The Value of Forecast Improvements: Evidence from Advisory Lead Times and Vehicle Crashes

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1 September 2022

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September 1, 2022

Abstract

Scientific and technological advances are resulting in improved forecasts of risk, but do better forecasts result in better risk management? I investigate to what extent the improvements in lead time of winter weather advisories affect the frequency of motor vehicle crashes. I construct a data set of winter weather advisories, weather monitor readings, and vehicle crashes at the county-date level in 11 states in the US during 2006-2018. Using within county variation in lead time, I show that receiving winter advisories earlier reduces crash risk significantly. I also examine two potential mechanisms that might lead to these effects. First, using the mobile phone location data from SafeGraph, I show that longer lead times result in fewer visits by people to places outside their homes. Second, using snow plow truck location data, I show that road crews perform a greater level of winter maintenance activities when advisories arrive with longer lead time. Overall, this study provides evidence that improvements in forecast lead times result in meaningful economic benefits to society, and these benefits come from both the individual and institutional response to longer lead times.
(JEL: H41,I31,Q54,R41)

*Wisconsin School of Business, University of Wisconsin-Madison (email: vaibhav.anand@wisc.edu). I am deeply grateful to my advisors Justin Sydnor, Anita Mukherjee, Tyler Leverty, Dani Bauer, and Paul Block for their encouragement and guidance. I am also grateful to the Highway Safety Information System (HSIS) team, the Traffic Operations and Safety (TOPS) Laboratory at UW-Madison, and the Department of Transportation of the 11 US states for providing access to vehicle crash data, and to SafeGraph for providing access to anonymized mobile phone location data. Any conclusions drawn from analysis of the aforementioned data are the sole responsibility of the author of this paper. Partial financial support from the Wisconsin Alumni Research Foundation's UW2020 grant is gratefully acknowledged. The remaining errors in the paper are mine.

1 Introduction

Advances in predictive technology are improving forecasts in several areas–the outcome of an election, the spread of a contagious disease, or the eruption of a volcano. This is particularly true for meteorology, where weather forecasts are getting more accurate and available earlier–sometimes days or weeks in the future (Bauer et al. 2015). However, improvements in weather forecasts are costly, and require significant public investments in meteorological operations and research (Alley et al. 2019). Although, in theory, better forecasts should enable better risk management (Millner and Heyen 2021), there are several reasons why this may not be true in practice. People may not pay attention to forecasts (Golman et al. 2017), may choose not to act on forecasts,[1] or may not have sufficient means to respond to forecasts.[2]

In this paper, I investigate if forecast improvements result in meaningful benefits to society in the context of winter weather forecasts and motor vehicle crashes. I focus on improvements in the lead time of forecasts, i.e., how far in advance a forecast is available before the predicted event occurs. The literature on the effect of forecast lead time on risk management is scarce. Most studies examine this question in a lab setting and find that longer lead time can have mixed effect on risk management (Hoekstra et al. 2011, Weyrich et al. 2020).[3] On one hand, longer lead time may allow people and organizations to plan better and take more effective actions; on the other hand, getting forecasts too early may adjust their expectations about risk and make the weather look less hazardous.

Motor vehicle crashes are a significant economic and health hazard to people.[4] Winter weather results in particularly risky driving conditions on the road and greatly increases the likelihood of vehicle crashes (Qiu and Nixon 2008).[5] Winter weather advisories, often

[1]There could be various reasons. People may not trust forecasts. For example, a 2017 YouGov Poll in the United Kingdom shows just above 50% of respondents trust weather forecasters' opinion on weather forecasts (Smith 2017). People may also perceive the advisory in a forecast as a symbolic threat to their freedom and may choose not to comply (Cherry et al. 2021).

[2]Uncertainty about the benefits of risk mitigating actions may also result in inaction. Li and Peter (2021) provide a comprehensive review.

[3]In a sole empirical study, Simmons and Sutter (2008) examine the effect of tornado warning lead time on tornado related fatalities and injuries. Their results suggest that, conditional on receiving a warning, longer lead time does not reduce injuries or fatalities.

[4]In US, every year more than 2.5 million people get injured and nearly 35,000 people die in more than 6 million vehicle crashes (Bureau of Transportation Statistics 2021). For the year 2010 alone, the total economic cost of all vehicle crashes in the country is estimated to be 871 billion dollars (Blincoe et al. 2015). Since 2010, the number of crashes and injuries have increased by more than 20%, and the number of fatalities have increased by 10%.

[5]In a review study, Qiu and Nixon (2008) find that snowfall can increase the likelihood of crashes by 84%

issued several hours in advance by the National Weather Service, can inform people about the approaching adverse weather and ensuing risky driving conditions. This information may help mitigate crash risk by encouraging people to change their travel plans such as avoiding driving or allocating more time to drive slow during that day, or by helping road crews to plan and manage roads proactively. This paper aims to assess whether longer lead time on winter advisories actually results in these benefits, and whether these benefits are economically meaningful.

Using a novel combination of county-date level data on winter weather advisories, weather monitor readings, and vehicle crashes for 11 US states during 2006-2018, I examine whether longer lead time on winter advisories results in fewer crashes.[6] In my research design, conditional on forecasted event type and realized weather on a day, the effect of lead time on crash risk is identified off the variation in lead time within a county-year-month. The identification assumption is that once we control for the type of winter event forecasted and the realized weather on a day, the variation in advisory lead time is orthogonal to any unexplained factor affecting the crash risk within a county-year-month. This residual variation in lead time is likely to be a result of random variation in weather systems or variation in the forecasters' judgement calls.[7]

My empirical strategy attempts to address the following key challenges in identifying the causal effect of weather forecast lead time on a loss outcome. First, places that receive advisories with shorter lead time may differ in their risk of loss from those that receive longer lead time advisories. To address this potential endogeneity, my estimates are identified off the variation in lead time within the same county. Second, adverse weather with longer forecast lead time is often more severe and is likely to result in more loss. To address this, I use weather monitor readings on snow, rain, and temperature at the county-date level which control for the realized severity of weather. Finally, adverse weather events often have low occurrence rate such as flash floods, tornadoes, and hurricanes, and they may not always result in losses that can be measured precisely and granularly, say at a county level. Thus, an

and likelihood of injuries by 75%.

[6]The 11 states are Illinois, Indiana, Iowa, Maine, Massachusetts, Michigan, Minnesota, New Jersey, Ohio, South Dakota, and Wisconsin. Crash data for Illinois, Iowa, and Minnesota are available to me only for the years 2010-2018, 2009-2018, and 2010-2015, respectively. For the other eight states, the crash data are available for the whole period of 2006-2018.

[7]Human forecasters use weather prediction model outputs, current weather observations, and a rule-based guidance for issuing advisories. Often multiple forecasters work together in shifts to issue advisories for the same area.

empirical design using such events may not have sufficient variation in outcomes to estimate the lead time effects with desired statistical significance. I use winter weather as the adverse event, and daily vehicle crashes as the loss outcome. Both winter weather and vehicle crashes occur with reasonable frequency in my sample.

I find that longer lead time on a winter advisory results in significantly fewer crashes on days the advisory is issued for. A one standard deviation increase in advisory lead time reduces daily crashes by 6% on the same day. Longer lead time on advisories may cause some of the travelling plans to shift to an earlier or a later date. So, I also examine whether some reduction in crashes on the day of the advisory is explained by a shift in crashes to a different date. I find that a one standard deviation increase in advisory lead time increases daily crashes by 2.5% on the previous day but does not affect crashes on the following day significantly. Preliminary calculations show that longer lead times result in net reduction of 8 crashes per 100,000 people annually. I quantify the dollar benefits of longer lead time through their effect on reducing crash risk using the economic cost estimates of vehicle crashes from Blincoe et al. (2015).[8] My estimates suggest that, relative to advisories with zero lead time, winter advisories with longer lead times result in annual economic savings of nearly 110 million USD in my sample. To give a sense of magnitude, these savings are about 10% of the annual budget of the National Weather Service and about 2% of the annual budget for the entire meteorological services and research of the US federal government.

I also examine two potential mechanisms that might explain these effects of longer lead times on crash rates. First, using the mobile phone location data from SafeGraph for the 11 states in my sample, I examine whether longer lead times result in fewer visits by people outside their homes. Second, using the snowplow truck location data for the state of Iowa, I examine whether road crews perform a greater level of winter maintenance activities when advisories arrive with longer lead time. I show that both the visits by individuals and road maintenance activities respond to lead times on winter advisories. People visit fewer places on the day of the advisory when there is a longer lead time. Road maintenance activities increase with lead time for the same as well as the previous day of the advisory. My analysis suggests that the value of better forecasts may come from both the individual and institutional risk mitigation efforts.

[8]Blincoe et al. (2015) estimate the economic cost of vehicle crashes in the US for the year 2010. They account for both the direct and the indirect economic costs (value of life, lost productivity, workplace losses, and congestion costs) of crashes to society.

This paper, to the best of my knowledge, provides the first empirical evidence that getting forecast advisories earlier results in better risk management.[9] Martinez (2020) uses the improvements in hurricane path accuracy to show that benefits from receiving accurate forecasts outweigh costs of improvements. On similar lines, Rosenzweig and Udry (2019) and Shrader (2020) also show that firms' response to long-run forecasts of risk is higher when forecasts are more accurate. While these studies show that accurate forecasts are valuable, this paper shows that there is value to getting forecasts earlier.

This paper also contributes to the emerging literature on the role of forecasts in adaptation to and mitigation of weather risk. Most literature on this subject focuses on the role of seasonal or long-run weather forecasts in production decisions of firms. Downey et al. (2021) show that construction firms adjust labor usage based on long-run rainfall forecasts. Shrader (2020) shows that albacore fishing vessels use three-month ahead ENSO forecasts to make decisions about their fishing effort and expenditures. Rosenzweig and Udry (2019) examine the role of 2-4 month ahead monsoon forecast in investment and labor decisions of farmers in India. In a recent study, using a theoretical model, Millner and Heyen (2021) show that people can be better off using short-run forecasts when reliable long-run forecasts are not available. My contribution is to provide the empirical evidence that both individuals and institutions can and do use short-run weather advisories to mitigate risk in routine activities such as driving and winter road management. In this respect, my paper is close to Neidell (2009) and Shrader et al. (2022). Neidell (2009) shows that people respond to day-ahead pollution alerts while planning daily activities. Shrader et al. (2022) show that accurate short-run forecasts of temperature on a day reduce mortality from extreme temperatures. My paper complements this literature by providing evidence that the value of short-run forecasts and advisories can come from risk mitigation actions of both the individuals and institutions.

Finally, this study also contributes to a large economic literature that examines policy implications for mitigating vehicle crash risk. Vehicle crashes are a leading cause of property damage, injuries, and deaths worldwide. Most existing research examines man-made factors of crash risk such as cellular usage (Bhargava and Pathania, 2013; Abouk and Adams, 2013; Karl and Nyce, 2019, 2020; Faccio and McConnell, 2020), alcohol consumption (Carpenter and Dobkin, 2009; Hansen, 2015), sleep (Smith 2016), and violation of traffic rules (DeAn-

[9] Most studies examine the effect of forecast lead time using surveys or lab experiments, and find that longer lead time can have mixed effect on risk management (Hoekstra et al., 2011; Weyrich et al., 2020).

gelo and Hansen, 2014; Gallagher and Fisher, 2020). My paper extends this literature by examining the role of weather advisory lead times in reducing weather related crash risk. In a related study, Ferris and Newburn (2017) show that wireless alerts for flash floods reduce road accidents in Virginia. My contribution is to show that early communication of weather advisories can result in meaningful reductions in weather related crash risk through the actions of drivers as well as road maintenance crews.

There are some limitations to this study. First, this paper aims to quantify the economic benefits of longer lead times of winter advisories given existing weather forecasting technologies. It cannot provide guidance on if or how the National Weather Service should change the process of generating weather advisories. Second, there is a potential limitation to using the crash data based on the police accident reports. My sample includes the number of vehicle crashes to the extent they are reported to the police.[10] Third, although this paper shows that both the number of visits by individuals and activities by road crews may contribute to reduction in crashes due to longer lead time, it does not quantify the extent to which these two mechanisms might lead to those effects. Further, there are likely other actions taken by people and organizations, which I do not examine, that may explain some of the reduction in crash risk due to longer lead times. When winter advisories are available earlier, commuters may drive slow, choose alternative modes of transport, or visit places closer to their homes and workplaces. The data available limit my ability to examine this broader range of potential channels. This paper however provides the first evidence that longer lead times on weather advisories may really enable these mechanisms, and result in meaningful benefits to the society. Future work in this area may explore these mechanisms in more details.

The chapter is organized in six sections. Section 2 describes the data and the empirical strategy. Section 3 presents results on the effect of advisory lead time on vehicle crash risk. Section 4 discusses the robustness of main results. Section 5 discusses two potential mechanisms. Section 6 concludes.

[10]Minor crashes that result in property damage below a certain threshold might not be reported. I discuss this limitation in some detail in section 2.

2 Data and Empirical Strategy

2.1 Data Description

This paper uses a novel combination of three data sets: motor vehicle crash data from police accident reports maintained by the department of transportation of respective states, daily weather monitor readings from the National Oceanic and Atmospheric Administration's (NOAA) Global Historical Climate Network (GHCN) database, and a database of weather advisories issued by the National Weather Service (NWS).

2.1.1 Vehicle Crash Data

My analysis uses detailed police accident reports of motor vehicle crashes maintained by the Department of Transportation (DoT) of each state. I assembled this data set through requests to a state's DoT, the Highway Safety Information System (HSIS) database, or through internet downloads from the respective DoT's website. I limit my analysis to those Midwest and Northeast states for which I was able to obtain data for the years between Jan 1, 2006 to Dec 31, 2019.[11] These states are Illinois, Iowa, Indiana, Maine, Massachusetts, Michigan, Minnesota, New Jersey, Ohio, South Dakota, and Wisconsin.[12] These crash reports provide time, date, and county location for all the crashes. Using this information, I calculate the total number of crashes on a date in a county.

