	(3.289)	(2.206)	(1.428)
Occupation F.E.	Y	Y	Y	Y	Y
Weekday F.E.	Y	Y	Y	Y	Y
Month F.E.	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y
Observations (workers)	16,428	16,428	16,428	16,428	16,428
R-squared	0.057	0.046	0.032	0.023	0.017

Notes: ATUS data observation period from 2003 to 2019. Sample is restricted to workers aged 16-65 on their working days, defined as days workers spend 60 minutes working excluding commuting. Self-employed and part-time workers are excluded. Estimates computed using ATUS 2003-2019 sampling demographic weights. Robust standard errors are shown in parentheses. Dependent variables are the total commuting time (in minutes), and the proportion of commuting by car, public, walking and cycling mode of transport (in percentages), respectively. Y determines whether the specifications include or not controls for fixed effects. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Table A5. Baseline estimates omitting hourly earnings

VARIABLES	(1) Total commuting	(2) % car	(3) % public	(4) % walking	(5) % bicycle
Rainy day	-0.363	1.991***	-1.061***	-0.746**	-0.184
	(0.719)	(0.455)	(0.296)	(0.295)	(0.164)
Snowfall	-0.115**	0.145***	-0.075***	-0.063***	-0.008
	(0.053)	(0.028)	(0.018)	(0.017)	(0.008)
Maximum temperature	-0.008	0.172***	-0.097***	-0.069***	-0.006
	(0.027)	(0.017)	(0.012)	(0.011)	(0.006)
Being male	6.333***	-1.514***	0.129	0.682*	0.703***
	(0.794)	(0.561)	(0.370)	(0.362)	(0.197)
Age	0.505**	-0.098	0.084	-0.009	0.023
	(0.219)	(0.138)	(0.096)	(0.085)	(0.049)
Age squared	-0.465*	0.180	-0.108	-0.023	-0.049
	(0.260)	(0.161)	(0.111)	(0.099)	(0.056)
Native citizen	-6.819***	4.962***	-2.940***	-2.265***	0.243*
	(0.888)	(0.623)	(0.434)	(0.397)	(0.139)
Secondary education	-0.948	3.016***	-1.687**	-0.778	-0.552*
	(1.403)	(1.014)	(0.704)	(0.665)	(0.311)
University education	2.448*	2.571**	-1.133	-1.064	-0.374
	(1.363)	(1.004)	(0.699)	(0.657)	(0.307)
Full time worker	5.535***	1.982**	0.419	-2.153***	-0.247
	(0.961)	(0.775)	(0.467)	(0.571)	(0.247)
Public sector worker	-3.666***	-0.690	-0.132	0.617	0.206
	(0.946)	(0.751)	(0.534)	(0.433)	(0.270)
Live in couple	1.503*	4.027***	-2.357***	-1.739***	0.069
	(0.875)	(0.566)	(0.400)	(0.329)	(0.200)
Number of children	-1.995***	-0.013	0.025	0.135	-0.147
	(0.595)	(0.374)	(0.269)	(0.204)	(0.141)
Family size	1.499***	0.636**	0.005	-0.589***	-0.052
	(0.476)	(0.318)	(0.236)	(0.162)	(0.126)
Constant	18.831***	73.078***	13.056***	12.775***	1.091
	(5.297)	(3.730)	(2.880)	(2.000)	(1.120)
Occupation F.E.	Y	Y	Y	Y	Y
Weekday F.E.	Y	Y	Y	Y	Y
Month F.E.	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y
Observations (workers)	21,664	21,664	21,664	21,664	21,664
R-squared	0.057	0.040	0.028	0.022	0.012

Notes: ATUS data observation period from 2003 to 2019. Sample is restricted to workers aged 16-65 on their working days, defined as days workers spend 60 minutes working excluding commuting. Self-employed workers are excluded. Estimates computed using ATUS 2003-2019 sampling demographic weights. Robust standard errors are shown in parentheses. Dependent variables are the total commuting time (in minutes), and the proportion of commuting by car, public, walking and cycling mode of transport (in percentages), respectively. Y determines whether the specifications include or not controls for fixed effects. * *p*-value < 0.1, ** *p*-value < 0.05, *** *p*-value < 0.01.

