May 2015; revised October 2017 ■ RFF WP 15-19-REV2

WORKING PAPER

Voluntary Exposure Benefits and the Costs of Climate Change

Benjamin Leard and Kevin Roth

1616 P St. NW
Washington, DC 20036
202-328-5000 www.rff.org

RESOURCES FOR THE FUTURE

Voluntary Exposure Benefits and the Costs of Climate Change

Benjamin Leard and Kevin Roth*

September 14, 2017

Abstract

We identify behavioral responses, defined as "voluntary exposure benefits," that have the potential to offset measured costs of climate change. We quantify these responses for the transportation sector. We find warmer temperatures and reduced snowfall are associated with an increase in fatal accidents. While the application of these results to climate predictions suggests that weather patterns for the end of the century would lead to 381 additional fatalities per year, the associated welfare losses are almost completely offset by voluntary exposure benefits from increased traveling. Our results motivate

*Leard: Resources for the Future, 1616 P St. NW, Washington, D.C. 20036, e-mail: *leard@rff.org*. Roth: Christensen Associates, e-mail: *kdroth@lrca.com*. The authors thank Edson Severnini and Sol Hsiang for useful suggestions and are grateful to seminar participants at 2016 AEA AERE session, CMU Heinz College, UC-Irvine, and USC for helpful comments.

carefully examining behavioral mechanisms to accurately estimate the welfare effects of climate change.

Key Words: Traffic Accidents, Exposure, Climate Change

JEL Classification Numbers: Q58, Q52, H23, R41

1 Introduction

Understanding the channels by which climate change will affect the economy is required to estimate the costs of climate change and to develop adaptation strategies. Extreme heat may result in direct costs such as increased mortality from heat stress and lower productivity. Economists have also made clear that individuals are likely to engage in costly defensive activities to mitigate these outcomes (Harrington and Portney, 1987). For example, where heat aggravates respiratory illness, individuals may use medication and air conditioning to reduce exposure to risk (Deschênes et al., 2017; Graff Zivin and Neidell, 2014). In such cases, measuring direct costs is a lower bound of the true welfare effects because it omits these defensive expenditures.

Less attention has been paid to situations where climate change generates costs that are, at least partially, explained by voluntary exposure to risk. Warmer weather facilitates spending time outdoors. Choosing to spend time outdoors provides many benefits, but also exposes individuals to air pollution, crime, UV radiation, and traffic. Where costs from these risks occur as part of a utility maximizing decision to spend time outside, these costs must be offset with the welfare gain from spending time outside. But the costs of time spent outside in terms of illness or death are often easier to measure than the benefits.

To understand the welfare consequences of climate change, it is important to examine exposure to risk. Where climate change aggravates an existing risk, individuals will engage in costly behavior to avoid exposure to that risk, but when climate change increases the utility of an activity with an associated risk, individuals will voluntarily increase exposure to that risk. We define the resulting welfare effects of the latter case as voluntary exposure benefits. In the extreme case of an entire sector's change in observed risk being caused by voluntary exposure, the net welfare costs of climate change would be zero or negative. Whether or not an observed increase in risk is accompanied by additional costs from defensive expenditure or offsetting benefits can be ascertained by examining exposure. Where individuals avoid risk, there are additional costs; where individuals engage in more of the risky activity, there are offsetting welfare benefits. Problematically, in many empirical settings there is almost no information on exposure to determine which effect generates the direct cost.

In this paper we analyze these issues in the context of the transportation sector by estimating the relationship among weather, traffic accidents, and travel demand. We examine the transportation sector because even small changes to traffic fatalities will carry large costs. Worldwide, nearly 1.24 million people die in traffic accidents annually (WHO, 2013). To quantify the effects of climate change on traffic accidents, we examine the effect of weather on accidents and generate future outcomes with climate change using simulated future weather. By exploiting plausibly random daily variation in temperature, rainfall, and snowfall, we are able to estimate the effect of weather on transportation outcomes.

We find a large and statistically significant relationship between weather and traffic fatalities. Unsurprisingly, we find precipitation plays a role in fatal car crashes. But we also find large effects for temperature. As temperature rises, an increasing number of fatalities involve pedestrians, bicycles, and motorcycles, or ultra-light duty (ULD) accidents. Warmer weather is intuitively linked to more exposure as people will derive utility from spending additional time outside walking, biking, or motorcycling for transportation or leisure purposes. We measure this exposure directly by estimating the demand for ULD trips as a function of weather.

To estimate these effects, we use detailed data on police-reported accidents, daily travel logs of households, weather, and climate change prediction data. We find that for a day with temperature above 80°F there is an 8.6 percent increase in fatality rates compared with a day at 50-60°F. Our estimates indicate that the majority, but not all, of this effect is due to fatalities involving individuals traveling by ULD modes. We also find evidence that individuals avoid ULD travel on cold days, while estimates for demand on hot days are positive but imprecise. While not the predominant effect, we cannot rule out the possibility that reduced cognitive ability plays a role in light-duty vehicle crashes on hot days, and we find some evidence that drivers avoid trips with light-duty vehicles on the hottest days, consistent with defensive behavior.

We estimate that the discounted costs of additional traffic fatalities caused by climate change are $37.6 billion from 2015 to 2099, an amount on the same order of magnitude as others such as profit changes to the agriculture industry (Deschênes and Greenstone, 2007; Fisher et al., 2012) and social welfare effects from criminal activity (Ranson, 2014). But we find that welfare gains from increased travel almost completely offset these costs. Our results imply that omitting voluntary exposure behavior from welfare analysis may lead to a significant overestimate of climate change costs.

2 Literature Review

The economics literature has studied the impact of climate change using temperature and occasionally precipitation data in a variety of areas such as agriculture (Deschênes and Greenstone, 2007; Fisher et al., 2012), and economic growth (Dell et al., 2014). Graff Zivin and Neidell (2014) examine how weather influences time allocation showing that warmer weather draws individuals outdoors, possibly exposing them to extreme pollution events.

Our work is related to other literature documenting the relationship between temperature and cognition ability. Seppanen et al. (2006) document that performance is 91 percent of optimal performance when the temperature is 30 degrees Celsius or 86 degrees Fahrenheit. Since 93 percent of traffic accidents are caused by human error (NHTSA, 2008), weather could very well play a role in our setting.

Our study is also related to work on crime and conflict that has found a strong relationship between heat and violent activity (Hsiang et al., 2013; Ranson, 2014). Deschênes and Moretti (2009) use mortality data from the Multiple Causes of Death files and include regressions for motor vehicle deaths. They find some evidence for a decrease in fatalities from cold weather, which they conjecture is due to avoided travel.[1]

Our work is related to the literature on equilibrium adjustments to shocks. Colmer (2016) estimates the labor market response to temperature changes in India. This study finds that warmer weather reduces agricultural productivity. But this change in productivity can at least partly be explained by a reallocation of labor away from the agricultural sector. Therefore, the productivity loss is not simply that per worker output is reduced, but that fewer workers are available. This result highlights the importance of accounting for labor decisions in computing the costs of weather changes. Our

[1]Several papers from the traffic safety literature explore the relationships between weather outcomes and traffic accidents. This literature has primarily estimated the impact of rainfall or snowfall on accident frequency (Eisenberg, 2004), but does not examine the relationship with temperature or the impact of climate change. An exception is Froom et al. (1993), who show that high temperatures are associated with higher rates of helicopter pilot errors.

analysis of the temperature-fatality relationship yields a similar conclusion: we find that warmer weather leads to more fatalities, but this relationship is defined by an increase in miles traveled by more dangerous modes of travel, as opposed to an increase in the per mile fatality rate.

We also contribute to a growing literature on avoidance behavior. We extend the analytical framework presented in Harrington and Portney (1987), which shows that accounting for avoidance behavior can be critical for accurately estimating the welfare costs of environmental pollution, and omitting avoidance behavior can lead to an underestimate of the full welfare costs. We build on this framework by considering the possibility that individuals may voluntarily expose themselves to additional costs, and we find that omitting this behavioral adjustment can lead to an overestimate of the full welfare costs of an environmental change. The avoidance framework has been applied empirically in recent work by Deschênes and Greenstone (2011) and Barreca et al. (2013) in the context of climate change and Moretti and Neidell (2011), Graff Zivin and Neidell (2013), and Deschênes et al. (2017) in the context of local air pollution. These studies confirm the importance of accounting for avoidance behavior by leveraging alternative empirical approaches. We contribute to the empirical avoidance literature by evaluating empirically the importance of accounting for voluntary exposure behavior in the context of traffic accidents in the United States. We find that behavioral adjustments account for virtually all of the cost changes, reaffirming conclusions from prior literature that accounting for behavior is critical to complete an accurate assessment of an environmental change.

3 Framework for Estimating Welfare Effects of Climate Change

In this section, we present a simple framework for characterizing the welfare effects of climate change on traffic accidents. Since traffic accidents are associated with traveling, we model welfare effects in the context of demand for and cost of traveling. We model the aggregate demand for travel using a marginal willingness to pay (MWTP) function v which is dependent on weather, W, and miles traveled, m, $v = v(W, m)$. We assume that the cost to travel one mile, which includes monetary and non-monetary costs, is independent of miles traveled but depends on weather to allow for the possibility that the probability of an accident depends on weather. To focus on the effects of daily weather changes on accidents, we assume that other per mile traveling costs are not affected by weather changes.[2] Note that an increase in the per mile accident cost increases one-for-one the marginal cost per mile. We denote the marginal cost of a mile traveled by $p = p(W)$.

We assume that travelers completely internalize all private costs of

[2]This is a reasonable assumption at the daily level. Other costs of travel, such as gasoline costs, may be affected by monthly demand or supply shocks stemming from weather changes. In our empirical analysis, we control for these shocks with monthly level controls.

traveling, including the potential accident costs. This implies that travelers, in deciding how much to drive/walk/bike, accurately recognize the risks associated with each mode and adjust their traveling in response to changes in these risks. In our empirical section, we find evidence that travelers do respond to changes in accident risk, especially for more dangerous weather events, e.g., heavy rainfall or snowfall.

3.1 Equilibrium and Welfare

In equilibrium, MWTP equals the cost per mile, so that the equilibrium number of miles traveled, m^*, solves $v(W, m^*) = p(W)$. Total welfare in equilibrium, which we measure as consumer surplus, is equal to the difference between MWTP and marginal cost per mile for all miles traveled:

$$Welfare = \int_0^{m^*} v(W, m)dm - p(W)m^*. \tag{1}$$

The integral represents total benefits of traveling and the second term in Equation (1), $p(W)m^*$, represents the total costs incurred to travelers. This specification allows weather to change the total cost of traveling through changing the probability of an accident or through changing the total demand for travel.