One limitation of using police accident reports is that they likely undercount the number of vehicle crashes (Bhargava and Pathania, 2013; Blincoe et al., 2015). States typically require a vehicle crash to be reported to the police if the crash results in injury or death of a person, or property damage in excess of a threshold dollar amount. The threshold for property damage varies by state and is typically between 500-1000 USD in the eight states in my sample. As a result, minor crashes that result in a small property damage or minor injury may go unreported.

Using the police accident reports may also lead to potential biases in my estimate of the effect of lead time on crash risk. First, there are differences across states in the criteria for

[11] The earliest digitized winter weather advisories are available from Jan 1, 2006.

[12] Crash data for Illinois, Iowa, and Minnesota are available to me only for the years 2010-2018, 2009-2018, and 2010-2015, respectively. My results are robust to limiting my sample to eight states for which I have crash data for all the years during 2006-2018.

reporting a crash to the police. Similarly, the reporting criteria may also vary over time in my study. However, my empirical strategy exploits the variation in lead time and crashes within the same county, year, and month. As long as the reporting criteria do not change in a county within a month, my results may not be affected by the variations in the criteria. Second, if crash reporting patterns are correlated with the lead time on winter advisories, then my estimate of the effect of lead time on crash risk may be biased. When winter weather is worse, people may be less inclined to wait on road to file a crash report. Police may also find it difficult to respond and reach promptly to crash sites on days with worse weather conditions, which often experience higher crash rates due to weather. However, my empirical strategy controls for the realized weather conditions on a day. So, conditional on the realized weather, crash reporting patterns are less likely to be correlated with advisory lead time. Also, as I show in this study, longer lead times on advisories result in more winter road maintenance activities. So, longer lead times are more likely to enable police to respond earlier and record a crash report. If this is the case, then my estimates will be biased upward, i.e. toward finding a less negative or more positive effect of lead time on crash risk.

2.1.2 Weather Advisory Data

I obtain weather advisory data from the archive of watch, warnings, and advisories ('advisories' henceforth) issued by the National Weather Service (NWS). The historical data on these advisories are digitized and maintained by the Iowa Environmental Mesonet (IEM) group of Iowa State University. This data set is a collection of geospatial format files that provide information on geographic coverage, timing, and other details for the warning message for all weather advisories issued since 1986. Data on winter weather advisories are fully available only after 2005.[13]

Weather advisories are typically issued to a county by one of the 122 local weather forecast offices operated by the National Weather Service. A weather forecast office (WFO) typically serves a county warning area that consists of 20 to 50 counties, often across state boundaries. The office is primarily tasked with providing short-term weather forecasts (up to 7 days ahead) and weather advisories to the counties in their designated county warning areas. According to the National Weather Service guidelines, the primary goal of winter

[13]The digital archival of the NWS advisories relies on NWS's Valid Time Extent Code (VTEC) system which allows for systematic parsing of the information in advisories. The VTEC system for winter advisories was operational by November 2005.

advisories is to provide people enough lead time to take appropriate action, and to describe the severity, location, timing and evolution of hazardous winter weather events occurring or forecast to occur.[14] For this study, I consider those advisory messages that inform people about any of the following weather events: blizzard, snow storm, freezing rain, lake effect snow, ice storm, and snow squall.[15]

There are three types of advisories–watch, advisory, and warning. Watches are issued when the event is likely but its occurrence, location, timing are uncertain. Advisories and warnings are issued when the event is occurring or has a high probability of occurrence. For this study, I treat the three types of advisories in the same way. Figure D.5 shows an example of a winter weather 'advisory' issued by the Milwaukee weather forecast office to alert counties about a forecasted adverse winter weather event. The advisory was issued for 20 counties in the state of Wisconsin at 2:53 PM on February 4, 2019. The adverse weather event related to this advisory was forecasted to occur between 6 PM on February 5 to 6 AM February 6.

The archive database provides the time an advisory is issued by the local weather forecast office, the name of the issuing weather forecast office, the time the advisory goes in effect (i.e., the forecasted time of onset of the hazardous event), the time the advisory expires, the nature of the hazardous event, and the names of affected counties. This information allows me to capture for each date and county whether a winter advisory is active in the county on that date, and the lead time of the advisory, i.e. the time between the advisory issuance and the predicted onset of the event. An advisory can remain active for more than a day. For the first day of an active advisory, I estimate the lead time as the difference between the time of issuance and the time when the advisory goes in effect that day. For the subsequent days, I estimate the lead time as the number of hours passed since the issuance of the advisory until the beginning of the current day, i.e. 0000 hours on the day. If there are multiple updates made to an advisory for a weather event, I consider the issuance time of only the first advisory issued to estimate the lead time. For example, a local forecast office may have issued a Watch on January 10 at 6 am CST for a likely snow storm to affect a county between 5 pm on January 10 and 11 am on January 12. At 12 pm on January 10, the forecast office may issue an updated advisory that upgrades the 'Watch' to a 'Warning'.

[14] NWSI 10-513 accessed from https://www.nws.noaa.gov/directives/sym/pd01005013curr.pdf

[15] I do not include advisories that inform only about wind chill. Although, wind chill causes extremely hazardous conditions for health, it may not directly affect the crash risk.

In this example, for my purposes the advisory is issued at 6 am on January 10, it goes in effect at 5 pm on January 10, and remains active for three dates– January 10, 11 and 12. I estimate the lead time of the advisory as 11 hours for January 10, 18 hours for January 11, 42 hours for January 12.

2.1.3 Daily weather observations

I obtain daily snowfall amount, rainfall amount, and minimum and maximum temperatures from the National Oceanic and Atmospheric Administration's (NOAA) Global Historical Climate Network (GHCN) database. This database provides daily weather monitor readings for weather stations across the 50 US states and the District of Columbia. It is an aggregation of records from several agencies that in turn collect the monitor readings from their network stations.

The reported daily minimum and maximum temperature readings are the recorded temperatures at a specific time on a day. The reported daily snow and rain readings are the accumulated amounts for the last 24-hour period. Most agencies require their network stations to report monitor readings once a day at a fixed hour, typically around 7 AM local time. While most stations report within a few hours of the suggested reporting time, some stations may report several hours later. This variance in reporting time creates potential problem for the estimation of snowfall and rainfall amount during a calendar day. To address this, while calculating the daily snow and rain amounts, I consider monitor readings for only those weather stations that report between 5 am and 9 am.

For each county, I estimate the daily accumulated snowfall, accumulated rainfall, and minimum and maximum temperature recorded by aggregating the weather monitor readings. Prior studies often aggregate temperature and air pollution monitor readings for a region as the inverse distance-weighted average of all available readings from the monitors located within a radius of the region centroid (e.g., Currie and Neidell (2005) and Heutel et al. (2017)). Unlike temperature or air pollution, rain and snow accumulations may not have smooth spatial variation. An aggregation using weighted average of all monitor readings within a radius may result in loss of variation in observations for snow and rain, particularly for counties with fewer weather stations. So, I aggregate weather readings as the simple average of all available monitor readings for the stations located within the county boundary. County and date pairs that do not have any valid monitor readings are dropped from the sample.

2.1.4 Variable and Primary Sample Construction

My primary sample includes all county-date observations, with or without an active winter advisory, for the 11 states during 2006-2019. For each county and date, I construct the following variables: total number of crashes, total snow accumulation, total rain accumulation, minimum and maximum temperature observed, indicator for whether a winter advisory is active, and the advisory lead time in hours. I create additional variables to account for whether a day is a workday or a holiday in that county.[16] I also create a variable to indicate the name of the local weather forecast office that is tasked to issue weather advisories to the county.

The nature of winter season may vary from one year to another. However, a winter season overlaps two calendar years. To account for this, I construct a new variable 'seasonal year' that starts from September 1 in a given year and ends on August 31 of the next year. Since my data span 14 calendar years from January 1, 2006 to December 31, 2019, my primary sample covers 13 seasonal years, i.e. from September 1, 2006 to August 31, 2019. In the data, each seasonal year is denoted by the beginning year number, i.e. seasonal year 2006 cover dates from September 1, 2006 to August 31, 2007. The 13 seasonal year values go from 2006 to 2018. In this paper from here onward, I use 'year' to always mean a 'seasonal year' unless noted otherwise.

I drop observations with missing weather variables on the current day, previous day, and the next day. I also drop county-date observations with negative values for advisory lead time and duration. The primary sample contains 2,195,305 county-date observations over the sample period of 13 years (2006-2018) across 734 counties from 11 states.It includes all county-date observations that receive an advisory as well as that do not receive an advisory. Of the total observations, 103,233 county-dates receive an active advisory.

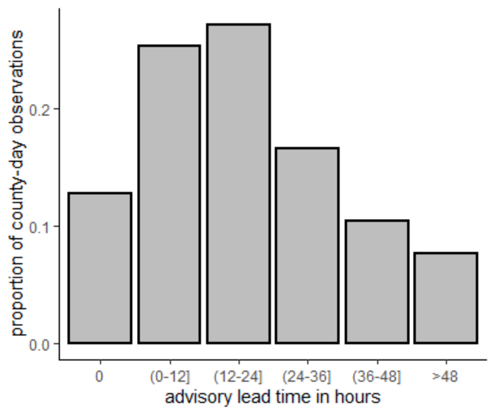
2.2 Empirical Strategy

My empirical strategy estimates the effect of advisory lead time on crash risk by exploiting the variation in lead times. Figure 1 plots the distribution of lead time for county-dates that receive an advisory. The bars plot the proportion of county-date observations (y-axis) that receive a winter advisory with lead time in one of the six lead time bins (x-axis). Of all the

[16] Using the information on website timeanddate.com, I create a list of federal and state holidays during 2006-2019 calendar years.

county-dates with an active winter advisory, about 13% receive the advisory with zero lead time, about 54% receive the advisory with lead time between 0 and 24 hours, and about 33% receive the advisory with more than 24 hours of lead time. The empirical design compares days that receive longer lead time advisory with days that receive shorter lead time advisory.

Figure 1: Distribution of Winter Advisory Lead times



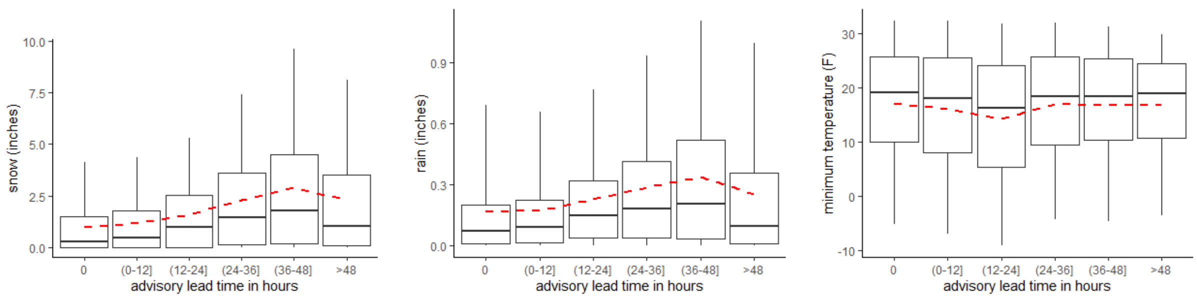
Notes: The figure plots the distribution of lead time of winter advisories in the sample. The bars plot the proportion of county-date observations (y-axis) that receive a winter advisory with lead time in one of the six lead time bins (x-axis).

A potential challenge to this empirical design is that days receiving a longer lead time advisory may have different weather conditions from days receiving a shorter lead time advisory. Figure 2 shows that days that receive an advisory with longer lead time also receive more snow and rain. This suggests that winter weather is likely more severe and hazardous for driving on days that receive an advisory earlier. To account for this difference in severity of weather, my empirical design controls for the realized weather using weather monitor readings for snow, rain, and temperature, and their mutual interactions in the county on that date.

Another potential challenge to the empirical design is that places receiving winter advisories earlier may have different crash risk from places receiving advisories later. Similarly, years that receive shorter lead time advisories can be different from years that receive longer lead time advisories. For example, forecasting technology and frequency of crashes in a county can change over the years (or months).

To address these issues, my empirical design uses the variation in advisory lead times within the same county-year-month. The identifying assumption is that controlling for the

Figure 2: Distribution of rain, snow, and minimum temperature by advisory lead time



(a) Snow (inches) (b) Rain (inches) (c) Minimum temperature (F)

Notes: The figures show the distribution of observed snow (Panel A), rain (Panel B), and minimum temperature (Panel C) at the county-date level by advisory lead time for the main sample. Box and whisker plot the distribution of observed weather element (y-axis) for county-dates that receive the winter advisory with lead time in one of the six 12-hour bins (x-axis). The lower hinge, mid-line, and upper hinge of boxes show the 25th, the 50th, and the 75th percentile. Whiskers stretch from the 5th percentile to the 95th percentile. The dotted red line plots the mean.

observed weather, within a county-year-month, the variation in advisory lead time is likely orthogonal to any other unexplained factors affecting the crash risk. My primary specification is the following:

$$\begin{aligned} Crash_{cd} &= \psi Advisory_{cd} + \beta Leadtime_{cd} \\ &+ \quad \boldsymbol{\gamma_{d-1}} \mathbb{W}_{c,d-1} + \boldsymbol{\gamma_{d}} \mathbb{W}_{cd} + \boldsymbol{\gamma_{d+1}} \mathbb{W}_{c,d+1} + \boldsymbol{\lambda} \mathbb{X}_{cd} + \Phi_{cym} + \epsilon_{cd} \end{aligned} \tag{1}$$

where $Crash_{cd}$ is the number of crashes per 100,000 people in county c on date d. $Advisory_{cd}$ is an indicator variable which is 1 if there is a winter advisory issued on date d for county c, else it is 0. $Leadtime_{cd}$, the key variable of interest, is the lead time of the advisory on date d in county c in hours. When no advisory is active for a county-date, the lead time variable is set equal to 0. So, $Advisory_{cd}$ captures the effect of an advisory issued with zero lead time. $Leadtime_{cd}$ captures the effect of an additional hour of lead time on crash risk. Φ_{cym} are fixed effects, for each combination of county, year, and month, that allow me to use the within county-year-month variation in advisory lead time and crashes. These also control for all observable and unobservable factors that might affect crash risk within a county-year-month.