Table A6. Baseline estimates including average temperature

VARIABLES	(1) Total commuting	(2) % car	(3) % public	(4) % walking	(5) % bicycle
Rainy day	-0.305	1.563***	-0.828***	-0.517*	-0.218
	(0.721)	(0.475)	(0.304)	(0.309)	(0.172)
Snowfall	-0.054	0.123***	-0.057***	-0.062***	-0.004
	(0.060)	(0.029)	(0.020)	(0.015)	(0.009)
Average temperature	0.021	0.139***	-0.075***	-0.057***	-0.007
	(0.028)	(0.019)	(0.012)	(0.012)	(0.007)
Being male	5.680***	-1.811***	0.409	0.657*	0.744***
	(0.826)	(0.595)	(0.378)	(0.392)	(0.217)
Age	0.375*	-0.099	0.107	-0.016	0.007
	(0.228)	(0.145)	(0.100)	(0.090)	(0.052)
Age squared	-0.332	0.181	-0.136	-0.013	-0.032
	(0.271)	(0.169)	(0.117)	(0.105)	(0.059)
Native citizen	-6.593***	5.299***	-2.937***	-2.627***	0.266*
	(0.928)	(0.675)	(0.464)	(0.434)	(0.146)
Secondary education	-0.449	2.261**	-1.372*	-0.594	-0.295
	(1.407)	(1.034)	(0.733)	(0.660)	(0.290)
University education	1.656	2.020**	-1.055	-0.829	-0.136
	(1.372)	(1.017)	(0.728)	(0.639)	(0.286)
Full time worker	5.292***	2.220***	0.304	-2.306***	-0.218
	(0.975)	(0.852)	(0.501)	(0.637)	(0.266)
Public sector worker	-4.250***	-0.251	-0.550	0.572	0.229
	(0.958)	(0.725)	(0.474)	(0.444)	(0.274)
Hourly earnings	0.222***	-0.031*	0.030**	0.003	-0.002
	(0.034)	(0.017)	(0.012)	(0.010)	(0.006)
Live in couple	1.416	4.004***	-2.270***	-1.810***	0.077
	(0.897)	(0.595)	(0.416)	(0.346)	(0.213)
Number of children	-2.094***	-0.095	0.080	0.129	-0.114
	(0.623)	(0.394)	(0.276)	(0.219)	(0.149)
Family size	1.615***	0.728**	-0.059	-0.598***	-0.071
	(0.490)	(0.333)	(0.242)	(0.174)	(0.132)
Constant	15.707***	77.038***	9.823***	12.162***	0.977
	(5.386)	(3.808)	(2.861)	(2.091)	(1.190)
Occupation F.E.	Y	Y	Y	Y	Y
Weekday F.E.	Y	Y	Y	Y	Y
Month F.E.	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y
Observations (workers)	19,312	19,312	19,312	19,312	19,312
R-squared	0.068	0.038	0.025	0.023	0.013

Notes: ATUS data observation period from 2003 to 2019. Sample is restricted to workers aged 16-65 on their working days, defined as days workers spend 60 minutes working excluding commuting. Self-employed workers are excluded. Estimates computed using ATUS sampling demographic weights. Robust standard errors are shown in parentheses. Dependent variables are the total commuting time (in minutes), and the proportion of commuting by car, by public, walking and cycling mode of transport (in percentages), respectively. Y determines whether the specifications include or not controls for fixed effects. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Table A7. Intertemporal estimates

VARIABLES	(1) Total commuting	(2) % car	(3) % public	(4) % walking	(5) % bicycle
Lagged rainy day $(t-1)$	0.197	0.624	-0.128	-0.371	-0.125
	(0.847)	(0.575)	(0.381)	(0.360)	(0.196)
Rainy day (t)	-0.500	1.765***	-1.004***	-0.607*	-0.155
	(0.849)	(0.573)	(0.373)	(0.357)	(0.210)
Lagged snowfall $(t-1)$	-0.922	-0.070	-0.455	-0.015	0.540
	(0.609)	(0.771)	(0.283)	(0.285)	(0.584)
Snowfall (t)	-0.047	0.151***	-0.061***	-0.074***	-0.016**
	(0.059)	(0.032)	(0.021)	(0.017)	(0.008)
Lagged max. temperature $(t-1)$	0.027	0.050	-0.058*	0.017	-0.008
	(0.063)	(0.048)	(0.033)	(0.030)	(0.014)
Maximum temperature (t)	-0.030	0.129***	-0.046	-0.088***	0.005
	(0.065)	(0.048)	(0.033)	(0.030)	(0.015)
Being male	5.737***	-1.774***	0.375	0.655*	0.745***
	(0.833)	(0.597)	(0.381)	(0.396)	(0.214)
Age	0.406*	-0.100	0.106	-0.007	0.001
	(0.227)	(0.146)	(0.101)	(0.090)	(0.052)
Age squared	-0.365	0.184	-0.133	-0.025	-0.026
	(0.271)	(0.171)	(0.117)	(0.105)	(0.060)
Native citizen	-6.753***	5.277***	-2.945***	-2.600***	0.267*
	(0.936)	(0.677)	(0.466)	(0.435)	(0.148)
Secondary education	-0.439	2.389**	-1.455**	-0.628	-0.306
	(1.418)	(1.041)	(0.739)	(0.665)	(0.293)
University education	1.529	2.159**	-1.135	-0.895	-0.129
	(1.375)	(1.022)	(0.733)	(0.643)	(0.289)
Full time worker	5.132***	2.168**	0.366	-2.337***	-0.196
	(0.979)	(0.858)	(0.504)	(0.644)	(0.263)
Public sector worker	-4.171***	-0.308	-0.534	0.629	0.213
	(0.965)	(0.731)	(0.478)	(0.448)	(0.276)
Hourly earnings	0.224***	-0.028	0.028**	0.002	-0.002
	(0.035)	(0.017)	(0.012)	(0.010)	(0.006)
Live in couple	1.392	3.995***	-2.278***	-1.828***	0.111
	(0.905)	(0.599)	(0.419)	(0.350)	(0.211)
Number of children	-2.084***	-0.106	0.088	0.134	-0.116
	(0.628)	(0.397)	(0.278)	(0.221)	(0.148)
Family size	1.652***	0.721**	-0.056	-0.598***	-0.066
	(0.494)	(0.335)	(0.244)	(0.175)	(0.131)
Constant	15.707***	73.056***	12.389***	13.605***	0.951
	(5.397)	(3.939)	(2.933)	(2.182)	(1.271)
Occupation F.E.	Y	Y	Y	Y	Y
Weekday F.E.	Y	Y	Y	Y	Y
Month F.E.	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y
Observations (workers)	19,158	19,158	19,158	19,158	19,158
R-squared	0.069	0.042	0.028	0.025	0.014