3.2 Welfare Effects

We compute marginal welfare effects stemming from changes in weather by differentiating Equation (1) with respect to weather. Applying Leibniz's rule for differentiation under the integral sign yields

$$\frac{dWelfare}{dW} = \frac{dm^*}{dW}v(W, m^*) + \int_0^{m^*} \frac{\partial v}{\partial W}dm - p(W)\frac{dm^*}{dW} - \frac{dp}{dW}m^*. \quad (2)$$

The third and fourth terms in Equation (2) represent the traditional measure of welfare changes due to a change in weather, since they measure how total costs change in response to a change in weather: $-p(W)\frac{dm^*}{dW} - \frac{dp}{dW}m^* = -\frac{d}{dW}[p(W)m^*]$. Past studies rely on changes in observed costs to measure welfare; in our context, the costs are traffic accidents. But these studies omit potentially relevant sources of welfare, including potential benefits to market participants. The first and second terms in Equation (2) represent welfare changes caused by a change in miles traveled and MWTP for miles traveled. We denote these terms as voluntary exposure. If these terms are positive, then travelers are receiving voluntary exposure benefits in response to a change in weather. These benefits are easily explained by the fact that travelers may have higher demand for traveling when the weather is sunny and warm. Regardless of the sign of these first two terms, omitting them completely from the quantification of the welfare effects of climate change will be inaccurate.

Furthermore, the equilibrium condition $v(W, m^*) = p(W)$ implies that the first term completely offsets the third term in Equation (2). The offseting terms represent the welfare benefits and costs stemming from a change in miles traveled. The costs are completely offset by the change in welfare benefits that travelers receive from a change in miles traveled. This offsetting implies that the traditional measure of welfare, which includes $-p(W)\frac{dm^*}{dW}$, may be grossly inaccurate if most of the changes in costs are due to a change in miles traveled. In sharp contrast, the derived welfare effects include the movement of the demand curve for miles traveled (the term $\int\limits_0^{m^*} \frac{\partial v}{\partial W} dm$) and a change in marginal costs of traveling (the term $-\frac{dp}{dW}m^*$), where the remaining terms in Equation (2) offset one another. Therefore, separating a change in total costs of traveling, $-\frac{d}{dW}[p(W)m^*]$, from a change in marginal costs of traveling, $-\frac{dp}{dW}m^*$, is necessary to obtain an accurate measurement of the welfare costs of climate change.

Note that although our framework is applied to the context of traveling and traffic accidents, it is applicable in other settings with known climate change impacts. For example, our framework can be easily applied to the contexts of crime or respiratory disease, where individuals are deciding how much time to spend outdoors. Demand for outdoor activity is a function of weather, and the marginal cost of outdoor activity, which includes the risk of being a part of a crime or aggravating a respiratory disease, is a function of weather.

Our framework may be extended to multiple markets to obtain more precise estimates of climate change impacts. In our context, we differentiate between alternative modes of travel, since weather changes are likely to influence each mode differently and accident risk of each mode varies tremendously. Therefore, we must estimate marginal cost and demand responses for each mode to make welfare assessments. To compute the welfare effects of climate changes for multiple markets, researchers can add up the welfare changes illustrated in Equation (2) across markets. In the empirical analysis to follow, we isolate welfare effects for two forms of miles traveled exposed to weather: miles traveled by a light-duty vehicle (LDV) and by walking, biking, or motorcycling, or any other ultra-light duty (ULD) mode. This disaggregation proves important for evaluating welfare, motivating a careful assessment of the type of demand responses measured.

The framework we present is consistent with the philosophy and design of Integrated Assessment Models (IAMs). These models derive outcomes from a utility and profit maximizing model of decision making, "integrating knowledge from two or more domains into a single framework" (Nordhaus (2013), p.1070). Our approach integrates the climate-traffic accidents and climate-traveling relationships into one unified framework that we deem necessary for accurately measuring costs and benefits of climate change. IAMs increasingly incorporate reduced-form estimates from the climate econometrics literature that exploits variation in weather. Our framework motivates for this incorporation to integrate outcomes *and* any behavior that may be associated with outcomes. Incorporating outcomes alone, for example by adding the relationship between climate change and traffic accidents into a climate damage function, would provide a misleading assessment of the costs of climate change, since this procedure would be omitting the private utility changes from changes in travel due to climate change.

4 Data and Summary Statistics

4.1 Data Sources

4.1.1 Accident, Injury, and Fatality Data

We obtain the population of police-reported accidents for 20 states from the State Data System (SDS) maintained by the National Highway Traffic Safety Administration (NHTSA). These data are collected and used by the NHTSA to provide analysis and policy recommendations for U.S. DOT. The benefit of these data is that they include not only fatalities, as recorded in other sources, but also non-fatal accidents. We are primarily interested in fatal accidents because they are costly and contribute to the overall fatality-temperature relationship (Deschênes and Greenstone, 2011). Nevertheless, information on other types of accidents helps to narrow the channels through which the relationship arises. For example if the primary channel is cognition, we would expect to see an increase in Property Damage Only (PDO) accidents as well as fatal crashes.

Accident reports, completed by police officers, are administered at the state level. These files are requested annually by the NHTSA from the state agencies that computerize the data, which are then formatted for consistency and compiled into the SDS.[3] We obtained permission to use SDS data from Arkansas, California, Florida, Georgia, Iowa, Illinois, Kansas, Michigan, Minnesota, Missouri, Montana, Nebraska, New Mexico, New York, North Carolina, Ohio, Pennsylvania, South Carolina, Washington, and Wyoming.[4]

While there is considerable variation in what each state records, all states in our sample provide a record of each police reported accident, the day when the accident occurred, the county where the incident occurred, the types of parties involved (e.g., light-duty vehicle, motorcycle, bicycle, pedestrian) and the number of fatalities involved.[5] Others variables such as vehicle

[3]The agencies that usually collect the data are state police, state highway safety department, or the state's Department of Transportation.

[4]Years of coverage in the SDS data include AR 1998-2010, CA 1995-2008, FL 1995-2008, GA 1995-2008, IA 2001-2005, IL 1995-2009, KS 1994-2008, MI 1995-2009, MN 1995-2007, MO 1995-2008, MT 1995-2008, NE 2002-2008, NM 1991-2010, NY 2002-2010, NC 1999-2008, OH 2000-2010, PA 1991-1999 and 2003-2010, SC 1997-2008, WA 1994-1996 and 2002-2010, and WY 1998-2007.

[5]We note that an accident appears in our dataset only if the police file a report. For Property Damage Only (PDO) accidents, police may have different reporting thresholds by state, and policy changes may affect reporting rates over time, which we can control for with county-year-month fixed effects. There is, however, some concern that if bad weather results in more accidents, departments may become overwhelmed, resulting in a higher threshold for filing. If this is the case then we underestimate the effect of weather on accidents. This concern is less important for fatalities, which form our primary analysis,

information or factors contributing to the accident are subject to considerable state-level variation in the manner and detail with which they are recorded. Our main regressions focus on fatalities, PDO accidents, and injuries. Thus we are able to largely avoid variables that are inconsistently recorded.[6] We also make use of fields that record whether or not the accident involved any ULD parties, which is almost universally recorded.[7] However, in some robustness checks in the appendix we use a subset of states with intoxicated or young operators, which are subject to more variation among states and years.[8]

4.1.2 NHTS Daily Travel Data

We construct household vehicle miles traveled (VMT) and trip count from the 1990 National Personal Transportation Survey and the 1995, 2001, and

---

because they will always be reported (Blincoe et al., 2014).

[6]Injuries are often but not always recorded as five levels of severity including fatality, incapacitation, injury, possible injury and property damage only. Incapacitation, injury, and possible injury are included in 'crashes with an injury.' There are two state-year combinations where injuries cannot be discerned and are dropped from the analysis.

[7]Besides pedestrian, motorcycle, and bicycle, we also include mopeds, motorized scooters, pedalcycles, unicycles, and tricycles.

[8]See Appendix Table A5 for estimation results of these specifications. Because some states do not disaggregate drugs from alcohol use, we consider drivers to be intoxicated if they are tested to be beyond the legal limit for alcohol or if they are reported to have taken any illicit drug.

2009 National Household Travel Surveys (NHTS). Administered by the U.S. DOT Federal Highway Administration, these surveys are representative cross sections of randomly selected U.S. households.[9]

For our analysis, we use the NHTS travel diaries, which are trip-by-trip travel logs for a single individual. Each trip reports where the respondent went (name of place), what time the trip started and ended, why the respondent made the trip, how the respondent traveled, and the travel distance of the trip, in miles.[10]

Staff at the Federal Highway Administration and Oak Ridge National Laboratory helped us acquire the confidential version of the NHTS data files that contain either zip code or county of residence for all households in each sample.[11] The restricted files that we acquired include the day, month, and

[9]Each wave is a survey of the non-institutionalized population of the United States using Computer-Assistant Telephone Interviewing (CATI) Technology. The 2009 survey had an average response rate of 19.8 percent.

[10]The NHTS specifies that the beginning of a travel day is 4:00 a.m. An example of a recorded trip taken from the 2001 User Guide is the following: "from 7:14 p.m. to 7:22 p.m., return home, by car, 1 mile."

[11]The 2001 confidential file includes zip codes for most households but has limited county information. We assign households to counties using the 2000 U.S. Census zip code to county cross walk. In a few cases, the zip codes reported in the NHTS data do not match any zip codes in the 2000 U.S. Census cross walk. In these cases, we use the 2010 U.S. Census zip code to county cross walk or the U.S. Department of Housing and Urban Development zip code to county cross walk.

year of the household's assigned day of travel.

We take several steps to clean and merge the travel diary data. Since our unit of analysis is the household, we aggregate trip count and VMT to the household level for three categories of trips: light-duty, ULD, and public transit. After minor data cleaning, we arrive at a final sample of 283,857 household by travel day observations.[12]

4.1.3 Historical Weather Data

Daily weather data come from the National Climatic Data Center (NCDC) Global Historical Climatology Network-daily, which provides daily minimum and maximum temperature and total daily rainfall and snowfall for weather stations in the United States. This database collects and performs quality control for weather data from land based weather stations around the globe and is archived by the National Oceanic and Atmospheric Administration. We use data from 2,607 stations located in all 50 states and the District of Columbia.[13] We use the weather station data to calculate daily, county-level weather using methods from prior literature.[14]

[12] See Appendix A.1 for more details.