$\mathbb{W}_{cd}$ includes the non-parametric functional forms of observed snow, rain, and minimum temperature, and their mutual interactions for county c on date d. Specifically, $\mathbb{W}_{cd}$ is defined as:

$$\mathbb{W}_{cd} = \{snowbin_{cd}, rainbin_{cd}, tempbin_{cd}, snowbin_{cd} \times tempbin_{cd}, rainbin_{cd} \times tempbin_{cd}\}$$

where $snowbin_{cd}$, $rainbin_{cd}$ and $tempbin_{cd}$ are three separate vectors of indicator variables that are 0 or 1 based on which bin snowfall, rainfall, and temperature in county c on date d fall in. I use six bins of snow in inches: {<0.01, 0.01-0.5, 0.5-1, 1-2, 2-3, 3-5,>5}, six bins of rainfall in inches: {<0.01, 0.01-0.25, 0.25-0.5, 0.5-1, 1-1.5, 1.5-2, >2}, and five bins for temperature in Fahrenheit: {<5, 5-23, 23-41, 41-60, >60}. $\mathbb{W}_{cd}$ also includes two interacted sets of snow and rain with temperature to account for the effect of precipitation through temperature.[17] I also include $\mathbb{W}_{c,d-1}$ and $\mathbb{W}_{c,d+1}$, one day lag and one day lead variables of observed weather, respectively, to control for any effect of previous and next day's weather on crashes.[18]

$\mathbb{X}_{cd}$ includes additional controls. Driving patterns and traffic volume may vary by day of the week and based on whether the day is a workday or a holiday. I control for the day of week effects by including the categorical variable $DayofWeek$ which takes one of the seven values based on what day of week it is on date d. I control for the effects of holidays by including an indicator variable $Workday$ which is 1 if the date d is a workday in county c, else it is 0.[19] I also control for seasonality in the traffic volume by including the categorical variable $Weeknum$ that takes a value between (01–53) based on the week number of the year the date d falls in, as defined in ISO 8601.

In my preferred specifications, I also include two additional control variables. First, I control for the type of forecasted weather event for which the advisory is issued. The seven event types in my sample are blizzard (BZ), ice storm (IS), lake effect snow (LE), snow squall (SQ), winter storm (WS), severe winter weather (WW), and freezing rain (ZR). Certain weather events may systematically receive advisories with longer lead-time compared to other events. At the same time, people may react differently to advisories issued for certain event types. To control for any potential bias, I include a categorical variable $AdvisoryType$ that

[17]Snow or rain on days with below freezing temperatures may result in more hazardous driving conditions compared to warmer days.

[18]Previous and next day's weather may affect crashes in more than one way. The previous day's snow accumulation may be large enough to pose risky conditions the next day. Also, a portion of realized snow and rain amounts for a day may be attributed to previous or next day's realized weather and misreported, especially for continuing weather events that overlap multiple days.

[19]To construct this variable I use the list of state and federal holidays from the website www.timeanddate.com.

takes one of the seven values based on the event type for which the advisory is issued for.[20] Second, I also control for the time of weather advisory issuance. The nature of an advisory as well as people's reaction to it may systematically depend on when the advisory is issued. To control for this potential source of bias, I include a categorical variable $AdvisoryTime$ that takes one of the four values from $\{0000-0600, 0600-1200, 1200-1800, 1800-2400\}$ based on which hour bucket the issuance time falls in.

I weight all regressions by county population. Errors are clustered at the 'weather forecast office (WFO)–date' level to account for error structure correlations between counties on a day that receive advisories from the same weather forecast office.

2.2.1 Displacement Effect

It is possible that longer lead-time on advisories causes some vehicle crashes to happen on an earlier or a later day. This may happen for various reasons. When people are informed of a potential adverse weather event in advance, they may choose to change their travel plans to earlier or later dates. For example, upon receiving a snow storm advisory for the next day, people may travel to purchase groceries and other necessities before the adverse weather. Similarly, some travelers may postpone their travel plans to the subsequent day. To estimate such displacement effects, I estimate the following variation of the primary specification in equation 1:

$$\begin{aligned} Crash_{cd} = & \sum_{i=-1,0,1} \beta_i Leadtime_{c,d+i} + \sum_{i=-1,0,1} \psi_i Advisory_{c,d+i} \\ + & \quad \boldsymbol{\gamma_{d-1}} \mathbb{W}_{c,d-1} + \boldsymbol{\gamma_d} \mathbb{W}_{cd} + \boldsymbol{\gamma_{d+1}} \mathbb{W}_{c,d+1} + \boldsymbol{\lambda} \mathbb{X}_{cd} + \Phi_{cym} + \epsilon_{cd} \end{aligned} \tag{2}$$

where $Leadtime_{c,d-1}$, $Leadtime_{c,d}$, and $Leadtime_{c,d+1}$ are the lead time of advisories on the date $d-1$, d, and $d+1$. The coefficient β_i on the variable $Leadtime_{c,d+i}$ is the estimate of the effect of an additional hour of lead time on advisory active for date $d+i$ on crashes that occur on date d. For example, if d denotes January 15, then β_{-1}, the coefficient on $Leadtime_{c,d-1}$, captures the effect of an additional hour of lead time on the advisory active for January 14 on vehicle crashes that occur on January 15. Similarly, β_{+1} captures the effect of an additional hour of lead time on the advisory active for January 16 on vehicle crashes that occur on January 15.

[20] When no advisory is issues, the variable take the value 'NoAdv'.

Another interpretation of the coefficients on variables $Leadtime_{c,d-1}$, $Leadtime_{c,d}$, and $Leadtime_{c,d+1}$ is that they capture the effect of an additional hour of lead time on advisory active for date d on crashes that occur on date $d+1$, d, and $d-1$, respectively. So, β_{-1}, the coefficient on $Leadtime_{c,d-1}$, captures the effect of today's advisory lead-time on crashes that will occur tomorrow, and β_{+1}, the coefficient on $Leadtime_{c,d+1}$, captures the effect of today's advisory lead-time on crashes that occurred yesterday. In the subsequent discussion, it is the latter interpretation that I will use while discussing the results and implications.

2.2.2 Identifying Assumption

The identifying assumption of my empirical design is that within a county-year-month, conditional on realized weather and forecasted event type, the residual variation in advisory lead time is uncorrelated with any other unexplained factors that might affect the crash rate. There are two potential sources of this residual variation in lead time. First, there could be variation in how snow storms and other winter weather phenomena develop. This variation might result in some storms being predicted earlier than others. Once I control for the severity of weather using the observed weather variables, within a county-year-month, the variation in weather system is likely to be random and uncorrelated with other factors affecting the crash risk.

The second potential source of residual variation in the lead time is the process of issuing winter advisories. These advisories are issued by human forecasters working in the local weather forecast offices. Forecasters primarily use the quantitative forecasts of weather elements and pre-agreed severity criteria to issue the advisory. The severity criteria consist of objective thresholds for weather elements, such as a threshold for the forecasted amount of snow accumulation in a 12-hour period. However, the criteria acts more like a guidance than a strict rule. Forecasters can use their judgement to issue an advisory for an event that poses significant risk even if it does not meet the severity criteria. Thus, subjective judgement is a potential source of variation in advisory lead time. Further, multiple forecasters often work in the same office on different shifts during a day. This could result in additional variation in the judgement calls on when to issue an advisory.

These variations in weather systems together with the variations in subjective decisions made by human forecasters are likely to be uncorrelated with the other factors affecting the crash risk, within a county-year-month, after controlling for the observed weather, forecast event type, and the other time varying features of the day (e.g., day of week, workday, and week of year). The underlying assumption is that variation in weather systems and human judgment calls are not based on any unobservable information that is correlated with the riskiness of driving conditions.[21]

3 Effect of Advisory Lead time on Crash Risk

3.1 Descriptive Analysis

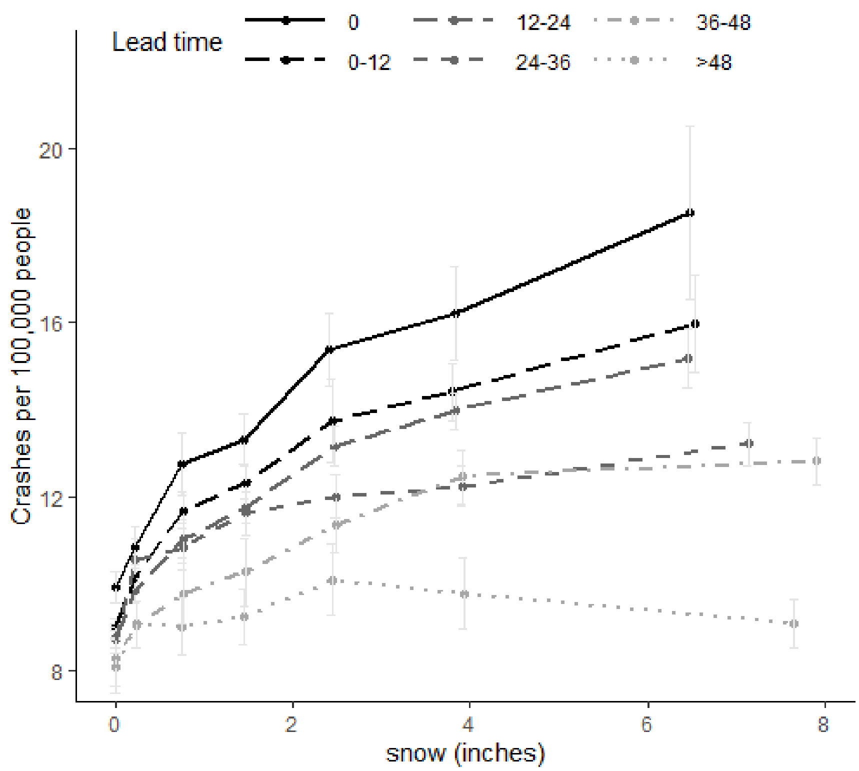
Figure 3 presents the descriptive evidence of the effect of advisory lead time on crash risk. The figure is a binned scatter plot of the average crashes per 100,000 people (x-axis) by average realized snow in inches (y-axis) within each of the six snow bins as mentioned in section 2.2. Each line in the plot corresponds to county-dates that receive advisory with lead time falling in one of the six bins of advisory lead times in hours: {0, (0,12], (12-24], (24,36], (36,48], >48}. The solid black line plots the average crashes by realized snow for those county-dates that receive winter advisory with zero lead time. The dark gray long-dashed line shows the average crashes by realized snow for those county-dates that receive winter advisory with lead time of more than zero hours but less than or equal to 12 hours, and so on. The markers with whiskers plot the average crashes per 100,000 people and the associated 95% confidence interval.

The figure suggests that snow storms that receive advisories with longer lead time result in fewer crashes. It shows that while the average number of crashes increases with realized snow amount, it is highest on days that receive an advisory with zero lead time for every level of snow. As we move to days in higher lead time bins, the average number of crashes decreases gradually for a given level of snow. The figure also shows that the difference in the average number of crashes by lead time is greater for days with higher amount of realized snowfall.

The descriptive evidence in Figure 3 uses the variation in lead time and crashes across all counties and months. It also does not control for the effects of other observed weather conditions or the county and month specific factors that may affect the likelihood of a vehicle crash. In the next section, I estimate the effect of lead time on crash risk using the fixed

[21] One possible violation of this assumption may be that forecasters issue these advisory based on some information, which is an unobservable to me, about the impact of weather on crash risk. If the information tells the forecaster that weather might increase the crash risk, the forecaster is likely to issue the advisory with longer lead time. If this is the case, the coefficients on lead time are likely to be biased upward, i.e., towards finding a less negative or more positive effect of lead time on crash risk. Thus, my results are robust to such violation.

Figure 3: Crashes per 100,000 people by snow for different advisory lead times



Notes: The figure shows the binned scatter plot of the average crashes per 100,000 people (x-axis) by average realized snow in inches (y-axis) within each of the six snow bins in inches, i.e., {<0.01, 0.01–0.5, 0.5–1, 1–2, 2–3, 3–5,>5}. The markers with whiskers plot the average crashes per 100,000 people and the associated 95% confidence interval. Each line in the plot corresponds to county-days that receive advisory with lead time falling in one of the six bins of advisory lead times in hours: {0, 0–12, 12–24, 24–36, 36–48, >48}. The solid black line joins the markers that plot the average crashes by realized snow for county-dates that receive winter advisory with zero lead time. The dark gray long-dashed line corresponds to the average crashes for county-dates that receive winter advisory with lead time of more than zero hours but less than or equal to 12 hours, and so on.

effect specification in Equation 1 that uses the variation within a county-year-month and controls for various observed factors that may affect crash risk.

3.2 Fixed Effects Analysis

Table 1 Columns 1–3 present the results from estimating Equation 1. Columns 4–6 present the results from estimating Equation 2. Columns 1 and 4 include controls for realized weather, day of week, holiday, and week number. Columns 2 and 5 include additional controls for the advisory event type. Columns 3 and 6 include additional controls for both the advisory event type and advisory issuance time. The coefficient on $Leadtime_{c,d}$ shows the effect of an additional hour of advisory lead time on vehicle crash rates on the day of the advisory. The coefficients on $Leadtime_{c,d-1}$ and $Leadtime_{c,d+1}$ show the effect of an additional hour of advisory lead time on vehicle crash rates one day after and one day before the day of the advisory, respectively.