Notes: ATUS data observation period from 2003 to 2019. Sample is restricted to workers aged 16-65 on their working days, defined as days workers spend 60 minutes working excluding commuting. Self-employed workers are excluded. Estimates computed using ATUS sampling demographic weights. Robust standard errors are shown in parentheses. Dependent variables are the total commuting time (in minutes), and the proportion of commuting by car, public, walking and cycling mode of transport (in percentages), respectively. Y determines whether the specifications include or not controls for fixed effects. * *p*-value < 0.1, ** *p*-value < 0.05, *** *p*-value < 0.01.

Table A8. Means of weather conditions, by climatic region

VARIABLES	Warmer region	Colder region	Warmer-colder
Precipitation (inches)	9.804	12.647	-2.843***
Rainy day (Precipitation ≥ 0.1 inches)	0.442	0.547	-0.105***
No rain	0.516	0.441	0.075***
Rainy day (0-0.1 inches)	0.042	0.012	0.031***
Rainy day (0.1-0.2 inches)	0.026	0.022	0.003*
Rainy day (0.2-0.3 inches)	0.014	0.013	0.001
Rainy day (0.3-0.4 inches)	0.013	0.015	-0.002
Rainy day (0.4-0.5 inches)	0.011	0.016	-0.005***
Rainy day (0.5-0.6 inches)	0.006	0.004	0.002*
Rainy day (0.6-0.7 inches)	0.007	0.012	-0.005***
Rainy day (0.7-0.8 inches)	0.007	0.006	0.001
Rainy day (0.8-0.9 inches)	0.005	0.005	0.001
Rainy day (more than 0.9 inches)	0.353	0.454	-0.101***
Snowfall (inches)	0.234	1.050	-0.817***
No snowfall	0.968	0.895	0.073***
Snowfall (0-0.1 inches)	0.002	0.001	0.001*
Snowfall (0.1-0.2 inches)	0.002	0.003	-0.001
Snowfall (0.2-0.3 inches)	0.001	0.003	-0.002***
Snowfall (0.3-0.4 inches)	0.001	0.003	-0.002***
Snowfall (0.4-0.5 inches)	0.000	0.003	-0.003***
Snowfall (0.5-0.6 inches)	0.001	0.000	0.000***
Snowfall (0.6-0.7 inches)	0.001	0.002	-0.001*
Snowfall (0.7-0.8 inches)	0.001	0.002	-0.001*
Snowfall (0.8-0.9 inches)	0.000	0.002	-0.001**
Snoefall (more than 0.9 inches)	0.022	0.085	-0.063***
Maximum temperature (ºF)	73.788	60.178	13.610***
Maximum temperature (≤ 30ºF)	0.006	0.080	-0.074***
Maximum temperature (31-35ºF)	0.007	0.054	-0.046***
Maximum temperature (36-40ºF)	0.016	0.068	-0.052***
Maximum temperature (41-45ºF)	0.026	0.068	-0.042***
Maximum temperature (46-50ºF)	0.034	0.062	-0.029***
Maximum temperature (51-55ºF)	0.048	0.070	-0.021***
Maximum temperature (56-60ºF)	0.067	0.071	-0.004
Maximum temperature (61-65ºF)	0.085	0.079	0.005
Maximum temperature (66-70ºF)	0.090	0.072	0.018***
Maximum temperature (71-75ºF)	0.098	0.080	0.019***
Maximum temperature (76-80ºF)	0.119	0.095	0.024***
Maximum temperature (81-85ºF)	0.129	0.102	0.027***
Maximum temperature (86-90ºF)	0.127	0.069	0.058***
Maximum temperature (91-95ºF)	0.094	0.025	0.070***
Maximum temperature (96-100ºF)	0.033	0.005	0.028***
Maximum temperature (> 100ºF)	0.020	0.001	0.020***

Notes: Figures are sample means. * imply 10% level of significance, ** imply 5%, and *** imply 1%.