[13] See Appendix Table A3 for more detail.

[14] Prior literature has documented that missing weather station data can account for a substantial portion of the variation in weather measures if naively averaged (Auffhammer et al., 2013). Therefore we impute data using a regression of temperature or precipitation for a detector on its nearest neighbor. County level weather is generated by averaging detectors within 200km using inverse distance weighting to the county population centroid

4.1.4 Weather Prediction Data

CCSM4 is the model used in the Fifth Assessment of the International Panel on Climate Change to predict future climate and weather under a variety of scenarios.[15] We use scenario RCP6.0, which represents a middle-of-the-road prediction of future warming and changes in precipitation. It represents a future with a balanced development of (fossil fuel and non fossil fuel) energy technology.[16] Although it is less carbon development than the CCSM4 RCP8.5 scenario, it still entails 2.3°C (4.2°F) of warming in the United States. In the appendix, we examine outcomes for other climate change scenarios and

---

as defined by the US Census. Weather is first calculated as a continuous measure for each county using the stations and then binned. See Appendix A.2 for further details. In Appendix Table A10, we also present estimates using PRISM data averaged at the county level and we assign precipitation to rainfall when the average temperature on that date is above freezing or snowfall when it is below freezing.

[15] We use the CCSM4 model exclusively for future weather predictions because CCSM4 is one of the few models that report separate outputs for rainfall and snowfall. In contrast, most models report a single precipitation variable that combines rainfall and snowfall. Since we expect rainfall and snowfall to have different impacts on accidents and travel demand, it is crucial to use climate predictions that report separate values for each precipitation type.

[16] Other scenarios represent extreme predictions. For example, the RCP8.5 scenario represents a fossil-fuel intensive future, while RCP4.5 represents a predominantly non fossil fuel future.

an alternative model and find that our broad conclusions are unchanged.[17]

We obtained the CCSM4 RCP6.0 scenario daily weather predictions from the Centre for Environmental Data archival website, made available through the British Atmospheric Data Centre. The data include predictions from January 1, 2006, to December 31, 2100 for 0.94 degree latitude by 1.25 degree longitude grid points throughout the entire world. Available weather variables include average, minimum, and maximum daily temperatures and rainfall and snowfall rates.[18] The grid used for this prediction is fairly coarse and many counties do not have a grid point.[19] To assign predicted weather outcomes to counties, we therefore use the same method that was used to assign observed weather to counties based on weather station locations.[20] Based on this we assign weather predictions to each county centroid. We then assign the county weather predictions to weather outcome bins for our

[17]We examine outcomes from climate scenarios RCP4.5 and RCP8.5 using CCSM4 output. We also report outcomes using prediction data from the A1B middle-of-the-road warming scenario presented in the Fourth IPCC Report using the Hadley 3 climate prediction model, which has been used in prior economics literature. See Appendix Table A19 and Figure A.2 for the results from these models.

[18]See Appendix A.2 for more detail of data cleaning.

[19]This prevents us from using a "cookie-cutter" approach where all counties appearing in a cell in the weather prediction data get assigned the same weather prediction.

[20]Here, for every county, we locate every CCSM4 grid point that is within 200 km of the county's centroid. The weather predictions at these grid points are then averaged to predict daily county-level weather using inverse distance weighting to the county centroid.

econometric specifications.

4.1.5 Other Data Sources

To predict the change in fatalities nationwide, we require the average daily fatality rate by county, which the accident files provide for only 20 states. The Fatality Analysis Reporting System (FARS) tracks annual automobile fatalities for all states and provides information on the county in which the fatality occurred. This allows us to calculate average daily fatality rates from which to project changes in future fatalities. We sum the fatalities recorded by FARS data from 2000-2009 for each county and divide by the number of days to calculate this baseline fatality rate.[21]

4.2 Summary Statistics

Table 1 presents summary statistics for our two primary datasets used in the estimation. Panel A describes some key statistics of the SDS accident data by Census Region. Of the 46 million accidents in our data, 267,984 record a fatality, the vast majority of which do not involve a ULD mode. When aggregated by county-day, our unit of observation, we record the count of incidents for 6.79 million county-day observations, and where no incidents

[21] We also use the FARS data from 1975 to 2013 in the appendix as a check on our main fatality results. See Section A.3 for more detail and Appendix Table A10 for results.

occur, the day is assigned a count of zero.[22] In the average county there are 7.6 accidents per day per $100,000$ people, and 0.058 fatalities per day per $100,000$. The summary statistics by census region also reveal that there is considerable variation in temperature, rainfall, and snowfall among regions.[23]

Panel B describes the NHTS household travel survey data on trip count and VMT per household. Because the trip data are a random sample, they do not capture the total number of trips or miles driven in a county but have the benefit of wider coverage with observations in the majority of counties in all 50 states and the District of Columbia and are collected through the course of a year. The average household in our sample drives 54.2 miles using LDV modes and 0.8 miles per day using ULD modes with a total of 6.4 trips.

Panels C, D and E present the weather statistics used in our simulation. The sample includes all county-day measures in all states. Panel C depicts the observed weather data for 2000-2009, Panel D shows CCSM4 RCP6.0 predictions for 2006-2009, and Panel E has CCSM4 RCP6.0 scenario for 2090-2099.[24] Comparing Panels C and D we can see that in many sub-regions

---

[22]We assume that if a county has observations in a given year, all days where no accidents are recorded are assigned a zero.

[23]This regional variation without location based fixed effects may be cause for concern if, for example, colder climate is correlated with public transportation in cities like New York, Philadelphia, and Chicago, while low-density car oriented cities like Los Angeles and Atlanta are located in warm regions.

[24]In Appendix Table A3 we report disaggregated statistics by state for our observed weather station data for 2000-2009.

CCSM4 predicts 5th quantiles of temperatures in 2006-2009 that are colder than observed in the actual weather data from 2006-2009, while the median and 95th quantile are predicted to be slightly hotter than actually observed. This indicates that the baseline CCSM4 data display excessive dispersion and that an error correction method targeting the mean may not adequately correct the extreme events. Comparing Panel D with Panel E we note that nationally CCSM4 predicts warmer temperatures, an increase in rainfall (0.11 cm at the 95th quantile), and much lower snowfall. Panels C, D and E also demonstrates the importance of correcting future climate change weather predictions to baseline modeling discrepancies. Without this error correction, one might conclude that global warming would change temperatures more than CCSM4 predicts, because CCSM4 2006-2009 is a warmer baseline than the observed data. In our application where snowfall is important, without error correction the naive comparison of observed data with CCSM4 2090-2099 would suggest that climate change will increase snowfall for all regions except the Northeast. We briefly discuss the correction methodology we develop in section 6 with a fuller discussion in the Appendix.

5 Estimating the Effect of Weather on Accidents and Travel Demand

5.1 Estimation Methodology

This section details the econometric framework we use to determine the effects of weather on accidents and travel demand. Our main analysis uses a Poisson regression model because the distributions of our dependent variables are nonnegative and skewed. We first describe the estimation of accidents that is the framework used for fatalities, crashes involving ULDs and crashes involving only LDVs. Fatalities are far more expensive than injuries and PDO accidents and are our primary focus, but we also examine these categories for completeness and to help examine the reason for fatality changes. Next we describe the estimation of travel demand in terms of daily trip count and miles per trip for LDVs, ULD modes, and public transit.

5.1.1 Accidents

We chose a Poisson model for our initial analysis based on several aspects of our data. Accident counts are all non-negative, integer-valued random variables. For data characterized as a counting process, the Poisson distribution is the benchmark model (Cameron and Trivedi, 2013). Poisson regression will yield consistent estimates provided the conditional mean is correctly specified.[25]

We assume that the count of accidents on date d in county c given $\mathbf{x_{d,c}}$ is Poisson distributed with density

$$f(y_{d,c}|\mathbf{x_{d,c}}) = \frac{e^{-\mu}\mu^{y_{d,c}}}{y_{d,c}!}, \qquad y_{d,c} = 0, 1, 2, ... \tag{3}$$

We specify the mean μ using the conventional exponential mean function:

$$\begin{aligned} E[y_{d,c}|\mathbf{x_{d,c}}] = \mu = exp\Big(\sum_{j=1}^{8}\alpha^j T^j_{d,c} + \sum_{j=1}^{5}\beta^j R^j_{d,c} + \sum_{j=1}^{5}\gamma^j S^j_{d,c} + \\ \sum_{j=1}^{8}\alpha^j_{-1} T^j_{d-1,c} + \sum_{j=1}^{5}\beta^j_{-1} R^j_{d-1,c} + \sum_{j=1}^{5}\gamma^j_{-1} S^j_{d-1,c} + \theta_{scym} + \mathbf{z'_{d,c}}\delta\Big) \end{aligned} \tag{4}$$

where $T^j_{d,c}$ is an indicator for mean daily temperature on date d in county c lying within the bounds of bin j, $R^j_{d,c}$ is for rain, $S^j_{d,c}$ is snow, $T^j_{d-1,c}$, $R^j_{d-1,c}$, and $S^j_{d-1,c}$ indicate lagged weather, θ_{scym} is a state-county-year-month fixed effect, and $\mathbf{z_{d,c}}$ includes other possible covariates.

The appropriate functional form of the daily weather variables is unknown and we adopt the semi-parametric approach of Deschênes and Greenstone (2011). This concern is particularly relevant here, where even after

[25] Cameron and Trivedi (2013) note that for many common negative binomial models, consistency requires not only correct specification of the mean and variance but also that the data have a negative binomial distribution. A violation of the assumed Poisson distribution will allow for valid inference only if the standard errors are appropriately computed, which requires correction particularly when there is over- or under-dispersion.

controlling for precipitation, there may be differential effects above and below freezing that could be difficult to capture using a parametric specification.[26] We assume that the impact of temperature is constant within 10°F intervals, and constant for rain or snow falls between 0.0 cm$< x \leq$ 0.1 cm, 0.1 cm$< x \leq$0.5 cm, 0.5 cm$< x \leq$1.5 cm, 1.5 cm$< x \leq$ 3.0 cm, and 3.0 cm$< x$.[27] Because drivers who are unaccustomed to snow may face an elevated risk, we also create an indicator variable for snow of more than 0.1 cm following a month without any recorded snow.[28]

Our preferred empirical estimates include lagged variables of weather. The motivation for including these lags is that unfavorable travel conditions may cause individuals to delay travel. We therefore include lags of temperature and precipitation by one day, or one week, to account for this inter-temporal displacement.[29] In our setting we include shorter lags than

[26] For example, even after several days without snow, melting and refreezing may create slick roads.