Table 1: The effect of advisory lead time on crash risk

Dependent Variable:	crashes per 100,000 people					
	(1)	(2)	(3)	(4)	(5)	(6)
$Leadtime_{c,d}$	-0.045***	-0.037***	-0.035***	-0.049***	-0.041***	-0.039***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
$Leadtime_{c,d-1}$				0.008***	0.003	0.002
				(0.003)	(0.004)	(0.004)
$Leadtime_{c,d+1}$				0.007*	0.013***	0.016***
				(0.004)	(0.005)	(0.005)
Advisory Event Type						
BZ		1.77**	1.43		1.75*	1.32
		(0.900)	(0.921)		(0.913)	(0.938)
IS		2.85**	2.61*		3.09**	2.78**
		(1.37)	(1.38)		(1.33)	(1.35)
LE		2.24***	1.89***		2.22***	1.77***
		(0.279)	(0.344)		(0.286)	(0.367)
SQ		2.35*	1.76		2.34*	1.68
		(1.30)	(1.18)		(1.33)	(1.21)
WS		1.59***	1.26***		1.74***	1.32***
		(0.220)	(0.306)		(0.223)	(0.322)
WW		2.05***	1.75***		2.21***	1.82***
		(0.116)	(0.258)		(0.118)	(0.284)
ZR		2.59***	2.31***		2.72***	2.37***
		(0.278)	(0.340)		(0.288)	(0.360)
Controls						
Advisory issuance time	No	No	Yes	No	No	Yes
County-Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean Crashes (days with advisory)	11.1	11.1	11.1	11.1	11.1	11.1
Observations	2,195,305	2,195,305	2,195,305	2,195,305	2,195,305	2,195,305
R^2	0.18	0.18	0.18	0.18	0.18	0.18

Notes: The table shows the results from estimating the regression models in Equation 1 (Columns 1–3) and Equation 2 (Columns 4–6). The sample includes all county-date observations that receive as well as that do not receive a winter advisory. The dependent variable is crashes per 100,000 people. $Leadtime_{c,d}$, $Leadtime_{c,d-1}$, and $Leadtime_{c,d+1}$, the key variables of interest, are lead times (in hours) of winter advisories active on date d, $d-1$, and $d+1$. Additional controls include: Advisory Event Type which is a vector of seven indicator variables that capture which event type the advisory is issued for. The seven event types are Blizzard (BZ), ice rain (IS), lake effect snow (LE), snow squall (SQ), winter storm (WS), severe winter weather (WW), and freezing rain (ZR); Advisory Issuance Time which is a vector of four indicator variables that capture which hour bucket in $\{0000-0600, 0600-1200, 1200-1800, 1800-2400\}$ the advisory issuance time falls in. All specifications include controls for current, previous, and next day's weather, day of week, workday, and week of year effects. All specifications include county-year-month fixed effects. All regressions are weighted by county population. Standard-errors clustered at wfo-date level are in parentheses. Significance Level: ***: 0.01, **: 0.05, *: 0.1

The coefficient on $leadtime_{c,d}$ in columns 1 is -0.045 which means that an additional hour of lead time reduces crashes by 0.045 per 100,000 people on the same day the advisory is active. The coefficient on lead time decreases in magnitude to -0.037 when I control for the advisory event type in column 2. When I include an additional control for the advisory issuance time in column 3, the coefficient on $leadtime_{c,d}$ further decreases in magnitude to -0.035. The pattern is similar for columns 4–6. This suggests that a part of the reduction in crashes is explained by the type of forecasted event and the time at which the advisory is issued.[22] The fully specified model in column 6 is my preferred specification.

The coefficient on $leadtime_{c,d}$ in column 6 is -0.039 which means that an additional hour of lead time reduces crashes by 0.039 per 100,000 people on the same day the advisory is active. The coefficient is statistically significant at the 1% significance level. The coefficient on $leadtime_{c,d+1}$ is 0.016 and is significant at 1% level. This shows that an additional hour of lead time increases crashes by 0.016 per 100,000 people on the previous day. The coefficient on $leadtime_{c,d-1}$ is 0.002 and is not statistically significant.Given the average crash rate of 11.1 crashes per 100,000 people on days with an active advisory and a standard deviation of advisory lead time of 17.5 hours, increasing the advisory lead time by one standard deviation reduces crashes on the same day by 6.2% and increases the crashes on the previous day by 2.5%.[23] The overall effect of increasing the advisory lead time by one standard deviation on crashes is a reduction of 3.7%. These estimates suggest that though longer lead times reduce crash risk on the same day in a meaningful way, the increase in crashes on previous day erodes some of these benefits. Before I discuss the potential reasons for this displacement effect, it is helpful to examine how different levels of lead time affect crash risk.

Specifically, I examine whether the incremental effect of lead time improvement on crash risk varies with the level of lead time. For example, does increasing the lead time by an additional hour affect crash risk differently if the original lead time is 24 hours compared to when it is 48 hours? To investigate the incremental effect of lead time on crash risk, I estimate the following specification that includes a non-parametric functional form of the lead time variable:

$$\begin{aligned} Crash_{cd} = & \sum_{b \neq \{0\}} \beta_b Leadtime^b_{cd} + \psi Advisory_{cd} \\ & + \boldsymbol{\gamma_{d-1}} \mathbb{W}_{c,d-1} + \boldsymbol{\gamma_{d}} \mathbb{W}_{cd} + \boldsymbol{\gamma_{d+1}} \mathbb{W}_{c,d+1} + \boldsymbol{\lambda} \mathbb{X}_{cd} + \Phi_{cym} + \epsilon_{cd} \end{aligned} \tag{3}$$

where I replace the primary variable of interest $Leadtime_{cd}$ with five indicator variables $Leadtime^b_{cd}$. These indicator variables capture which lead time bin, $b \in \{$(0,12], (12-24], (24-36], (36-48], >48$\}$, the advisory lead time on date d in county c falls in. In the regression, I omit the lead time bin of exactly zero hours. This non-parametric functional form of the

[22]It is possible that, in addition to advisory lead time, people may also be responding to the advisory event type and the issuance time of the advisory. If advisory lead times are not random for different event types and issuance time, then the coefficient in column 1 and column 4 may be biased.

[23]The effect on crash rates on the day of the advisory of a one standard deviation increase in lead time is $0.039 \times 17.5/11.1 = 0.062$

lead time variable allows me to account for any non-linear effects of lead time on crashes. Thus, the coefficients β_b measure by how much the crash rate changes in a county when the advisory arrives with lead time in bin b relative to a lead time of zero hours. To examine the incremental effect of lead time on crashes on the previous and next day, I estimate a following variation of specification in equation 2:

$$\begin{aligned} Crash_{cd} = \sum_{i=-1,0,1} \sum_{b \neq \{0\}} \beta_i^b Leadtime^b_{c,d+i} + \sum_{i=-1,0,1} \psi_i Advisory_{c,d+i} \\ + \boldsymbol{\gamma_{d-1}} \mathbb{W}_{c,d-1} + \boldsymbol{\gamma_d} \mathbb{W}_{cd} + \boldsymbol{\gamma_{d+1}} \mathbb{W}_{c,d+1} + \boldsymbol{\lambda} \mathbb{X}_{cd} + \Phi_{cym} + \epsilon_{cd} \end{aligned} \tag{4}$$

where β_i^b measures by how much the crash rate on date $d+i$ changes in a county when the advisory active for date d arrives with lead time in bin b relative to a lead time of zero hours.

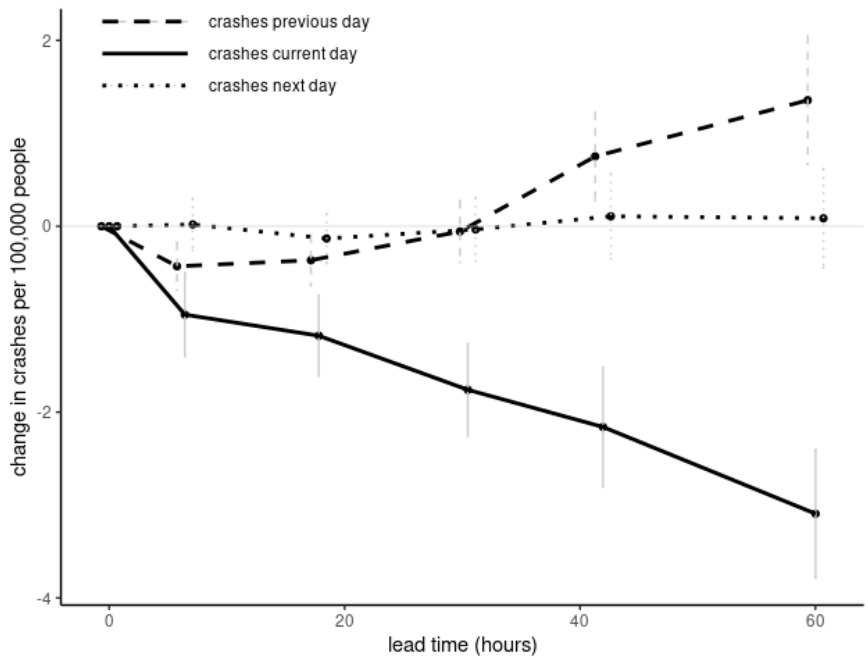
Figure 4 plots the estimated coefficients β_i^b based on the specification in equation 4. The markers with gray whiskers plot the estimated effect of advisory lead time (in hours on x-axis) and their 95% confidence interval on vehicle crashes per 100,000 people (y-axis). The x-axis coordinate of markers correspond to the average lead time in the corresponding bin. The black solid line corresponds to the estimates of the effect of lead-time on crashes that occur on the same day the advisory is active for. The dashed and dotted black lines correspond to the estimates of the effect of lead-time on crashes that occur on the previous and the next day, respectively.

The plot provides two insights. First, it shows that the effect of lead time on crash rate reduction for the same day remains meaningful even at longer levels of lead times. So, the estimate using the regression Equation 1 is not driven by a limited range of lead time duration. An advisory with lead time between 0 to 12 hours reduce crashes per 100,000 people by 0.95 relative to an advisory with zero lead time. For lead times longer than 12 hours, the marginal effect of every additional 12 hours is smaller initially but increases as the lead time increases. For example, relative to an advisory with zero lead time, an advisory with lead time between 12 to 24 hours reduces crash rate by 1.17 relative to a zero lead time advisory. i.e. additional lead time on advisories in 12-24 bin relative to those in 0-12 hour bin provides a reduction of 0.22 crashes per 100,000 only.[24] The incremental reductions in crash rate per 100,000 for three subsequent bins, relative to the corresponding previous bins, are 0.59, 0.40 and 0.93 respectively.[25]

[24] The average lead time in 0-12 and 12-24 hour bins are 6.4 and 17.8 hours respectively.

[25] The average lead time in 24-36, 36-48, and >48 hour bins are 30.5, 41.9, and 60 hours respectively.

Figure 4: The effect of advisory lead time on crashes per 100,000 people



Notes: The figure plots the estimated effect of advisory lead time on crashes per 100,000 people based on estimating the Equation 4. The dependent variable is crashes per 100,000 people. The sample includes all county-date observations that receive as well as that do not receive a winter advisory. The markers with whiskers plot the estimated effect of advisory lead time (in hours on x-axis) on vehicle crashes per 100,000 people (y-axis) along with the associated 95% confidence interval. The black solid line corresponds to the estimates of the effect of lead-time on crashes that occur on the same day the advisory is active for. The dashed and dotted black lines correspond to the estimates of the effect of lead-time on crashes that occur on the previous and the next day, respectively. The x-axis coordinate of markers correspond to the average lead time in the corresponding bin. There is a small horizontal shift added to markers' positions to avoid overlapping. Standard Errors are clustered at WFO-date level.

Second, the plot shows that the effect of longer lead time on previous day crash risk is positive and meaningful only for lead times longer than 30 hours. The dashed black line shows that for shorter lead time, the current day advisory either marginally reduces or does not affect the crashes on the previous day relative to an advisory with zero lead time. However, advisories with lead times longer than 30 hours, increase the crash rates on the previous day. An advisory with lead time between 36-48 hours increases the previous day's crashes by 0.75 per 100,000 people, while an advisory with longer than 48 hours lead time increases the previous day's crashes by 1.36 per 100,000 people.

These results suggest that even a few hours of lead time can provide opportunities to reduce crashes meaningfully. The incremental gains from smaller positive lead times suggest that there are mitigation mechanisms that people and organizations can use at short to moderately longer notice periods, say between 0 and 24 hours. Lead times longer than 24 hours seems to enable people to employ additional mitigation strategies that may result in larger reductions in crash rates for the same day. However, some of these strategies may also push crash risk up during the previous day. For example, longer than 30 hour lead times may allow people to move their travel plans earlier by one day. In this case, a longer lead time advisory may result in more traffic on the road the previous day and, hence, more crashes. Thus, some benefits from crash reduction on the current day may be eroded by the increase in crashes on the previous day.