[27] The primary restriction of bin choice lies in the NHTS household survey data, which are more limited than the SDS data for observations on days with extreme weather conditions. We have run specifications with more weather bins for our non-fatal accident and fatality regressions (see Appendix Table A11) and find nearly identical results to those estimated here.

[28] In robustness tests included in Appendix B, we also create a variable for infrequent rainfall after one month of no rain. This variable will also capture the effect of oil or debris that may be dislodged by infrequent rainfall.

[29] In many other fatality settings, for example, respiratory illness, there is a concern

are typical in this literature because it is unlikely that weather is bringing forward accidents that were bound to happen at a later date, but weather may defer trips increasing rates at a later date, although the time-span for such deferment is unlikely to be longer than a week.

Consistent estimation of Equation (4) requires that we control for unmeasured shocks that covary with weather. Both regressions include a set of state-county-year-month fixed effects to capture all unobserved determinants of incidents that vary at the county and monthly levels.[30] These fixed effects absorb both temporal and spatial changes related to population, employment, and gasoline prices, as well as policy changes such as drunk driving laws and graduated drivers licenses. Conditioning on these fixed effects, we identify α^j, β^j, and γ^j from weather deviations within a county in a given month. Once controlling for these factors, it seems plausible, due to the random nature of weather, that weather is orthogonal to unobserved

that inclement weather may harm only those who were likely to die shortly thereafter and this literature has stressed the inclusion of lags sufficiently long to capture the net effect (Deschênes and Moretti, 2009). In the main text we report the sum of coefficients from the contemporaneous and lagged weather. Appendix Table A6 gives the full disaggregated set of coefficients. We also include specifications with longer lag periods and more weather bins. In Appendix Table A14 we also examine aggregation of our data to the monthly level.

[30]In Appendix Tables A10, A12, and A13 we report estimation results for models that include state-month, county-year fixed effects, which are often used in studies with more aggregate data, and find results that are similar in sign and magnitude.

determinants of accidents and travel demand.

The first two moments of the Poisson distribution, $E[Y] = \mu$ and $V[Y] = \mu$ show the equidispersion property that is often violated. The presence of overdispersion, while still providing consistent estimates, will inflate the t-ratios in a Poisson model. To correct the standard errors we block bootstrap at the annual level.

5.1.2 VMT and Trips

To model travel demand we fit the following equation:

$$E[y_i|\mathbf{x_{d,c}}] = exp\Big(\sum_{j=1}^{8} \alpha^j T^j_{d,c} + \sum_{j=1}^{5} \beta^j R^j_{d,c} + \sum_{j=1}^{5} \gamma^j S^j_{d,c} + \sum_{j=1}^{8} \alpha^j_{-1} T^j_{d-1,c} + \sum_{j=1}^{5} \beta^j_{-1} R^j_{d-1,c} + \sum_{j=1}^{5} \gamma^j_{-1} S^j_{d-1,c} + \theta_{scym} + \mathbf{z'_{d,c}}\delta\Big) \tag{5}$$

We avoid log-linearizing and then estimating the equation using ordinary least squares for several reasons. First, there are some households that have zero daily trips or miles for which log-linearization is infeasible. Second, as shown by Santos Silva and Tenreyro (2006), Jensen's inequality implies that interpreting the coefficients from such an estimate as an elasticity can be incorrect in the presence of heteroskedasticity. Instead, we estimate Equation (5) using Poisson regression.[31] The covariates include county-year-

[31] In Appendix Table A15 we examine other functional forms of our trip demand model, including the Inverse Hyperbolic Sine Function. See Appendix Table A15 for more details.

month fixed effects, first snowfall, and controls for household characteristics. These controls include the household size, the number of adults, vehicles, and workers in the household, the NHTS defined life-cycle stratum and income group, race, and the day of the week on which the household was followed. The estimation procedure is identical to that of Equation (4) except that we now bootstrap the standard errors at the state-by-survey-year level.

5.2 Results

5.2.1 Estimates of the Impact of Weather on Accidents

We estimate Equation (4) for three mutually exclusive and collectively exhaustive types of accidents: accidents involving a fatality, PDO accidents, and accidents involving an injury. Table 2 presents the estimates of the impact of temperature, rainfall, and snowfall on these three types of accidents. We present the sum of the current and lagged coefficients to account for any inter-temporal offsetting that may occur for a given weather fluctuation. In each regression, the temperature bin of 50–60°F is omitted, implying that each estimated coefficient is the percent change in accidents compared to a day at 50–60°F. Bins for rainfall of 0 cm and snowfall of 0 cm are also omitted.

The initial set of columns, (1) through (5), display point estimates associated with weather variables on fatalities. In column (1), our central specification, we find that temperature has a strong and statistically significant effect on fatalities. Compared with a day at 50°F, fatality risk rises from -13.7 percent at <20°F to 8.6 percent for a day at >80°F. The estimated effects for precipitation are somewhat complex. While snowfall increases fatalities, rainfall decreases total fatalities. We suspect this is because drivers avoid trips or drive cautiously enough to reduce overall fatality risks on rainy days, which we will confirm with our PDO accident and travel demand regressions.[32]

The following columns examine the source of these effects and test the robustness of our fatality result. In column (2) we estimate the daily count of fatalities, omitting fatalities where any party involved was a ULD mode, leaving only fatalities where all parties were LDVs.[33] The estimated coefficients are small and generally insignificant, with one potentially important exception being the >80°F bin with a 5.2 percent increase in

[32]Note that the number of observations is larger than the total count of fatalities in our dataset. This is because all days within a county-year-month are included, many of which are zero. Whenever a county-year-month group has only zero outcomes, the group is omitted, reducing the sample size for regressions such as that in column (3) because ULD crashes are relatively rare. In Appendix Table A17, we present regression results for the fatalities model that restricts the sample to the most restrictive set of observations used. In Appendix Table A10 under the column titled FARS, we also estimate our fatality model, Equation (4), using the FARS records of fatal accidents between 1975 and 2013, finding results are nearly identical to those that we find with the SDS data. See Appendix A.3 for a detailed description of FARS. These data cover only fatal crashes but in all states.

[33]We also include heavy-duty vehicles over 4,000 lbs.

fatalities. If this increase was due to more drivers on the road, we could attribute this effect to exposure. But, as we will show in the travel demand estimates, the hottest days are associated with less LDV travel, which is consistent with heat aggravating an existing risk. The effects from rainfall are also largely removed but snowfall effects remain positive.

Column (3) uses only the sample of fatalities where at least one party traveled by a ULD mode. Compared with a day at 50°F, a day below 20°F sees a 60 percent decrease in fatalities, while a day above 80°F sees a 17 percent increase. These magnitudes are large because ULD accidents are a relatively small share of fatalities. With a small base, a change of a few fatalities will result in a large percentage change. Together columns (2) and (3) suggest that ULD fatalities may be a minority of total fatalities but they are the primary mechanism of the temperature-fatality relationship found in column (1). Cognition changes from temperature may contribute to these accidents, but are unlikely to be the primary factor as one would expect the minimum number of fatalities to occur between 60°F and 80°F when comfort is highest, but instead we find the minimum at days when temperatures are below freezing.[34]

In column (4) we consider the possibility that weather may affect behavior

[34] In Appendix A.4 we estimate models of compositional changes to hold fixed the number of daily accidents. We find that given an accident the likelihood that it involves a ULD vehicle increases with temperature. We also find that fatalities are no more likely to involve alcohol, young drivers, or males as temperatures increase.

beyond the one-day lag of our main specification in column (1). In this specification we include additional lags for the entire week and find that the sum of the contemporaneous and all lagged coefficients is nearly identical to that with only a single lag.[35] Column (5) examines only the set of counties considered large or medium metro counties by the National Center for Health Statistics 2006 Urban-Rural Classification Scheme. The gradient of point estimates from coldest to hottest temperature bins remains as strong as when estimated from the entire sample, suggesting that our results are not driven by counties with low population.[36] In column (6) we examine the daily PDO accident count as a function of weather. We find that heat does not increase accidents over 50°F. If the mechanism for increased fatalities were cognition or aggression, it would be surprising that small crashes follow a different pattern. We mostly find effects of temperatures below freezing, which could be due to persistent ice. We also find that rainfall or snowfall increases PDO accidents. Our largest rainfall coefficient is associated with the > 3 cm bin, indicating that PDO accidents increase by 18.7 percent over a day without rainfall. The effect of snowfall is more than two times larger, with a day of > 3 cm snowfall increasing PDO accidents by 43.8 percent. This suggests that

[35]This specification also removes the possibility our effects are individuals simply picking the warmest day of the week for discretionary travel or ULD travel as exercise, helping to differentiate between relative and absolute effects.

[36]Because the fixed effect specification removes all county-year-month groups without any variation, the central specification will generally contain more urban counties.

precipitation generates more accidents but drivers, through either reduced trips or careful driving, reduce the per accident fatality rate. In the case of rainfall these behavioral changes lower the total fatalities, but for snowfall the increase in accidents is so large that the total fatality rate increases, albeit less than the accident rate. Finally, column (7) reports the effect of weather on accidents with at least one injury but no fatalities. There is a slight positive association between temperature and accidents with injuries. The precipitation effects display a similar pattern as that for accidents but of a smaller magnitude. For example a day with snowfall of > 3 cm is associated with an increase in injuries of only 26.2 percent. Broadly these results are a transition between PDO accidents and fatalities.

It seems reasonable to suspect that local populations may adapt to common weather conditions and that warm locations may see a smaller effect of hot weather than cold locations. Furthermore it may be possible that technology and other safety programs may hold some promise in reducing the relationship between temperature and fatalities. We explore these hypotheses in Table 3. In columns (1) and (2) we run our regressions on the coldest and hottest counties in our sample. While there are differences in the point estimates between these columns the standard errors are generally too large to distinguish between the two. Considering the point estimates we do not see clear evidence of adaptation. Breaking the sample into an early and late time period also does not show overwhelming evidence of innovation that protects individuals from the effects of weather. These estimates, presented in columns (3) and (4), are somewhat more interesting in that they suggest he temperature-fatality relationship has increased over time.