3.3 Economic Value of Longer Lead Times

In this section, I estimate the economic value of longer lead times of winter advisories based on their impact on vehicle crashes. Specifically, I estimate the economic savings due to the reduction in crashes as a result of advisories that arrive with some positive lead time relative to a hypothetical scenario when all advisories arrive with zero lead time. This method attributes a baseline economic value of zero dollars to the benefits from advisories with zero lead time.[26]

First, I estimate the total number of crashes avoided as a result of advisories with positive lead times relative to the hypothetical scenario of zero lead time on all advisories. To do this, I start with the estimated regression model in Equation 2. This provides the model predicted number of vehicle crashes per 100,000 people in county c on date d for the observed lead time on advisories. I denote the predicted crashes by $\hat{crash}_{cd}^{obs}$. Specifically, I use the estimates from the fully specified specification in model 6 of Table 1 to calculate the predicted crashes $\hat{crash}_{cd}^{obs}$, i.e.

$$\begin{aligned}\hat{crash}_{cd}^{obs} &= \sum_{i=-1,0,1} \hat{\beta}_i Leadtime_{c,d+i} + \sum_{i=-1,0,1} \hat{\psi}_i Advisory_{c,d+i} \\ &+ \quad \hat{\boldsymbol{\gamma}}_{\boldsymbol{d-1}} \mathbb{W}_{c,d-1} + \hat{\boldsymbol{\gamma}}_{\boldsymbol{d}} \mathbb{W}_{cd} + \hat{\boldsymbol{\gamma}}_{\boldsymbol{d+1}} \mathbb{W}_{c,d+1} + \hat{\boldsymbol{\lambda}} \mathbb{X}_{cd} + Cn\hat{Yr}Mn_{cym}\end{aligned} \tag{5}$$

Replacing the actual lead times with zero in Equation 5 will provide the estimated crashes in county c on date d, i.e. $\hat{crash}_{cd}^{zero}$, under a scenario where the advisory comes with zero lead time. Thus, the predicted number of avoided crashes per 100,000 people due to the

[26]In theory, a forecaster may not need specialized skills or costly resources to provide a winter advisory with zero lead time. Since, such an advisory can always be issued after the onset of the event, investments in scientific advances and technology are likely to be needed for generating advisories with positive lead times.

positive lead time on advisory in county c on date d is

$$\begin{aligned}\delta_{cd} &= \hat{crash}_{cd}^{zero} - \hat{crash}_{cd}^{obs} \\ &= \sum_{i=-1,0,1} \hat{\beta}_i Leadtime_{c,d+i}\end{aligned} \tag{6}$$

In other words, δ_{cd} is the number of additional crashes per 100,000 people in county c on date d if we replace the actual lead time on advisory with zero hours.

Next, I estimate the economic savings from the predicted number of avoided crashes using the economic cost estimates of vehicle crashes from Blincoe et al. (2015), a study conducted by the National Highway Traffic Safety Administration of the Department of Transportation. Blincoe et al. (2015) estimate the economic cost of vehicle crashes in the US for the year 2010. They account for both the direct costs (value of life, medical costs, legal, emergency service, insurance administration, and property damage costs) and the indirect economic costs (lost productivity, workplace losses, and congestion costs) of crashes. They estimate that the average economic cost in 2010 dollars of a property damage only (PDO) crash is 6,000 USD per-damaged-vehicle, of an injury crash is 21,000 USD per person,[27] and of a fatal crash is 1.4 million USD. I calculate the average cost of a single crash as the weighted average of the costs of three types of crashes, where the weights are the proportions of PDO, injury, and fatal crashes in the US in 2018.[28] These calculations estimate the average cost of a single crash to be around 20,000 USD in 2018 dollars.[29]

Using these estimates, the total economic value of winter advisory lead times in reducing vehicle crashes in my sample is given by

$$\sum_{cd} \delta_{cd} \times population_{cd} \times 20,000 \tag{7}$$

where $population_{cd}$ is the population (in 100,000 people) of county c in the calendar year the date d falls in.

[27] The cost of injury varies from 4,000 USD for minor injury to 1 million USD for serious injuries. I estimate the average cost of an injury crash using the proportions of different injury levels in 2010. My estimations are limited by the assumption that mix of injuries remains same over time and geography.

[28] For the purposes of this study, the proportions of three types of crashes have not changed much over time. The proportion of PDO, injury, and fatal crashes in 2010 and 2018 are (70%, 29.5%,0.5%) and (71.4%, 28.1%,0.5%) respectively.

[29] 17,300 USD in 2010 dollars.

My estimates suggest that, during 2006-2018 in the sample, positive lead times on winter advisories reduce roughly 8 crashes per 100,000 people each year. These avoided crashes result in an annual economic savings of approximately USD 110 million in my sample. To give a sense of magnitude, during 2018, the total annual budget of the NWS was around USD 1 billion and that of the US federal government for the entire meteorological services and research was nearly USD 4.8 billion.This suggests that there are meaningful economic benefits from longer lead times on winter advisories through their effect on crash risk.

4 Robustness Check

4.1 Effect of quantitative forecasts

The identification assumption in my empirical strategy is that once we control for the type of winter event forecasted and realized weather on a day, the variation in advisory lead time is orthogonal to any unexplained factor affecting the crash risk within a county-month-year. My main specification in equation 2 controls for the realized weather and the type of winter event forecasted but not for the predicted severity of the event. If longer lead time on an advisory is positively correlated with the predicted severity of the weather event, then it is plausible that people might be responding to the predicted severity instead of the longer lead time. A winter advisory message usually contains text that may provide both qualitative and quantitative description of the forecasted weather conditions such as the forecasted amount of snow, precipitation, and temperature (Figure D.5 in appendix). It is likely that people get informed about the predicted severity of the forecasted event through this message in the advisory. However, in my data on winter weather advisories, I do not observe this textual message and do not have access to the predicted severity. So, if the advisories for events with higher predicted severity also come with longer lead time, then my main specifications may not be able to estimate the causal effect of lead time on crash risk. In this section, I use an alternative source of forecasts of weather severity to perform a robustness check to show that my results are robust to controlling for the predicted severity of the weather on the day of the advisory.

In my robustness test, I modify the main specifications by including controls for the forecasted amount of snow, precipitation, and minimum temperature on the day of the advisory. I obtain historical daily forecast data from the National Digital Forecast Database (NDFD) for the period January 2010 to December 2018 for the 11 states in my sample. The NDFD data provide gridded forecasts of weather elements generated by the Weather

Forecast offices (WFOs) and Weather Prediction Center (WPC). I obtain data for snow, temperature, and quantitative precipitation forecast (QPF). The QPF measures the total liquid amount resulting from all types of precipitation events such as snow, sleet, icy rain, and rain. However, there is no straightforward way to separate the QPF forecast into snow and rain. I will refer to QPF as precipitation in the rest of this section. The data of snow and precipitation forecasts provide the forecasted amount of snow and precipitation with a lead time of up to 54 and 72 hours.[30] The data on temperature provide the forecasted minimum temperature for the 24–hour period, with a lead time of up to 72 hours.

I use these gridded forecasts to calculate the county level forecasts for each date in my sample.[31] For a county-date in my main sample, I construct 12 additional variables that measure the forecasted value of daily snow, precipitation, and temperature for different lead times. The variables on snow forecast measure the daily snow forecasted 0 to 24, 12 to 36, 24 to 48, and 30 to 54 hours in advance. The variables on precipitation forecast measure the daily precipitation forecasted 0 to 24, 12 to 36, 24 to 48, 36 to 60, and 48 to 72 hours in advance. The variables on temperature forecast measure the daily minimum temperature forecasted 24, 48, and 72 hours in advance. For each forecast variable, I created additional indicator variables that capture the bin in which the forecast value for the day falls. These bins for snow, precipitation, and temperature forecasts are the same as the bins used for the categorical variables for the observed snow, precipitation, and temperature. I use six bins of snow in inches: {<0.01, 0.01-0.5, 0.5-1, 1-2, 2-3, 3-5,>5}, six bins of precipitation in inches: {<0.01, 0.01-0.25, 0.25-0.5, 0.5-1, 1-1.5, 1.5-2, >2}, and five bins for temperature in Fahrenheit: {<5, 5-23, 23-41, 41-60, >60}.

Using this sample, I re-estimate the six specifications included in Table 1 by adding the controls for forecasted snow, precipitation, and temperature. Specifically, I include the indicator variables of forecasts and their interaction with the categorical variables of the respective observed weather element. The following controls are added to each of the six

[30]The data obtained on snow forecasts for lead time of more than 54 hours contain a large number of missing observations. To give a comparison, 94% of county-date observations that receive an advisory in my sample have lead time of less than 54 hours.

[31]For the snow and precipitation, I add the forecasted amount for all the grids that fall within a county. For the temperature, I take the simple average of the forecasted amount for all the grids that fall within a county.

specification from Table 1

$$
\begin{aligned}
&\sum_m \sum_l \kappa^s_{lm} snowf^m_{cdl} + \sum_m \sum_l \kappa^p_{lm} pptf^m_{cdl} + \sum_m \sum_l \kappa^t_{lm} tempf^m_{cdl} \\
+&\sum_m \sum_n \sum_l \sigma^s_{lmn} snowf^m_{cdl} \times snowobs^n_{cd} \\
+&\sum_m \sum_n \sum_l \sigma^p_{lmn} pptf^m_{cdl} \times rainobs^n_{cd} \\
+&\sum_m \sum_n \sum_l \sigma^t_{lmn} tempf^m_{cdl} \times tempobs^n_{cd}
\end{aligned} \tag{8}
$$

where $snowf^m_{cdl}$ is the indicator variable that is 1 or 0 if the snowfall forecast with lead time l for date d in county c falls in bin m. Similarly, $pptf^m_{cdl}$ and $tempf^m_{cdl}$ denote the indicator variables for precipitation and temperature forecasts. $snowobs^n_{cd}$ is the indicator variable that is 1 or 0 if the observed snowfall in county c on date d falls in bin n. Similarly, $rainobs^n_{cd}$ and $tempobs^n_{cd}$ denote the indicator variables for observed rain and temperature.

Table 2: The effect of advisory lead time on crash risk controlling for forecasted weather

Dependent Variable:	crashes per 100,000 people					
	(1)	(2)	(3)	(4)	(5)	(6)
$Leadtime_{c,d}$	-0.046***	-0.035***	-0.034***	-0.050***	-0.039***	-0.038***
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)
$Leadtime_{c,d-1}$				0.007**	0.005	0.005
				(0.004)	(0.005)	(0.005)
$Leadtime_{c,d+1}$				0.009**	0.012**	0.012**
				(0.005)	(0.006)	(0.006)
Controls						
Forecasted weather	Yes	Yes	Yes	Yes	Yes	Yes
Advisory issuance time	No	No	Yes	No	No	Yes
County-Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,293,473	1,293,473	1,293,473	1,293,473	1,293,473	1,293,473
R^2	0.20	0.20	0.20	0.20	0.20	0.19

Notes: The table shows the results from estimating the regression models in Equation 1 (Columns 1–3) and Equation 2 (Columns 4–6) with additional controls for forecasted weather as described in Equation 8. The sample includes all county-date observations during 2010-2018 that receive as well as that do not receive a winter advisory. The dependent variable is crashes per 100,000 people. $Leadtime_{c,d}$, $Leadtime_{c,d-1}$, and $Leadtime_{c,d+1}$, the key variables of interest, are lead times (in hours) of winter advisories active on date d, $d-1$, and $d+1$. Additional controls include: Advisory Event Type which is a vector of seven indicator variables that capture which event type the advisory is issued for. The seven event types are Blizzard (BZ), ice rain (IS), lake effect snow (LE), snow squall (SQ), winter storm (WS), severe winter weather (WW), and freezing rain (ZR); Advisory Issuance Time which is a vector of four indicator variables that capture which hour bucket in $\{0000-0600, 0600-1200, 1200-1800, 1800-2400\}$ the advisory issuance time falls in. All specifications include controls for current, previous, and next day's weather, day of week, workday, and week of year effects. All specifications include county-year-month fixed effects. All regressions are weighted by county population. Standard-errors clustered at wfo-date level are in parentheses. Significance Level: ***: 0.01, **: 0.05, *: 0.1

Table 2 shows the result of estimating the six specifications from Table 1 after including the controls mentioned in equation 8. The coefficient on $leadtime_{c,d}$ in Table 2 is negative and statistically significant at 1% level across all specifications. Moreover, its magnitude in Table 2 is close to that in Table 1 for all specifications. The results for the effect of previous and next day's lead time are also consistent. These results suggest that the effect of lead time on crash risk measured in Table 1 is likely not explained by the predicted severity of the forecasted event.

5 Mechanisms

The benefits of longer lead time may come from both individual and institutional risk mitigation efforts. In this section, I examine two potential mechanisms through which longer lead times on winter advisories may reduce vehicle crashes. First, longer lead time may result in fewer crashes by reducing road traffic. The traffic reduction might in turn result from people deciding to change travel plans and visiting fewer places, as well as business and school closures that also reduce commuting. I examine this mechanism using mobile phone location data from SafeGraph. The second potential mechanism is that longer lead time may allow road crews to plan in advance and perform better road management before, during, and after the snow storm. Better road treatment and ice-control activities can make roads less risky during adverse winter weather, resulting in fewer crashes. I examine this mechanism using high frequency snow plow operations data from the state of Iowa.

5.1 Effect of advisory lead time on visits

To test whether longer lead times reduce vehicle crashes by reducing travel, I examine whether longer lead times result in fewer visits by people outside of their home. In order to access data on visits, I use the mobile phone location data collected by SafeGraph for the period January 2018-December 2019 for the 11 states in my sample.[32] Using the latitude and longitude location data of a smartphone, SafeGraph determines the total number of daily visits by unique visitors to various points of interests (POI). These POIs include almost all types of places of interest that people may visit outside of their homes such as retail stores, restaurants, hotels, offices, factories, hospitals or schools. SafeGraph provides the category of POI based on the North American Industry Classification System (NAICS). For each county-date, I aggregate the number of visits to all POIs as well as by five types of POI based on NAICS categories: retail, leisure (includes restaurants), commercial, educational, and healthcare. The sample for this analysis includes 433,395 county-date observations from 739 counties for the 11 states. Of these, 26,189 county-dates receive a winter advisory.[33]

[32] The earliest publicly available visit data from SafeGraph is from January 2018.

[33] In this sample, crash data is available for 309,972 county-date observations for the nine states. Of these, 18,924 county-dates receive an active winter advisory. Crash data from Minnesota and Illinois are not

To estimate the effect of lead time on visits, I estimate the following fixed-effects specification, which is similar to the one in equation 1.

$$\begin{aligned} visits_{cd} &= \beta Leadtime_{cd} + \psi Advisory_{cd} \\ &+ \quad \boldsymbol{\gamma_{d-1}} \mathbb{W}_{c,d-1} + \boldsymbol{\gamma_{d}} \mathbb{W}_{cd} + \boldsymbol{\gamma_{d+1}} \mathbb{W}_{c,d+1} + \boldsymbol{\lambda} \mathbb{X}_{cd} + \Phi_{cym} + \epsilon_{cd} \end{aligned} \tag{9}$$

$visits_{cd}$ is the total visits to all POIs by unique visitors per 100,000 people in county c on date d. $Advisory_{cd}$ is an indicator variable that is equal to 1 when there is an active winter advisory for county c on date d, else it is equal to 0. $Leadtime_{cd}$ is the lead time in hours on advisory active for county c on date d. When no advisory is active, $Leadtime_{cd}$ is equal to 0. The coefficient on $Advisory_{cd}$ estimates the effect of a winter advisory per se on visits, whereas the coefficient on $Leadtime_{cd}$ estimates the effect of an additional hour of advisory lead time on visits conditional on an advisory issued for that date. $\mathbb{W}_{cd}$ are controls for realized weather in county c on date d. $\mathbb{X}_{cd}$ includes controls for day of week, holiday, and week number. In some specifications, I also control for advisory event type and advisory issuance time. Φ_{cym} are county-year-month fixed effects that allow me to use the within county-year-month variation in lead time and visits. I also estimate the effect of lead time of advisories issued one day prior and one day later on visits using the specification similar to the one in equation 2:

$$\begin{aligned} visits_{cd} &= \sum_{i=-1}^{1} \beta_i Leadtime_{c,d+i} + \sum_{i=-1}^{1} \psi_i Advisory_{c,d+i} \\ &+ \quad \boldsymbol{\gamma_{d-1}} \mathbb{W}_{c,d-1} + \boldsymbol{\gamma_{d}} \mathbb{W}_{cd} + \boldsymbol{\gamma_{d+1}} \mathbb{W}_{c,d+1} + \boldsymbol{\lambda} \mathbb{X}_{cd} + \Phi_{cym} + \epsilon_{cd} \end{aligned} \tag{10}$$

The coefficient β_{-1}, β_0, and β_{+1} are the estimates of percentage change in visits in county c on date d due to an additional hour of lead time of an advisory issued on day $d-1$, d, and $d+1$, respectively.

Columns 1–3 of Table 3 present the regression results for the specification in equation 9. Columns 4–6 present the regression results for the specification in equation 10. Specifications in Columns 1 and 4 have controls for day of week, holiday, and week number. Columns 2 and 5 have additional controls for advisory event type. Columns 3 and 6 have additional controls for both advisory event type and advisory issuance time. The figures in bracket are standard errors clustered at WFO-date level. All specifications include county-year-month fixed effects.

available to me for the year 2019.

Table 3: The effect of advisory lead time on visits to all POIs

Dependent Variable:	visits to all POIs per 100,000 people					
	(1)	(2)	(3)	(4)	(5)	(6)
$Leadtime_{c,d}$	-15.0***	-8.16***	-8.54***	-14.6***	-6.92***	-7.22***
	(2.17)	(2.50)	(2.56)	(2.21)	(2.49)	(2.59)
$Leadtime_{c,d-1}$				-6.75***	-1.44	-1.88
				(2.00)	(2.27)	(2.36)
$Leadtime_{c,d+1}$				5.19**	0.552	0.107
				(2.49)	(2.60)	(2.77)
Advisory Event Type						
BZ		-1,138.7**	-1,121.4**		-1,226.9***	-1,178.3**
		(504.2)	(521.2)		(442.5)	(460.6)
IS		1,383.6**	1,364.0*		1,346.7*	1,368.0**
		(696.9)	(696.6)		(702.3)	(686.9)
SQ		490.2***	495.6***		474.4***	510.7***
		(124.6)	(158.0)		(134.7)	(165.9)
WS		-447.2***	-446.9***		-513.3***	-477.6***
		(132.1)	(156.4)		(133.3)	(157.3)
WW		-92.5*	-97.6		-144.4***	-113.4
		(51.3)	(104.0)		(51.6)	(103.2)
Controls						
Advisory issuance time	No	No	Yes	No	No	Yes
County-Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean visits (all days)	7,133	7,133	7,133	7,133	7,133	7,133
Mean visits (days with advisory)	5,440	5,440	5,440	5,440	5,440	5,440
Observations	433,395	433,395	433,395	433,395	433,395	433,395
R^2	0.54	0.54	0.54	0.54	0.54	0.54

Notes: The table shows the results from estimating the regression models in Equation 9 (Columns 1–3) and Equation 10 (Columns 4–6). The sample includes all county-date observations during Jan 2018–Aug 2019 that receive as well as that do not receive a winter advisory. The dependent variable is all visits per 100,000 people. $Leadtime_{c,d}$, $Leadtime_{c,d-1}$, and $Leadtime_{c,d+1}$, the key variables of interest, are lead times (in hours) of winter advisories active on date d, $d-1$, and $d+1$. Additional controls include: Advisory Event Type, a vector of seven indicator variables that capture which of the five event types the advisory is issued for: Blizzard (BZ), ice rain (IS), snow squall (SQ), winter storm (WS), and severe winter weather (WW); Advisory Issuance Time which is a vector of four indicator variables that capture which hour bucket in $\{0000-0600, 0600-1200, 1200-1800, 1800-2400\}$ the advisory issuance time falls in. All specifications include controls for current, previous, and next day's weather, day of week, workday, and week of year effects. All specifications include county-year-month fixed effects. All regressions are weighted by county population. Standard-errors clustered at wfo-date level are in parentheses. Significance Level: ***: 0.01, **: 0.05, *: 0.1

Columns 1–6 of Table 3 show that the coefficient on $Leadtime_{cd}$ is negative and statistically significant at the 1% level. The coefficient in column 1 (column 4) means that for an additional hour of lead time on advisory active for county c on date d, the visits fall by 0.28% (0.27%).[34] However, the coefficient on $Leadtime_{cd}$ falls in magnitude once the specification controls for the effect of advisory event type. The coefficient on $Leadtime_{cd}$ in column 2 (column 5) is -8.16 (-6.92).Based on the most specified model 6, the coefficient is -7.22. This suggests that an additional hour of lead time reduces visits by 0.13% on the same day.[35]

I also estimate the effect of lead time on visits to different categories of POIs using the specification in column 6 of Table 3. Table 4 presents these estimates. Column 1 shows

[34] The coefficient in column 1 is -15. The mean visits on days with advisory are 5,440. so, the percentage change is $15/5440 \times 100$ for the specification in column 1.

[35] Appendix B.3 discusses the effect of advisory event type on visits in detail.

the estimates of the effect of lead time on total visits. Columns 2-6 show the estimates of lead time effect on visits to POIs categorized as retail, leisure, commercial, education, and health, respectively. The figures in bracket are standard errors clustered at WFO-date level. All specifications include county-year-month fixed effects.

Table 4: Effect of advisory lead time on visits by POIs

Dependent Variables:	all visits	retail	leisure	commercial	education	health
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$leadtime_{c,d}$	-7.22***	-2.18***	-1.93**	-1.04**	-1.26	-0.825***
	(2.59)	(0.780)	(0.863)	(0.429)	(0.863)	(0.316)
$leadtime_{c,d-1}$	-1.88	-0.703	-0.770	-0.091	-0.387	-0.015
	(2.36)	(0.695)	(0.761)	(0.391)	(0.814)	(0.283)
$leadtime_{c,d+1}$	0.107	0.440	-0.243	0.266	-0.412	-0.022
	(2.77)	(0.811)	(0.980)	(0.456)	(0.767)	(0.344)
Controls						
Advisory event type	Yes	Yes	Yes	Yes	Yes	Yes
Advisory issuance time	Yes	Yes	Yes	Yes	Yes	Yes
county-year-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean (days with advisory)	5,439.8	2,008.2	1,463.9	604.4	671.5	502.0
Mean (all days)	7,133.3	2,576.1	2,080.5	804.5	833.7	590.7
Observations	433,395	433,395	433,395	433,395	433,395	433,395
R^2	0.537	0.391	0.386	0.377	0.615	0.718

Notes: The table shows the results from estimating the regression models in Equation 10 with controls which are similar to those included in Column 6 of Table 3. The sample includes all county-date observations during Jan 2018–Aug 2019 that receive as well as that do not receive a winter advisory. The dependent variables for specification in Columns 1–6 are visits to all, retail, leisure, commercial, education, and health PoIs per 100,000 people, respectively. $Leadtime_{c,d}$, $Leadtime_{c,d-1}$, and $Leadtime_{c,d+1}$, the key variables of interest, are lead times (in hours) of winter advisories active on date d, $d-1$, and $d+1$. Additional controls include: Advisory Event Type, a vector of seven indicator variables that capture which of the five event types the advisory is issued for: Blizzard (BZ), ice rain (IS), snow squall (SQ), winter storm (WS), and severe winter weather (WW); Advisory Issuance Time which is a vector of four indicator variables that capture which hour bucket in $\{0000-0600, 0600-1200, 1200-1800, 1800-2400\}$ the advisory issuance time falls in. All specifications include controls for current, previous, and next day's weather, day of week, workday, and week of year effects. All specifications include county-year-month fixed effects. All regressions are weighted by county population. Standard-errors clustered at wfo-date level are in parentheses. Significance Level: ***: 0.01, **: 0.05, *: 0.1

Table 4 shows that longer lead times on advisories reduce visits to all categories of PoIs for the same day. The effect of an additional hour of lead time varies from -0.11% to -0.19% for different types of visits. The effect is statistically significant at conventional levels for all but educational visits. This suggests that additional lead time on advisories may result in change of travel plans by people or change in hours of operations by businesses. The coefficients on $leadtime_{c,d-1}$ and $leadtime_{c,d+1}$ are small and statistically insignificant. The results do not provide evidence to suggest that the increase in crashes on previous day is due to the shift in visits.[36]

[36]While the coefficient on $Leadtime_{c,d+1}$ for total, retail, and commercial POIs in Table 4 is positive, it is small and statistically insignificant.

Although the results in Table 3 and Table 4 show that longer lead times reduce visits on the day of the advisory, it is not clear to what extent these reductions in visits can explain the reduction in crashes due to longer lead time. Table 1 and Table 4 show that an additional hour of lead time reduces crashes by 0.35% and visits by 0.13% on the day of the advisory. If the change in visits were to explain all the change in crashes, a 1% reduction in visits should reduce crashes by 2.7% on a day with winter advisory. My estimate from Table B.2 shows that on days with no advisory, a 1% reduction in visits reduces crashes by 0.22%. So, for the change in visits to explain all the change in crashes, the size of the effect of visits on crashes on days with advisory has to be nearly 12 times greater than that on days with no advisory.

My analysis does not preclude other mechanisms that may reduce crashes through individual risk mitigation efforts. While I observe the number of visits on a day, I do not observe whether people visit different places or use different modes of transport for their visits. People may also budget longer time for commute to drive more safely. Future studies may examine to what extent these individual risk mitigation mechanisms can explain the reduction in crashes due to longer lead times.

5.2 Effect of lead time on winter road maintenance

Most states have departments responsible for plowing snow and performing ice-control activities on roads during winter weather. In general, county highway departments maintain state and national highways, and Department of Transportation (DoT) maintains the local roads. These activities are primarily de-icing or anti-icing. Snow plowing is one of the most familiar de-icing activities that removes the accumulated snow and ice from the road. De-icing is often performed during or after a winter snow storm, which may also include the application of dry salt or salt mixed with liquid chemical ('prewetted salt') (Fu et al. 2006). Anti-icing activities, on the other hand, reduces snow or ice accumulation by preventing its direct contact with the road (NASEM, 2004). In most cases salt or another anti-icing agent, usually a liquid brine solution, is applied on the road surface before a snow storm.

State DoTs use specialized in-house systems to obtain information on weather and road conditions. In addition to these systems, they also rely on winter weather forecasts and advisories issued by the WFO to make road treatment decisions. Longer lead times on advisories may help road crews to prepare in advance and perform better road management operations. For example, road crews are more likely to apply salt or other anti-icing material in advance when a snow storm advisory arrives with longer lead time (NASEM, 2004).

Similarly, more snow plows may be kept ready to perform snow plowing and salt application during and after the snow storm.

In this section, I examine the hypothesis that road crews perform a greater level of road maintenance activities when advisories arrive with longer lead time. To test this hypothesis, I use the Snow Plow Truck Location data for the state of Iowa maintained by the DoT for the period October 2014 to April 2019.[37] This data is a detailed location and operation level data that is collected by the Automated Vehicle Location (AVL) system of each snow plow. The AVL system tracks and stores the location, speed, direction, snow plow position, and application rate of any solid or liquid material for every snow plow. These data are collected by the AVL system every few seconds.

For my analysis, I aggregate the high frequency observations at the county-date level to calculate the following six measures of road maintenance activity: (1) total distance travelled in miles by snow plow, (2) total duration in hours that snow plows are active, (3) total distance in miles plowed (when plow is engaged), (4) total solid material applied in lbs, (5) total liquid material applied in gallons, and (6) total prewet material (salt mixed with liquid) applied.

To examine the effect of lead-time on road treatment activity, I estimate the following fixed-effect specification which is similar to equation 1

$$\begin{aligned} activity_{cd} = & \sum_{i=-1}^{1} \beta_i Leadtime_{c,d+i} + \sum_{i=-1}^{1} \psi_i Advisory_{c,d+i} \\ + \quad & \boldsymbol{\gamma_{d-1}} \mathbb{W}_{c,d-1} + \boldsymbol{\gamma_d} \mathbb{W}_{cd} + \boldsymbol{\gamma_{d+1}} \mathbb{W}_{c,d+1} + \boldsymbol{\lambda} \mathbb{X}_{cd} + \Phi_{cym} + \epsilon_{cd} \end{aligned} \tag{11}$$

$activity_{cd}$ is the measure of activity per 100,000 people in county c on date d. I estimate a separate specification for each of the six activities listed above. The coefficient β_{-1}, β_0, and β_{+1} are the estimates of the effect of an additional hour of lead time of an advisory issued on day $d-1$, d, and $d+1$, respectively, on the road treatment activity in county c on date d. A positive value of the coefficient β_0 on $leadtime_{c,d}$ will suggest that longer lead-time increases road treatment activity on the same day. The positive values of the coefficient β_{-1} and β_{+1} on $leadtime_{c,d-1}$ and $leadtime_{c,d+1}$ will suggest that longer lead-time increases road

[37]The historical data is available as geodatabase at https://data.iowadot.gov/documents/historic-snow-plow-truck-location-avl/explore

treatment activity on the next day and the previous day, respectively.[38] $\mathbb{W}_{cd}$ are controls for realized weather in county c on date d. $\mathbb{X}_{cd}$ includes control for day of week, holiday, week number, advisory event type, and advisory issuance time. Φ_{cym} are county-year-month fixed effects that allow me to use the within county-year variation in lead time and road treatment activities.