Considering the channel of ULD crashes may help to explain these somewhat puzzling test for adaptation. If the decision to use a ULD mode primarily determines the temperature-fatality relationship, the role of climate in determining the propensity to walk or ride a motorcycle on a 70°F day may be limited and mostly determined by daily weather rather than climate. The increasing relationship between temperature and fatalities over time would also seem puzzling, at first, considering the safety improvements to automobiles in recent years and declining fatality rates overall. But ULD crashes have not followed this trend providing an explanation for this result. Motorcycle deaths, in particular, have not decreased over time but rather increased from 2,056 in 1997 to 5,050 ten years later in 2007. If a growing share of the year is snow free, individuals may make vehicle or housing choices that facilitate more frequent walking, biking, or commuting by motorcycle. Adaptation may not only be an investment in capital that protects individuals from weather but also in capital that exposes them to weather.

5.2.2 Estimates of the Impact of Weather on Travel Demand

The estimated effects of weather on daily fatalities are suggestive of an exposure mechanism for ULD accidents but the mechanism for the remaining LDV effects is unclear. In this section we further explore these mechanisms using the NHTS logs of daily household travel. Table 4 gives the point estimates and standard errors for a regression of weather on several aspects of travel demand. Our coefficient estimates are again the sum of contemporaneous and lagged effects.[37] Given the limited amount of data, statistical precision is lower than in the prior section, but some broad patterns are found in these results.

The estimates in column (1) indicate that mean daily temperatures below 20°F see 7.5 percent fewer LDV miles per household. Warmer days do not show evidence of a statistically significant change in demand but the bin above 80°F does have a negative point estimate. This provides some evidence that the increase in LDV fatalities above 80°F cannot be attributed to additional driving and exposure as a mechanism. Similarly the point estimates for precipitation are marginally significant but consistently negative. For LDVs it appears possible that precipitation and possibly hot weather aggravate an existing risk and avoided trips are an additional defensive expenditure.

Because our travel demand estimates are based on a self-reported survey, it is possible households record trip count with more precision than miles. While miles are a complete measure of adjustment, distance can be difficult to judge and is often rounded. In column (2), we examine the total trip as a function of weather. We find similar patterns as the total miles regression but the bin above 80°F finds a larger effect and greater precision, again showing

[37] See Appendix Table A9 for the disaggregated results.

avoided travel.[38] This provides some evidence that LDV fatalities on the hottest days may be due to aggravated risk, leaving open the possibly of cognition as a mechanism.

In columns (3) and (4) we present results with only ULD travel by households. In column (3) we document a positive correlation between temperature and ULD miles below 60°F. Above this temperature the point estimates continue to grow but are not precisely estimated. Comparing these estimates with those in column (1), we can see that the changes in demand are an order of magnitude larger than for LDV travel. On days below 20°F demand decreases by 78 percent. As might be expected these exposed modes of transit are also unpopular on days with precipitation. The ULD trip count, estimated in column (4), shows that cold temperatures and rainfall also decrease the trip demand. The general pattern confirms our earlier fatality results that ULD demand is closely linked to temperature.

The final column, (5), examines only trips taken with public transit options such as bus and subway. Our strongest results come from cold days when users reduce trip demand. Although not measured with precision, the

[38]In the appendix, we combine distance with the duration of the trip to generate speed. Speed can be a function of driver choice but also of congestion, complicating interpretation of the speed estimates. But one might be concerned that deadly crashes were generated by higher intensity crashes. In Appendix Table A16 we do not find any evidence that fatalities are due to speed effects. If anything, drivers reduce speed on days with temperatures over 80°F and when there is snowfall, again suggesting defensive behavior.

point estimates are negative for very hot days when waiting for buses and subways is also unpleasant.

Several general observations can be made from these estimates. In Table 4 we find no evidence that ULD travel is reduced as temperature and fatality risk increase. This suggests an exposure mechanism. For LDV travel a different picture emerges where elevated fatality risk on days above 80°F (or accident risks on cold, rainy, or snowy days) could be reducing demand and possibly a defensive action against aggravated risk due to weather.[39]

6 Simulation of Future Outcomes

The estimates above present a mixed picture of the effect of climate change on traffic accidents. While our estimates suggest warmer temperatures will result in more fatalities, a transition from snow to rain will reduce fatalities. It is also possible that changes in travel demand will offset or exacerbate these costs.

To calculate the net welfare effect we calculate the change in an outcome, Δy, for example fatalities, by summing the daily changes, $\sum_d \sum_c \Delta y_{d,c}$,

[39]These results are robust to alternative functional form assumptions. We estimate an alternative model that can handle zero values, the Inverse Hyperbolic Sine, in Appendix Table A15 and find that our results are broadly consistent with those reported using the Poisson model.

across counties indexed by c and days indexed by d where:

$$\Delta y_{d,c} = \left[\sum_{j=1}^{8} \left(\widehat{\alpha}^{j} + \widehat{\alpha}^{j}_{-1}\right) \cdot \left(\widehat{T}^{j}_{d,c} - T^{j}_{d,c}\right)\right] y_{d,c} +$$
$$\left[\sum_{j=1}^{5} (\widehat{\beta}^{j} + \widehat{\beta}^{j}_{-1}) \cdot \left(\widehat{R}^{j}_{d,c} - R^{j}_{d,c}\right)\right] y_{d,c} + \left[\sum_{j=1}^{5} (\widehat{\gamma}^{j} + \widehat{\gamma}^{j}_{-1}) \cdot \left(\widehat{S}^{j}_{d,c} - S^{j}_{d,c}\right)\right] y_{d,c}. \tag{6}$$

The $\widehat{\alpha}^{j}, \widehat{\beta}^{j}, \widehat{\gamma}^{j}$ and $\widehat{\alpha}^{j}_{-1}, \widehat{\beta}^{j}_{-1}, \widehat{\gamma}^{j}_{-1}$ terms denote our estimated contemporaneous and lagged coefficients from Equation (4), respectively, which are summed to give the net effect of a day with particular weather conditions. The $\widehat{T}^{j}_{d,c}$, $\widehat{R}^{j}_{d,c}$ and $\widehat{S}^{j}_{d,c}$ represent indicators for future weather on date d in county c within bin j. Equation (6) generates the percent change in fatalities by multiplying the number of bin changes by the marginal effect of a bin change. This percent change is then multiplied by the baseline daily level of fatalities in the county $y_{d,c}$.[40] Evaluating Equation (6) requires a baseline and a predicted future weather. It is natural to use observed weather as the baseline and the output from climate forecasting models as the future. We base our

[40]Because our SDS data have fatality rates, $y_{d,c}$, for only 20 states, we use FARS data averaged from 2000 to 2010 to generate average daily fatality rates at the county level. For simulations of LDV and ULD fatalities, injuries, and PDO accidents, we project the county baseline using a Poisson model by regressing the outcome variable (e.g., LDV fatalities) on the fatality rate and population by county for the counties in the SDS data and use the estimated coefficients to impute missing counties. For our trip demand simulations we use the observed average per household in each county in our NHTS sample, and where no NHTS data is given in a county, we apply the national average.

weather predictions on the CCSM4 RCP6.0 Scenario, which includes daily (minimum, maximum, and average) temperature and precipitation from 2006 to 2099. Because climate models predict weather over a grid, it is a well known problem that the weather predicted in the baseline years from 2006 to 2009 will not match observed weather outcomes particularly in areas with complex terrain (Wilcke et al., 2013). If these baseline discrepancies are not adjusted, the simulation will generate changes that are the result of this baseline discrepancy as opposed to changes in weather.

Prior correction methods typically adjust either the current observed weather or prediction data by adjusting mean outcomes. These methods can only correct biases in the mean and not other moments of the distribution[41] and often imply unreasonable corrections to daily precipitation variables, which are truncated at zero.[42] To correct these biases with more intuitive outcomes, we draw on quantile-based methods used by atmospheric and

[41]Changes in weather variability are of particular interest for projecting crop yield changes (Schlenker and Roberts, 2009).

[42]Although additive methods are generally not used for precipitation, if $\xi_{\tau,c} > 0$ or $\psi_{\tau,c} > 0$, the corrected rainfall prediction will shift all days with zero precipitation to a positive value. Prior studies have usually corrected precipitation with a multiplicative method, which is undefined if $\sum_{d \in \tau} \overline{x}_{d,c} = 0$, forcing correction at a highly level temporal or spatial level to avoid, for example, warm dry regions without snowfall. Multiplicative correction methods also have no ability to generate or remove trace precipitation days and can only scale up or down already existing precipitation.

climate scientists (Wilcke et al., 2013).[43] Once $\widehat{T}^j_{d,c}$, $\widehat{R}^j_{d,c}$ and $\widehat{S}^j_{d,c}$ are corrected they are applied to equation (6).

6.1 Estimating Welfare Effects of Climate Change

We make assumptions regarding the terms in Equation (2) to estimate the welfare effects of climate change. The first is that we assume that the second term in Equation (2), $\int_0^{m^*} \frac{\partial v}{\partial W} dm$, is equal to zero. We make this assumption given that we are only able to measure how the equilibrium number of miles and not the full MWTP across the demand curve responds weather. The value of this approach is that our estimate does not depend on assumptions of how portions of the demand curve change that we cannot observe (e.g., a parallel shift versus a pivot). This assumption may understate the total effects of climate change positively or negatively. In our setting, where demand for miles increases, we think the likely reason is that the demand curve is shifting out resulting in additional benefits making our offsetting results conservative.[44]

We begin by calculating the change in total fatalities compared to the baseline. This represents the conventional approach capturing terms third

[43]The major advantages of these methods are that they correct all moments of the distribution, not just the mean, and that adjust both the frequency and amount of precipitation. See Appendix A.5 for a detailed discussion of the correction method used.

[44]To generate more miles but lower net welfare would require an increase in the value of marginal trips with a decrease in the value of inframarginal trips.

and fourth term in Equation (2). To capture the first term we next simulate the milage change. We assume that these miles generate the observed fatality-per-mile rates implied by our summary statistics. The net of these terms will result in the fourth term which we price using the value of a statistical life.

We also calculate the change in the price per mile of trips due to climate change by dividing the percent change in total accidents by the percent change in total miles traveled. This represents the first component of the fourth term, $\frac{dp}{dW}$, which (assuming the second term is zero) ultimately controls the sign of total welfare and determines if the sector sees net benefits or losses.

Our empirical exercise focuses on accident costs stemming from fatalities since these types of accidents comprise a large majority of total accident costs. We disaggregate changes for each type of travel mode, LDV and ULD, since weather changes may impact accidents and traveling decisions differently. In the appendix, we also present results for non-fatal accidents, which have costs and benefits that are much smaller in magnitude and we show that our broad conclusions remain unchanged when incorporating these accidents.