Table 5 presents the regression results. Column 1 shows the estimates of the effect of lead time on total distance travelled by snow plows. Columns 2-6 show the estimates of lead time effect on operating duration, distance plowed, solid, liquid, and prewet material applied, respectively. The figures in bracket are standard errors clustered at WFO-date level. All specifications include county-year-month fixed effects.

The table shows that snow plow trucks travel more distance and operate for longer hours on the day of the advisory. The estimates show that, on the day of advisory, for an additional hour of lead-time, snow plow trucks travel 0.8% more distance and operate for 1.2% longer duration. The results also show that the trucks apply more de-icing and anti-icing material on the previous day. The estimates show that, on the day prior to the advisory, for an additional hour of lead-time, the trucks apply 1.6% more solid, 2.4% more liquid, and 2.4% more prewet material. If longer lead times on advisories allow road crews to better plan their operations, we should expect an increase in early risk mitigation activities such as application of salt and other anti-icing material before the storm.

These results suggest that road maintenance operations increase when winter advisories arrive with longer lead time. In particular, both the de-icing and anti-icing activities increase with lead time. However, it is not clear to what extent this increase in activity can explain the reduction in vehicle crashes due to longer lead time. Prior research finds a negative correlation between winter road maintenance operations and vehicle crashes (Ye et al. 2014; Mahoney et al. 2017). Research suggests that application of de-icing and anti-icing chemicals is associated with fewer crashes. However, there is a lack of causal evidence on the extent to which the winter road maintenance operations reduce vehicle crashes. In my analysis, if the increased road maintenance operations were to explain all the reduction in crashes, then on average a 1% increase in snow plow trucks operating hours should reduce crashes by nearly 0.3% on the day of the advisory or a 1% increase in anti-icing material one day prior to the

[38] The coefficient on $leadtime_{c,d+1}$ literally measures the effect of tomorrow's advisory lead-time on today's road treatment activities. However, it can also be interpreted as the effect of today's advisory lead time on yesterday's road treatment activities.

Table 5: Effect of lead-time on road treatment activities

Dependent Variables:	Distance	Duration	Plow Distance	Solid	Liquid	Prewet
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$leadtime_{c,d}$	17.8**	0.794***	-0.935	153.8	-7.59	5.20
	(7.12)	(0.258)	(3.22)	(456.7)	(29.1)	(6.20)
$leadtime_{c,d-1}$	8.52	0.315	2.30	56.5	11.7	1.19
	(5.45)	(0.198)	(1.90)	(293.5)	(19.9)	(3.29)
$leadtime_{c,d+1}$	11.3	0.455*	-0.819	836.8**	87.9***	10.0**
	(7.61)	(0.268)	(2.26)	(410.0)	(30.9)	(4.80)
Controls						
Advisory Event Type	Yes	Yes	Yes	Yes	Yes	Yes
Advisory Issuance Time	Yes	Yes	Yes	Yes	Yes	Yes
County-Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep Var	2,123	64	461	51,699	3,740	425
Observations	50,796	50,796	50,796	50,796	50,796	50,796
R^2	0.41	0.44	0.25	0.29	0.18	0.10

Notes: The table shows the results from estimating the regression models in Equation 11. The sample includes all county-date observations during October 2014–April 2019 for the state of Iowa that receive as well as that do not receive a winter advisory. The dependent variables for specifications in Columns 1–6 are distance travelled by snowplows, operating duration of plows, distance plowed, solid material applied, liquid material applied, and prewet material applied, respectively, per 100,000 people. $Leadtime_{c,d}$, $Leadtime_{c,d-1}$, and $Leadtime_{c,d+1}$, the key variables of interest, are lead times (in hours) of winter advisories active on date d, $d-1$, and $d+1$. Additional controls include: Advisory Event Type, a vector of seven indicator variables that capture which of the five event types the advisory is issued for: Blizzard (BZ), ice rain (IS), snow squall (SQ), winter storm (WS), and severe winter weather (WW); Advisory Issuance Time which is a vector of four indicator variables that capture which hour bucket in $\{0000-0600, 0600-1200, 1200-1800, 1800-2400\}$ the advisory issuance time falls in. All specifications include controls for current, previous, and next day's weather, day of week, workday, and week of year effects. All specifications include county-year-month fixed effects. All regressions are weighted by county population. Standard-errors clustered at wfo-date level are in parentheses. Significance Level: ***: 0.01, **: 0.05, *: 0.1

advisory should reduce crashes by nearly 0.15%. A useful extension of this work might be to examine the causal effect of road maintenance activities on crash reduction.

My analysis in this section provides evidence that both the visits by individuals to places away from home and road maintenance activities respond to longer lead times on winter advisories. This suggests that both individuals and road crews pay attention to advisories and act on them. While it is unclear how much of the reduction in vehicle crashes can be explained by reduction in visits and increase in road maintenance operations, it is likely that there are other risk mitigation activities undertaken by people and organizations, which I do not examine, that may also explain some of the reduction in crashes due to longer lead times. Overall, this analysis suggests that the value of better forecasts come from both individual and institutional risk mitigation efforts.

6 Conclusion

Technology improvements are creating opportunities for better forecasts of risk. This is particularly true for weather forecasts. In the US, there have been significant public investments in meteorological services and research in recent years. Although, in principle, weather forecast improvements should provide meaningful benefits to society, it is not clear whether this happens in practice. This paper examines this question in the context of improvements in lead times of winter advisories and their effect on motor vehicle crash risk.

Using a data set that I assembled on winter weather advisories, weather monitor readings, and vehicle crashes at the county-date level in 11 states during 2006-2018, I examine whether longer lead times on winter advisories result in fewer vehicle crashes. Exploiting the county-year-month level variation in lead time, I show that receiving winter advisories earlier reduces crash risk significantly. A one standard deviation increase in advisory lead time reduces daily crashes by 6% on the same day, but increases daily crashes by 2.5% on the previous day. I quantify the economic benefits of longer lead time through their effect on reducing the crash risk. Preliminary calculations show that longer lead times, relative to zero lead time on advisories, result in an annual reduction of 8 crashes per 100,000 people. My estimates suggest that actual lead times on winter advisories issued during 2006-2018 have resulted in an annual economic savings of nearly 110 million dollars in the 11 states in my sample.

I also examine two potential mechanisms that might lead to these effects of longer lead times. First, using the mobile phone location data from SafeGraph, I examine whether longer lead times result in fewer visits by people outside of their homes. Second, using the snowplow truck location data, I examine whether road crews perform a greater level of winter maintenance activities when advisories arrive with longer lead time. I show that both the visits by individuals and road maintenance activities respond to lead times on winter advisories. People visit fewer places on the day of the advisory when there is a longer lead time. Road maintenance operations increase with lead time for the same as well as the previous day of the advisory.

This paper provides three insights. First, it provides evidence that lead time improvements in forecasts are valuable. In the context of vehicle crash risk, the paper shows that early communication of weather advisories can meaningfully reduce crashes due to adverse weather. Second, the results show that even marginal improvements, at the scale of a few hours, in forecast lead time can result in better risk management. This suggests that lead time improvements need not be at a larger scale (say, days) to provide meaningful opportunities for risk management. Third, this paper provides evidence that people and institutions pay attention to and use short-run weather forecasts for risk mitigation in routine activities.

This paper estimates the net effect of advisory lead time on crash risk. In the context of this study, there are several potential mechanisms through which longer lead times can reduce crash risk. While I examine two mechanisms that may explain the effect of lead times on crash risk, a natural and important extension of this work is to disentangle the role of these mechanisms and quantify the extent to which these mechanisms that might contribute to the observed effects of lead times. It would be useful to know to what extent the effect of lead time materializes through the efforts of households, businesses, and public institutions. Another important question to investigate is whether there are geographic variations in the benefits of advisory lead time and to what extent these variations are the result of decisions about investments and resource allocation in meteorological services, and whether policy intervention can result in any benefits.

7 Bibliography

Abouk, Rahi, and Scott Adams. 2013. "Texting Bans and Fatal Accidents on Roadways: Do They Work? Or Do Drivers Just React to Announcements of Bans?" *American Economic Journal: Applied Economics*, 5(2): 179–199.

Alley, Richard B., Kerry A. Emanuel, and Fuqing Zhang. 2019. "Advances in weather prediction." *Science*, 363(6425): 342–344.

Bauer, Peter, Alan Thorpe, and Gilbert Brunet. 2015. "The quiet revolution of numerical weather prediction." *Nature*, 525(7567): 47–55.

Bhargava, Saurabh, and Vikram S. Pathania. 2013. "Driving under the (Cellular) Influence." *American Economic Journal: Economic Policy*, 5(3): 92–125.

Blincoe, L. J., T. R. Miller, E. Zaloshnja, and B. A. Lawrence. 2015. "The Economic and Societal Impact Of Motor Vehicle Crashes, 2010 (Revised)." Report No. DOT HS 812 013. Washington, DC: National Highway Traffic Safety Administration.

Bureau of Transportation Statistics. 2021. "National Transport Statistics: Motor Vehicle Safety Data."

Carpenter, Christopher, and Carlos Dobkin. 2009. "The Effect of Alcohol Consumption on Mortality: Regression Discontinuity Evidence from the Minimum Drinking Age." *American Economic Journal: Applied Economics*, 1(1): 164–182.

Cherry, Todd L., Alexander G. James, and James Murphy. 2021. "The impact of public health messaging and personal experience on the acceptance of mask wearing during the COVID-19 pandemic." *Journal of Economic Behavior & Organization*, 187: 415–430.

Currie, Janet, and Matthew Neidell. 2005. "Air Pollution and Infant Health: What Can We Learn from California's Recent Experience?*." *The Quarterly Journal of Economics*, 120(3): 1003–1030.

DeAngelo, Gregory, and Benjamin Hansen. 2014. "Life and Death in the Fast Lane: Police Enforcement and Traffic Fatalities." *American Economic Journal: Economic Policy*, 6(2): 231–257.

Downey, Mitch, Nelson Lind, and Jeffrey G Shrader. 2021. "Adjusting to Rain Before It Falls." Working Paper.

Faccio, Mara, and John J. McConnell. 2020. "Death by Pokémon GO: The Economic and Human Cost of Using Apps While Driving." *Journal of Risk and Insurance*, 87(3): 815–849.

Ferris, Jeffrey S., and David A. Newburn. 2017. "Wireless alerts for extreme weather and the impact on hazard mitigating behavior." *Journal of Environmental Economics and Management*, 82: 239–255.

Gallagher, Justin, and Paul J. Fisher. 2020. "Criminal Deterrence When There Are Offsetting Risks: Traffic Cameras, Vehicular Accidents, and Public Safety." *American Economic Journal: Economic Policy*, 12(3): 202–237.

Golman, Russell, David Hagmann, and George Loewenstein. 2017. "Information Avoidance." *Journal of Economic Literature*, 55(1): 96–135.

Hansen, Benjamin. 2015. "Punishment and Deterrence: Evidence from Drunk Driving." *American Economic Review*, 105(4): 1581–1617.

Heutel, Garth, Nolan H Miller, and David Molitor. 2017. "Adaptation and the Mortality Effects of Temperature Across U.S. Climate Regions." National Bureau of Economic Research Working Paper 23271.

Hoekstra, S., K. Klockow, R. Riley, J. Brotzge, H. Brooks, and S. Erickson. 2011. "A Preliminary Look at the Social Perspective of Warn-on-Forecast: Preferred Tornado Warning Lead Time and the General Public's Perceptions of Weather Risks." *Weather, Climate, and Society*, 3(2): 128–140.

Karl, J. Bradley, and Charles Nyce. 2019. "How Cellphone Bans Affect Automobile Insurance Markets." *Journal of Risk and Insurance*, 86(3): 567–593.

Karl, J. Bradley, and Charles Nyce. 2020. "The Effect of Distracted Driving Laws on Automobile Liability Insurance Claims." *North American Actuarial Journal*, 24(4): 593–610. Publisher: Routledge.

Li, Lu, and Richard Peter. 2021. "Should we do more when we know less? The effect of technology risk on optimal effort." *Journal of Risk and Insurance*, 88(3): 695–725.

Martinez, Andrew B. 2020. "Forecast Accuracy Matters for Hurricane Damage." *Econometrics*, 8(2): 18. Number: 2 Publisher: Multidisciplinary Digital Publishing Institute.

Millner, Antony, and Daniel Heyen. 2021. "Prediction: The Long and the Short of It." *American Economic Journal: Microeconomics*, 13(1): 374–398.

Neidell, Matthew. 2009. "Information, Avoidance Behavior, and Health The Effect of Ozone on Asthma Hospitalizations." *Journal of Human Resources*, 44(2): 450–478. Publisher: University of Wisconsin Press.

Qiu, Lin, and Wilfrid A. Nixon. 2008. "Effects of Adverse Weather on Traffic Crashes: Systematic Review and Meta-Analysis." *Transportation Research Record*, 2055(1): 139–146. Publisher: SAGE Publications Inc.

Rosenzweig, Mark R., and Christopher R. Udry. 2019. "Assessing the Benefits of Long-Run Weather Forecasting for the Rural Poor: Farmer Investments and Worker Migration in a Dynamic Equilibrium Model." National Bureau of Economic Research w25894.

Shrader, Jeffrey. 2020. "Improving Climate Damage Estimates by Accounting for Adaptation." Social Science Research Network SSRN Scholarly Paper ID 3212073, Rochester, NY.