6.2 Results

Table 5 summarizes the fatality results of our simulation and welfare calculations using our quantile mapping method.[45] Each simulation in Panel

[45]In Appendix Table A18 we present welfare estimates of accidents and injuries, which are substantially smaller than our fatality results. Appendix Figure A.1 maps the projected

A details the changes in fatalities, and discounted costs, in 2090 and then for the entire period from 2000 through 2099 from LDV and ULD crashes. The brackets give the 95 percent confidence intervals.[46] Column (1) reports the effect of weather from LDV crashes using our estimates from Table 2 column (1). The net change in fatalities is an increase of 82 in 2090 and 4,142 for the period from 2000-2099. Applying the Department of Transportation's (DOT) VSL at $9.1 million and discounting at a 3 percent rate, this has a present value of $9.9 billion.[47] We note that none of these changes are, however, statistically distinguishable from zero.

Column (2) of Panel A examines changes in ULD fatalities, which are substantially larger and are statistically distinguishable from zero. By 2090 our estimates indicate in increase in fatalities by 299. This represents a 3.26 percent increase in ULD fatalities annually. This results in substantial costs over the next century. From 2000 through 2099 we expect 13,617 fatalities

fatality, injury, and accident effects by county.

[46]These confidence intervals incorporate the uncertainty of our point estimates but not the uncertainty across various climate change models. These are generated by drawing from a normal distribution with the mean and standard deviation of coefficient estimates given in Table 2. These draws are then applied to the predicted weather effects in each decade. From these values the mean and 95 percent confidence interval are calculated. When summing across decades, the mean and 95 percent confidence interval are assigned to the midpoint of the decade and linear interpolation is used between those years.

[47]We do not adjust the VSL amount for future changes in income. We use a 3 percent discount rate to be consistent with DOT assumed rates (Blincoe et al., 2014).

with a present discounted cost of $27.7 billion. While a few hundred fatalities annually is small compared to the roughly 30,000 fatal car crashes a year, our ultimate goal is to evaluate the costs of climate change through the channel of traffic fatalities as opposed to a goal of optimizing climate change to reduce traffic fatalities. Therefore the welfare costs of this channel should be added to, or compared with, those of other channels through which climate change may affect future generations as opposed to costs of traffic fatalities. The figure of $27.7 billion suggests substantial costs particularly for ULD modes, on the order of changes found in other areas such as agriculture (Deschênes and Greenstone, 2007) and crime (Ranson, 2014), but a complete picture requires estimating the changes to demand which will net out these costs if demand is shown to increase.

Panel B applies the estimates of the weather-travel demand relationship estimated in Table 4 to future weather outcomes.[48] While demand for LDV trips increases by 7 billion miles,[49] this increase is on a percentage basis small at 0.31% and is not statistically distinguishable from zero.[50] Column

[48]To calculate the change in demand from our estimates, we multiply the estimated percent change in demand times the number of miles taken daily in the county. To generate the daily number of miles, we use the average number of miles across households in the county in the NHTS data, which is multiplied by the number of households in the county. Miles are priced based on the average fatalities per LDV or ULD mile times the VSL.

[49]For comparison, drivers in the US currently drive roughly 3 billion miles annually.

[50]These benefits assumed to be $0.09 per mile which is the VSL multiplied by the per-mile fatality risk as given in Table 1 Panel A.

(2) presents estimates of the change in ULD miles travel. Although the predicted change in miles is smaller in magnitude, 1 billion miles in 2090, this change is statistically significant and substantially larger in percentage terms at 4.03%.[51] One of the key takeaways from comparing Panel A with Panel B is that fatalities increase more on a percentage basis than miles for LDVs implying net costs, while fatalities increase less than miles for ULDs implying net benefits.

The values in Panel C evaluate total welfare changes for the LDV and ULD modes. For LDV vehicles we summarize the effects of Panels A and B by calculating the change to cost per mile. For LDV modes we find a slight increase but for ULD modes net cost-per-mile is actually reduced even though this category saw larger increases in fatalities. Another way of interpreting this finding is to omit the conversion of fatalities to dollars. This result suggests that the increase in fatalities for ULD modes can be explained by an increased demand for travel in these modes. Because the individual LDV components are not statistically significant we cannot determine if welfare is affected, but taking the point estimates at face value, we note that welfare costs of LDV fatalities are reduced from $9.9 billion to $3.9 billion, a 60%

[51] These costs or benefits are valued at $2.65 per mile. We use the fatality risk per mile as implied by the SDS and NHTS data although it is likely this cost will change over time. We discuss the possible changes over the next century to this risk-per-mile measure for ULD and LDV trips in the next section.

reduction, when the demand shift is accounted for.[52] Taken together, our results suggest that excluding exposure benefits from cost-benefit analysis can dramatically overestimate the expected net costs from climate change.

6.3 Discussion

There are several relevant caveats to our welfare analysis and predictions of future fatalities. The first is that we cannot evaluate the change in MWTP for non-marginal trips, the second term in Equation (2). Here we have assumed a flat demand curve and that these changes do not generate welfare. Because demand for miles increases for both of our sectors, it seems likely that these effects are positive, but they could, in principle, be negative.

Our simulation also rests on the assumption that drivers rationally evaluate the fatality risk of driving, walking, bicycling, or using a motorcycle. Systematic over- or undervaluation of risk is plausible and climate change may aggravate such a market failure but without substantial evidence of such a phenomenon, rational expectations is, we believe, the safest assumption. Furthermore addressing this irrationality through a policy aimed at reducing

[52]It is important to note that offsetting can be sensitive to the climate scenario used because there can be substantial variation in the timing and location of weather changes. These additional trips are evaluated by their price, which only incorporates the risk of a fatality. We do not incorporate accident or injury costs because FARS does not track these and the SDS data only track crashes involving LDVs. We also evaluate LDV trips only using fatality costs, excluding other costs such as time and gasoline for consistency.

greenhouse gas emissions would rest on a second-best argument that agencies were unable to address this market failure directly.

We also assume that all aspects of driving besides the weather-travel and weather-accidents relationships that we estimate are held constant. Rather than thinking of these simulations as a literal prediction, the value of this exercise is to compare this channel with other potential channels through which climate change may influence costs and which mechanisms or policies may influence these costs. For example, our simulation does not account for future changes in the availability of driver-assistance technology (e.g., automatic lane changing) or fully autonomous vehicles. But this possibility does not weaken our conclusion that accounting for behavioral responses is important for accurately forecasting net costs of climate change. Driverless cars could dramatically reduce accident frequency, reducing the slope of the temperature-mortality relationship. But by reducing the marginal accident cost per mile, total miles would rebound, which may not reduce the relationship between trip demand and weather. As long as trip demand responds to weather and fatalities per mile are not zero, failure to account for voluntary exposure benefits would overestimate costs.

Fourth, we note that even if all additional deaths are due to voluntary exposure, this is not an argument against public policy to reduce this number. Increased fatalities may change the cost-benefit analysis of a particular policy. If warmer weather encourages more walking, biking, and motorcycling, a location may adapt by shifting public policy to address the dangers associated with these modes of travel.

A final limitation of our welfare calculations is that they do not incorporate private or public adaptation to warmer, rainier weather. Leaving adaptation out of our welfare calculations implies that our estimates overstate the long-run impacts of climate change. They also do not account for migration away from affected areas, as a form of private adaptation. But it is important to note that if the fatalities we estimate are due to voluntary exposure, unlike other forms of adaptation, migration should not be expected as these fatalities would not be associated with lower total utility. Such a dynamic may explain why, despite the documented negative outcomes associated with heat, the predominant migration pattern within the United States in recent decades has been towards warmer climates. Because our measure of voluntary exposure does not offset all costs, some of our estimates may be due to aggravated risk, which would encourage migration but previous estimates of migration in response to climate change suggest that it is likely to be modest (Albouy et al., 2016).

7 Conclusion

This paper estimates the impact of weather on traffic fatalities, injuries, and PDO accidents as well as total trip demand. We apply these estimates to the CCSM4 RCP6.0 climate change scenario corrected using quantile-mapping. We find that the net annual increase in fatalities will be 381 fatalities by

2090. While some crashes only involving light-duty vehicles on hot days may be due to psychological effects, most fatalities are due to increased demand for travel by pedestrians, bicycles, and motorcycles suggesting a voluntary exposure mechanism. These fatalities carry a total net present cost of $37.6 billion by the end of the century. Increased benefits from travel, however, offset more than 60 percent of LDV fatality costs and all of the ULD fatality costs.

One broader implication of this research is that voluntary exposure is an important mechanism for understanding the welfare implications of climate change. Our estimated effects appear to be the result of individuals being drawn outdoors and using forms of transportation that will not protect them in a crash. It is possible that individuals spending time outdoors will also be exposed to street crime or air pollution. In the agriculture sector, farmers may choose riskier but higher-profit crops, such as citrus, in warmer areas. Voluntary decisions may also be important for broader economic measures such as GDP. Warmer climate may allow for outdoor leisure activities that may or may not be captured by GDP or may increase the opportunity cost of working. In other domains, such as health effects of temperature for infants and elderly, a voluntary exposure mechanism seems less plausible.

Finally, it is important to note that the exposure mechanism will vary across countries, particularly for transportation. Compared with the United States, developing nations, and even some middle income countries, have larger fatality rates per capita, largely due to vehicles colliding with pedestrians (Kopitis and Cropper, 2005). Other countries like Sweden with extraordinarily low fatality rates have pursued a variety of urban design and legislative changes to reduce fatalities with policies such as replacing intersections with roundabouts to slow vehicles where they are likely to encounter pedestrians.[53] Relatively simple changes like these may prove to be effective, although unglamorous, adaption strategies to climate change.

[53]The "Vision Zero" policy was adopted by Sweden in 1997 to reduce fatalities to zero by 2020. Similar policy initiatives have now been adopted by other nations and cities including several in the United States.

References

Albouy, D., W. Graf, R. Kellogg, and H. Wolff (2016). Climate amenities, climate change and american quality of life. *Journal of the Association of Environmental and Resource Economists 3*(1), 205–246.

Auffhammer, M., S. M. Hsiang, W. Schlenker, and A. Sobel (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy 7*(2), 181–198.

Barreca, A., K. Clay, O. Deschênes, M. Greenstone, and J. S. Shapiro (2013). Adapting to climate change: The remarkable decline in the U.S. temperature-mortality relationship over the 20th century. *NBER Working Paper No. 18692*.

Blincoe, L., T. R. Miller, E. Zaloshnja, and B. A. Lawrence (2014, May). The economic and societal impact of motor vehicle crashes, 2010. Technical report, National Highway Traffic Safety Administration, Washington, DC.

Cameron, A. C. and P. K. Trivedi (2013). *Regression analysis of count data*, Volume 53. Cambridge University Press.

Colmer, J. (2016). Weather, labour reallocation, and industrial production: Evidence from India. *Mimeo*.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature 52*(3), 740–798.

Deschênes, O. and M. Greenstone (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review 97*(1), 354–385.

Deschênes, O. and M. Greenstone (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics 3*(4), 152–185.

Deschênes, O., M. Greenstone, and J. S. Shapiro (2017). Defensive investments and the demand for air quality: Evidence from the no$_x$ budget program and ozone reductions. *American Economic Review forthcoming.*

Deschênes, O. and E. Moretti (2009). Extreme weather events, mortality, and migration. *The Review of Economics and Statistics 91*(4), 659–681.

Eisenberg, D. (2004). The mixed effects of precipitation on traffic crashes. *Accident Analysis* & *Prevention 36*, 637–647.

Fisher, A. C., M. Hanemann, M. J. Roberts, and W. Schlenker (2012). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather: Comment. *American Economic Review 102*(7), 3749–3760.

Froom, P., Y. Caine, I. Shochat, and J. Ribak (1993). Heat stress and helicopter pilot errors. *Journal of Occupational and Environmental Medicine 35*(7), 720–732.

Graff Zivin, J. and M. Neidell (2013). Environment, health and human capital. *Journal of Economic Literature 51*(3), 689–730.

Graff Zivin, J. and M. Neidell (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics 32*, 1–26.

Harrington, W. and P. R. Portney (1987). Valuing benefits of health and safety regulation. *Journal of Urban Economics 22*, 101–112.

Hsiang, S. M., M. Burke, and E. Miguel (2013). Quantifying the influence of climate on human conflict. *Science 341*(6151).

Kopitis, E. and M. Cropper (2005). Traffic fatalities and economic growth. *Accident Analysis & Prevention 37*(1), 169–178.

Moretti, E. and M. Neidell (2011). Pollution, health, and avoidance behavior: Evidence from the ports of los angeles. *Journal of Human Resources 46*(1), 154–175.

NHTSA (2008). National motor vehicle crash causation survey: Report to Congress. *U.S. Department of Transportation, National Highway Traffic Safety Administration.*

Nordhaus, W. (2013). *Integrated economic and climate modeling.* Amsterdam: North Holland, Elsevier B.V.

Ranson, M. (2014). Crime, weather, and climate change. *Journal of Environmental Economics and Management 67*, 274–302.

Santos Silva, J. M. and S. Tenreyro (2006). The log of gravity. *Review of Economics and Statistics 88*(4), 641–658.

Schlenker, W. and M. J. Roberts (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of Sciences 106*(37), 15594–15598.

Seppanen, O., W. J. Fisk, and Q. Lei (2006). Effect of temperature on task performance in office environment. *Lawrence Berkeley National Laboratory*.

Wilcke, R. A., T. Mendlik, and A. Goblet (2013). Multi-variable error correction of regional climate models. *Climatic Change 120*, 871–887.

World Health Organization (2013). *WHO global status report on road safety 2013: Supporting a decade of action.* World Health Organization.

Table 1: Summary Statistics, Accidents and Travel Demand Data

Panel A. State Accident Data, 1991-2010											
	Accidents per 100,000	LDV Fatalities per 100,000	ULD Fatalities per 100,000	Temperature (°F) Quantile			Rainfall (cm) Quantile		Snowfall (cm) Quantile	
				5th	50th	95th	75th	95th	75th	95th
Census Region[a]	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Northeast	3.5	0.029	0.011	20.2	51.0	75.3	0.35	1.34	0.01	1.82
Midwest	8.5	0.056	0.007	17.2	53.0	79.0	0.22	1.25	0.00	0.94
South	8.8	0.064	0.014	37.2	65.9	82.7	0.33	1.69	0.00	0.00
West	5.7	0.072	0.014	23.6	53.3	76.4	0.09	0.75	0.00	0.84
All 20 States	7.6	0.058	0.010	21.3	56.4	80.4	0.23	1.30	0.00	0.68
Panel B. NHTS Daily Travel Data, 1990-1991, 1995-1996, 2001-2002, and 2008-2009										
	Daily HH	Daily LDV	Daily ULD	Temperature (°F) Quantile			Rainfall (cm) Quantile		Snowfall (cm) Quantile	
Census Region	Trips	Miles	Miles	5th	50th	95th	75th	95th	75th	95th
Northeast	6.4	52.5	0.8	19.8	50.4	74.9	0.32	1.30	0.00	2.23
Midwest	6.8	56.7	0.7	14.6	47.6	76.2	0.24	1.25	0.00	1.30
South	6.1	55.7	0.7	34.4	65.2	83.4	0.23	1.43	0.00	0.00
West	6.4	49.7	1.1	40.2	63.1	79.6	0.03	0.79	0.00	0.05
All States	6.4	54.2	0.8	24.1	59.2	81.5	0.22	1.27	0.00	0.50
Panel C. Observed Weather Station Data, 2000-2009										
				Temperature (°F) Quantile			Rainfall (cm) Quantile		Snowfall (cm) Quantile	
Census Region				5th	50th	95th	75th	95th	75th	95th
Northeast				21.6	54.8	79.7	0.33	1.48	0.00	1.24
Midwest				13.9	51.6	77.4	0.23	1.26	0.00	1.05
South				33.8	63.4	83.0	0.28	1.52	0.00	0.00
West				19.6	50.7	76.0	0.10	0.71	0.00	1.13
All Regions				21.8	57.2	81.1	0.24	1.33	0.00	0.51
Panel D. Baseline Predicted CCSM4, 2006-2009										
				Temperature (°F) Quantile			Rainfall (cm) Quantile		Snowfall (cm) Quantile	
Census Region				5th	50th	95th	75th	95th	75th	95th
Northeast				21.1	57.3	80.0	0.34	1.33	0.00	0.57
Midwest				13.8	55.3	84.3	0.23	1.08	0.00	0.66
South				32.2	65.3	83.9	0.38	1.32	0.00	0.01
West				17.3	49.5	77.9	0.17	0.87	0.01	2.01
All Regions				21.9	59.6	83.1	0.30	1.19	0.00	0.41
Panel E. Predicted Future CCSM4, 2090-2099										
				Temperature (°F) Quantile			Rainfall (cm) Quantile		Snowfall (cm) Quantile	
Census Region				5th	50th	95th	75th	95th	75th	95th
Northeast				25.9	61.2	84.2	0.37	1.46	0.00	0.28
Midwest				20.7	59.2	88.9	0.23	1.10	0.00	0.41
South				35.9	69.3	88.1	0.40	1.44	0.00	0.00
West				24.4	53.3	82.1	0.23	1.08	0.00	1.49
All Regions				27.2	63.6	87.5	0.31	1.30	0.00	0.19

Notes: Panel A details the state accident data for 20 states grouped by census region. Panel A statistics are based on 6,698,935 county-by-day observations of accidents, fatalities, and weather. Panel B describes the National Household Transportation Survey data of 283,857 households and their driving behavior for a 24 hour period. Panels C, D, and E describes the county-by-date weather observations used in the simulation from the National Climatic Data Center's Global Historical Climatology Network-daily and the CCSM4 RCP6.0 scenario predicting daily weather.
[a] See Appendix Table A2 for included states and further details.

Table 2: Poisson Regression of Accidents on Weather Variables

	Fatalities					PDO Accidents	Injuries
		LDV Crashes[a]	ULD Crashes[b]	Week of Lags[c]	Urban Counties[d]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean Temp.							
<20°F	-0.137***	-0.014	-0.600***	-0.093	-0.116*	0.098***	0.002
	(0.032)	(0.035)	(0.057)	(0.053)	(0.056)	(0.021)	(0.020)
20-30°F	-0.107***	0.017	-0.579***	-0.102***	-0.126***	0.028	-0.040**
	(0.027)	(0.031)	(0.043)	(0.025)	(0.036)	(0.016)	(0.015)
30-40°F	-0.085***	0.008	-0.413***	-0.081***	-0.076*	-0.028***	-0.067***
	(0.020)	(0.020)	(0.044)	(0.019)	(0.034)	(0.007)	(0.007)
40-50°F	-0.066***	-0.022	-0.203***	-0.061***	-0.035*	-0.024***	-0.045***
	(0.013)	(0.015)	(0.022)	(0.013)	(0.017)	(0.004)	(0.004)
60-70°F	0.051***	0.015	0.136***	0.050***	0.056***	-0.004	0.021***
	(0.011)	(0.012)	(0.012)	(0.011)	(0.013)	(0.004)	(0.003)
70-80°F	0.065***	0.018	0.181***	0.061***	0.068***	-0.010	0.023***
	(0.014)	(0.013)	(0.019)	(0.014)	(0.018)	(0.006)	(0.004)
>80 °F	0.086***	0.052*	0.170***	0.081***	0.081**	-0.010	0.016*
	(0.017)	(0.021)	(0.028)	(0.018)	(0.030)	(0.008)	(0.007)
Rainfall							
0-0.1 cm	-0.026***	0.001	-0.103***	-0.024**	-0.034*	0.022***	0.014***
	(0.008)	(0.009)	(0.019)	(0.008)	(0.014)	(0.003)	(0.004)
0.1-0.5 cm	-0.042***	0.008	-0.184***	-0.047***	-0.045**	0.069***	0.057***
	(0.011)	(0.011)	(0.015)	(0.012)	(0.015)	(0.004)	(0.005)
0.5-1.5 cm	-0.053***	0.020	-0.249***	-0.055***	-0.036*	0.108***	0.089***
	(0.014)	(0.013)	(0.025)	(0.014)	(0.017)	(0.006)	(0.007)
1.5-3 cm	-0.086***	-0.015	-0.290***	-0.117***	-0.018	0.152***	0.128***
	(0.017)	(0.023)	(0.043)	(0.020)	(0.024)	(0.010)	(0.010)
>3 cm	-0.033	0.065	-0.302***	-0.036	-0.004	0.187***	0.148***
	(0.029)	(0.034)	(0.060)	(0.032)	(0.051)	(0.014)	(0.015)
Snowfall							
0-0.1 cm	0.026	0.041*	-0.024	0.031*	0.005	0.023***	0.006
	(0.015)	(0.019)	(0.041)	(0.016)	(0.029)	(0.006)	(0.007)
0.1-0.5 cm	0.057**	0.073**	-0.027	0.053**	0.002	0.100***	0.078***
	(0.019)	(0.024)	(0.030)	(0.020)	(0.031)	(0.009)	(0.006)
0.5-1.5 cm	0.124***	0.133***	0.064	0.139***	0.078**	0.225***	0.183***
	(0.026)	(0.029)	(0.053)	(0.027)	(0.027)	(0.009)	(0.009)
1.5-3 cm	0.128***	0.122***	0.092	0.138***	0.064	0.354***	0.286***
	(0.028)	(0.033)	(0.077)	(0.039)	(0.043)	(0.011)	(0.009)
>3 cm	0.036	0.025	0.012	-0.008	-0.090	0.438***	0.262***
	(0.043)	(0.048)	(0.056)	(0.043)	(0.054)	(0.014)	(0.022)
Num. Obs.	3,174,278	2,846,607	1,132,759	3,174,278	781,078	6,755,606	5,151,670

Notes: The estimates are from a Poisson regression of the daily count of fatalities, property-damage-only (PDO) accidents, or injuries by county on weather, county-year-month fixed effects, and an indicator for first snowfall after 1 month without snow. Standard errors, in parentheses, are block bootstrapped by year. Reported coefficients and standard errors are the linear combination of the current and lagged estimates. Disaggregate results presented in Appendix Table A6.

[a] Includes only fatality counts where all participant were light-duty vehicles (also includes heavy duty vehicles).

[b] Includes only fatality counts where one participant was an ultra-light duty mode.

[c] Includes controls for 6 additional days of lags for each weather bin. Coefficients and standard errors include the sum of all current and lagged weather controls.

[d] Includes only counties classified as large or medium urban and suburban counties as classified by the National Center for Health Statistics 2006 Urban-Rural Classification Scheme.

Table 3: Poisson Regression of Fatalities–Adaptation

	Regional Sorting		Time Period Changes	
	Coldest Quartile	Hottest Quartile	1990-1999	2000-2010
	(1)	(2)	(3)	(4)
Mean Temp.				
<20°F	-0.196***	0.210	-0.095	-0.158***
	(0.050)	(0.219)	(0.050)	(0.033)
20-30°F	-0.138**	-0.114	-0.068	-0.130***
	(0.056)	(0.089)	(0.054)	(0.023)
30-40°F	-0.110**	-0.061*	-0.030	-0.109***
	(0.036)	(0.027)	(0.031)	(0.019)
40-50°F	-0.063	-0.044**	-0.063**	-0.066***
	(0.040)	(0.015)	(0.024)	(0.016)
60-70°F	0.147***	0.058***	0.051**	0.051***
	(0.024)	(0.017)	(0.018)	(0.013)
70-80°F	0.159***	0.087***	0.062**	0.068***
	(0.032)	(0.021)	(0.021)	(0.018)
>80°F	0.151	0.123***	0.079**	0.089***
	(0.082)	(0.022)	(0.028)	(0.021)
Rainfall				
0-0.1 cm	-0.051**	-0.037*	0.004	-0.040***
	(0.019)	(0.016)	(0.013)	(0.006)
0.1-0.5 cm	-0.090***	-0.020	0.000	-0.061***
	(0.026)	(0.013)	(0.014)	(0.010)
0.5-1.5 cm	-0.087*	-0.011	-0.011	-0.073***
	(0.036)	(0.014)	(0.023)	(0.013)
1.5-3 cm	-0.299***	-0.027	-0.048	-0.102***
	(0.062)	(0.024)	(0.033)	(0.022)
>3 cm	-0.167	0.014	-0.010	-0.049
	(0.221)	(0.048)	(0.048)	(0.034)
Snowfall				
0-0.1 cm	0.081**	0.050	0.021	0.034**
	(0.028)	(0.079)	(0.031)	(0.013)
0.1-0.5 cm	0.124***	0.018	0.041	0.067***
	(0.032)	(0.058)	(0.032)	(0.020)
0.5-1.5 cm	0.199***	0.082	0.057*	0.159***
	(0.053)	(0.072)	(0.028)	(0.030)
1.5-3 cm	0.349***	-0.160	0.063	0.162***
	(0.064)	(0.123)	(0.050)	(0.023)
>3 cm	0.297***	-0.006	0.048	0.038
	(0.057)	(0.158)	(0.074)	(0.047)
Num. Obs.	578,710	1,050,571	933,759	2,216,506

Notes: The estimates are from a Poisson regression of the daily count of fatalities by county on weather, county-year-month fixed effects, and an indicator for first snowfall after 1 month without snow. Standard errors, in parentheses, are block bootstrapped by year. Reported coefficients and standard errors are the linear combination of the current and lagged estimates.

Table 4: Poisson Regression of Travel Demand

	Light-Duty Vehicles		Ultra-Light Duty		Public Transit
	Household Miles	Trip Count	Household Miles	Trip Count	Trip Count
	(1)	(2)	(3)	(4)	(5)
Mean Temp.					
<20°F	-0.075*	-0.043	-0.780***	-0.329***	-0.291*
	(0.031)	(0.023)	(0.145)	(0.059)	(0.128)
20-30°F	-0.057*	-0.036*	-0.521***	-0.172***	-0.200
	(0.024)	(0.015)	(0.108)	(0.041)	(0.104)
30-40°F	-0.010	-0.021*	-0.363***	-0.124***	-0.054
	(0.015)	(0.010)	(0.086)	(0.031)	(0.055)
40-50°F	-0.022	0.001	-0.156*	-0.045*	-0.080
	(0.012)	(0.007)	(0.076)	(0.021)	(0.046)
60-70°F	0.005	-0.007	0.059	0.022	0.044
	(0.010)	(0.008)	(0.050)	(0.019)	(0.057)
70-80°F	0.003	-0.007	0.097	0.011	0.044
	(0.016)	(0.008)	(0.087)	(0.029)	(0.058)
>80°F	-0.010	-0.033*	0.129	0.005	-0.149
	(0.030)	(0.015)	(0.092)	(0.040)	(0.100)
Rainfall					
0-0.1 cm	-0.009	-0.013*	-0.162***	-0.020	0.016
	(0.010)	(0.006)	(0.046)	(0.017)	(0.050)
0.1-0.5 cm	-0.023*	-0.006	-0.264***	-0.079***	0.008
	(0.011)	(0.008)	(0.048)	(0.021)	(0.040)
0.5-1.5 cm	-0.012	-0.004	-0.266***	-0.107***	0.034
	(0.014)	(0.007)	(0.067)	(0.017)	(0.059)
1.5-3 cm	0.002	-0.032**	-0.602***	-0.116**	0.044
	(0.019)	(0.011)	(0.111)	(0.037)	(0.062)
>3 cm	-0.018	-0.041*	-0.349	-0.167**	0.190
	(0.038)	(0.021)	(0.274)	(0.065)	(0.143)
Snowfall					
0-0.1 cm	0.032	-0.011	0.160*	0.050	0.068
	(0.025)	(0.012)	(0.079)	(0.042)	(0.056)
0.1-0.5 cm	-0.008	-0.013	0.055	-0.090*	-0.041
	(0.024)	(0.014)	(0.095)	(0.036)	(0.080)
0.5-1.5 cm	-0.004	-0.007	-0.185	-0.134**	-0.182*
	(0.030)	(0.018)	(0.102)	(0.044)	(0.093)
1.5-3 cm	-0.085*	-0.087***	-0.055	-0.088	0.079
	(0.042)	(0.025)	(0.178)	(0.075)	(0.127)
>3 cm	-0.166**	-0.170***	0.016	-0.057	-0.023
	(0.060)	(0.035)	(0.111)	(0.071)	(0.164)
Num. Obs.	261,718	261,718	228,291	228,291	178,278

Notes: The estimates are from a Poisson regression of the daily count of trips and miles per trip for Light-Duty Vehicles, Ultra-LightDuty Modes, and Public Transit by household on weather, county-year-month fixed effects, an indicator for first snowfall after 1 month without snow and household controls. Household controls include count of vehicles in household, household size, number of workers in household, number of adults in household, NHTS life cycle stratum, race, NHTS defined income group, and day of week. Standard errors, in parentheses, are block bootstrapped by year.

Table 5: Estimates of the Change in Fatalities and the Present Discount Value Costs of Climate Change

	LDV	ULD
	(1)	(2)
Panel A. Fatality Changes[a]		
Net Change in 2090	82	299
	[-4, 161]	[263, 335]
	0.33%	3.26%
Sum of Net Changes 2000-2099	4,142	13,617
	[-308, 8,272]	[11,760, 15,500]
Sum of Costs 2000-2099[c]	$9.9	$27.7
($2015 Billions)	[-$0.8, $20.0]	[$23.1, $32.2]
Panel B. Mileage Changes[b]		
Net Change in 2090	7.10	1.00
(Billions of Miles)	[-2.89, 16.70]	[0.65, 1.36]
	0.31%	4.03%
Sum of Net Changes 2000-2099	292.62	47.3
(Billions of Miles)	[-227.93, 793.74]	[28.5, 66.9]
Panel C. Welfare (2000-2099)		
Per Mile Cost Change	$0.00046	-$0.00215
Net Costs[d,e]	$3.9	-$1.4
($2015 Billions)		

Notes: Net Present Cost estimates are reported in 2015 dollars. The net change estimates are the sum of county-level changes in weather on the listed outcome. All future weather simulations use quantile mapping to adjust current weather to the changes predicted by the CCSM4 RCP6.0 scenario. Values given in brackets indicate the 95 percent confidence interval. See text for further details of calculations and Appendix A18 for accident and injury costs. All costs assume a discount rate of 3 percent.

[a] For counties with missing daily average LDV, ULD, injuries, and accidents, rather than applying a national average, we impute using a Poisson regression of the daily count of incidents for states with SDS data on county population and fatalities.

[b] For counties without NHTS data we are missing LDV trips and ULD trips and we apply the national average.

[c] Assumes the value of a statistical life is $9.1 million (Blincoe et al., 2014).

[d] Uses the total cost of nationwide LDV fatalities divided by the annual number of LDV miles. This cost is on average $.09 per mile.

[e] Uses the total cost of nationwide ULD fatalities divided by the number of ULD miles per household per day (0.59), as taken from the NHTS data, multiplied by 365 days and the number of households in the census. This cost is on average $2.65 per mile.