Shrader, Jeffrey, Laura Bakkensen, and Derek Lemoine. 2022. "Fatal Errors: The Mortality Value of Accurate Weather Forecasts." Working Paper.

Simmons, Kevin M., and Daniel Sutter. 2008. "Tornado Warnings, Lead Times, and Tornado Casualties: An Empirical Investigation." *Weather and Forecasting*, 23(2): 246–258. Publisher: American Meteorological Society Section: Weather and Forecasting.

Smith, Austin C. 2016. "Spring Forward at Your Own Risk: Daylight Saving Time and Fatal Vehicle Crashes." *American Economic Journal: Applied Economics*, 8(2): 65–91.

Smith, Matthew. 2017. "Leave voters are less likely to trust any experts – even weather forecasters."

Weyrich, Philippe, Anna Scolobig, Florian Walther, and Anthony Patt. 2020. "Responses to severe weather warnings and affective decision-making." *Natural Hazards and Earth System Sciences*, 20(10): 2811–2821.

A Forecast data from NDFD

I obtain the historical daily forecast data from National Digital Forecast Database (NDFD). The NDFD data provide the gridded forecasts for snow, precipitation, and temperature are generated by the Weather Forecast offices (WFOs) and the Weather Prediction Center (WPC). I obtain the 6 hourly gridded data of snow and precipitation (QPF) forecasts in GRIB format from NDFD. The data on temperature forecasts is obtained for minimum temperatures over 24 hour period. The forecasts for all three elements are available with different lead times. In this section, I explain the process of converting the snow forecast over a 6-hour period to a forecast of snow over a desired 24-hour period. The process works similarly for precipitation.

The NDFD forecasts for snow are issued every 6 hours and are valid for the 6-hour periods. For example, for my purpose a 24-hour lead time snow forecast issued at 0600 AM 01-Jan-2010 is the amount of snowfall forecasted during 0600 AM-1200 PM on 02-Jan-2010. I construct the 24-hour lead time forecast for the period 1200 UTC to 1159 UTC (i.e. 0700 AM to 0659 AM EST) by adding the four separate 6-hour forecasts in the following way (say, for the period 1200 UTC 01-Jan-2010 to 1159 UTC 02-Jan-2010):

Table A.1: Example of NDFD Forecast valid times

Forecast valid period	Forecast issued at
1200 UTC 01-Jan-2010 to 1800 UTC 01-Jan-2010	1200 UTC 31-Dec-2009
1800 UTC 01-Jan-2010 to 0000 UTC 02-Jan-2010	1200 UTC 31-Dec-2009
0000 UTC 02-Jan-2010 to 0600 UTC 02-Jan-2010	1200 UTC 31-Dec-2009
0600 UTC 02-Jan-2010 to 1200 UTC 02-Jan-2010	1200 UTC 31-Dec-2009

The table shows the construction of 24-hour lead-time forecast for snow using the NDFD forecasts. The forecast is what is available to an individual at 1200 UTC 12-31-2009 for the snow during the period 1200 UTC 01-01-2020 – 1159 UTC 01-02-2010. (1200 UTC is 7 AM EST)

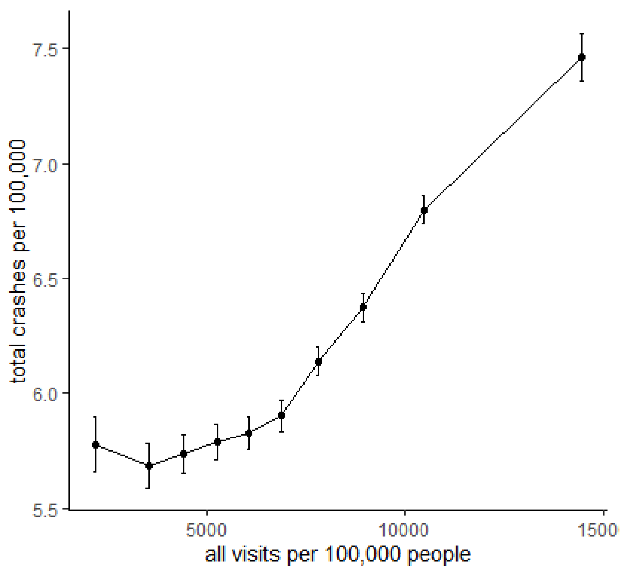
Thus, the above estimated 24-hour lead time forecast of snow amount for the period 7am 01-Jan-2010 EST to 7am 02-Jan-2010 EST is what an individual would receive at 7am EST on 31-dec-2009. (Since 1200 UTC is 7 AM EST same day).

B Visits and Crashes

B.1 Relation between visits and crashes

Longer lead time may reduce the number of people visiting several places. This may happen because either people change their travel plans or places such as businesses and schools decide to close or reduce the hours of operation when they receive weather advisory in advance. In both cases, the resulting effect is to reduce the number of people commuting to visit places outside of their homes. This in turn is likely to reduce the number of vehicles on the road and the number of crashes. Figure B.1 provides descriptive evidence for the relationship between visits and crashes for county-dates that receive no winter advisory. The figure shows a binned scatter plot of crashes per 100,000 people (x-axis) by average visits per 100,000 people (y-axis) within each of the ten decile bins for the visits. The markers with whiskers plot the mean and 95% confidence interval for crashes per 100,000 people. The figure shows a positive correlation between crashes and visits.

Figure B.1: Crashes by visits on days with no weather advisory



Notes: The figure shows the binned scatter plot of the average crashes per 100,000 people (x-axis) for the average visits per 100,000 people (y-axis) within each of the ten decile bins for visits. The sample includes 188,899 county-date observations that did not receive an advisory. The markers with whiskers plot the average crashes per 100,000 people and the associated 95% confidence interval.

To further examine the effect of visits on crashes, I estimate the following fixed-effect specification using county-date observations that do not receive any advisory.

$$\begin{aligned} log(crashes)_{cd} = & \beta log(visits)_{cd} \\ & + \boldsymbol{\gamma_{d-1}} \mathbb{W}_{c,d-1} + \boldsymbol{\gamma_{d}} \mathbb{W}_{cd} + \boldsymbol{\gamma_{d+1}} \mathbb{W}_{c,d+1} + \boldsymbol{\lambda} \mathbb{X}_{cd} + \Phi_{cym} + \epsilon_{cd} \end{aligned} \tag{12}$$

where $log(crashes)_{cd}$ and $log(visits)_{cd}$ are the log of crashes and visits in county c on date d. The rest of the specification is the same as discussed in equation 1. $\mathbb{W}_{c,d-1}$, $\mathbb{W}_{cd}$, and $\mathbb{W}_{c,d+1}$ are the controls for realized weather for the previous, current, and the next day, respectively. $\mathbb{X}_{cd}$ includes variables $DayofWeek$, $Workday$, and $Weeknum$ to control for the effects of day of week, holidays, and seasonality in traffic, respectively. Φ_{cym} are county-year-month fixed effects that allow me to use the within county-year-month variation in visits and crashes. The coefficient β on the primary variable of interest $log(visits)_{cd}$ measures the percentage change in crashes when visits increase by 1%. Table B.2 presents the regression estimates for equation 12. The coefficient on $log(visits)$ is 0.22 and statistically significant at 1% level. This shows that a one percent increase in visits increases crashes by 0.22%. Thus, days with higher visits to places away from home also have higher crash rate. Next, I examine whether longer lead time results in fewer visits to POIs.

Table B.2: Linear effect of advisory lead time on visits

Dependent Variable:	log(crashes)
Variables	
$log(visits)$	0.223***
	(0.016)
County-Year-Month Fixed Effects	Yes
Observations	291,133
R^2	0.127

Notes: The table shows the results from estimating the regression models in Equation 12. The sample includes all county-date observations during Jan 2018-Dec 2019 that do not receive a winter advisory. The dependent variable is log of crashes per 100,000 people. $log(visits)$, the key variables of interest, is log of total visits to places away from home per 100,000 people based on the mobile phone location data from SageGraph. The specification includes controls for current, previous, and next day's weather, day of week, workday, and week of year effects. Additionally, it includes county-year-month fixed effects. The regressions are weighted by county population. Standard-errors clustered at wfo-date level are in parentheses. Significance Level: ***: 0.01, **: 0.05, *: 0.1

B.2 Effect of advisory lead time on visits- Descriptive evidence

Figure B.2 plots the mean total daily visits to all POIs by average snow for different lead-time buckets on days that receive an active advisory. The figure is a binned scatter plot of the average visits per 100,000 people (y-axis) to all POIs by average realized snow in inches (x-axis) within each of the six snow bins as mentioned in section 2.2. Each line in the plot corresponds to county-days that receive advisory with lead time falling in one of the four bins of advisory lead times in hours: {0, (0,24], (24-48], >48}. The solid black line shows the average visits by realized snow for those county-dates which receive winter advisory with zero lead time. The gray long-dashed line shows the average visits by realized snow for those county-dates which receive winter advisory with lead time of more than zero hours but less than or equal to 24 hours, and so on.

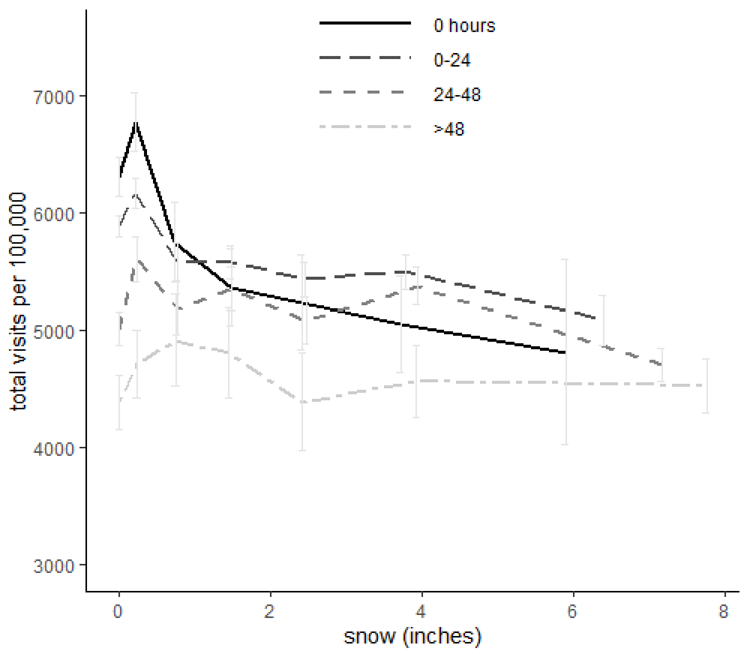


Figure B.2: Visits per 100,000 people by snow for different advisory lead times

Notes: The figure shows the binned scatter plot of the average visits per 100,000 people (x-axis) for the realized average snow in inches (y-axis) within each of the six snow bins in inches, i.e., {<0.01, 0.01–0.5, 0.5–1, 1–2, 2–3, 3–5,>5}. The markers with whiskers plot the average visits per 100,000 people and the associated 95% confidence interval. Each line in the plot corresponds to county-days that receive advisory with lead time falling in one of the four bins of advisory lead times in hours: {0, 0–24, 24–48, >48}. The solid black line joins the markers that plot the average visits by realized snow for county-dates that receive winter advisory with zero lead time. The dark gray long-dashed line corresponds to the average crashes for county-dates that receive winter advisory with lead time of more than zero hours but less than or equal to 24 hours, and so on.

The figure shows two key patterns. First, it shows that on days when an advisory arrives with zero lead time, visits are high for low amount of snow, but falls sharply as snow increases. However, on days when an advisory arrives with some lead time, the relation between visits and snow is relatively flat. As a result, visits do not fall as sharply when an advisory comes with some lead time as they fall when an advisory comes with no lead time. Second, the figure shows that with incremental lead time on advisory, the visits reduce for nearly all levels of snow. Overall, the figure suggests that longer lead time reduces visits for lower levels of realized snow.

B.3 Effect of advisory event type on visits

The results in Table 3 suggest that while people do respond to winter advisories and reduce visits, their response is driven by both the advisory event type and the advisory lead time. If the advisory event types that reduce visits by a greater number also have longer lead time, then a portion of the effect of lead time on visits in Columns 1 and 4 may be explained by the effect of advisory event type. Figure B.3 plots the regression estimates for the effect of the five categories of advisory event type on visits by the average lead time of advisories for those event types. The markers with whiskers plot the regression estimates with 95% confidence interval as shown in Table 3 column 6. The size of the markers corresponds to the number of county-date observations with advisories in that category of event type. The labels next to the markers show advisory event type and corresponding number of observations in brackets. For example, when the underlying winter event types are winter storm (WS) and winter weather (WW), the number of visits per 100,000 people falls by 478 and 113 respectively. At the same time, the average lead times on WS and WW advisories are 41.4 hours and 14.2 hours respectively. There are fewer visits on days when a winter storm advisory is active compared to those when a winter weather advisory is active. Comparison of coefficients on $Leadtime_{cd}$ in columns 4 and 6 of Table 3 shows that only about half of the reductions in visits is driven by the advisory lead time.

C Effect of lead time on road treatment activities

In this section, I estimate the effect of lead time on road treatment activities using a non-linear specification similar to that in equation 3 that allows the effect size to vary with lead time. Specifically, I replace each of the three primary variables of interest $Leadtime_{cd_i}$ with four indicator variables for each i which capture which lead time bin, $b \in \{(0,12], (12\text{-}24], (24\text{-}36], >36\}$, the advisory lead time on a day falls in. Figure C.4 plots the regression estimates for the specification that allows for the non-linear effect of lead time. The solid line plots the estimates of the effect of lead-time on same day activities. The dashed line plots the estimates of the effect of lead time on previous day activities. The figure shows that as lead-time increases, snow plow trucks travel more (panel a) and spend more time operating (panel b) on the day of the advisory, and apply more solid material (panel d), more liquid, and more prewet material (panel f) on the day prior to the advisory.

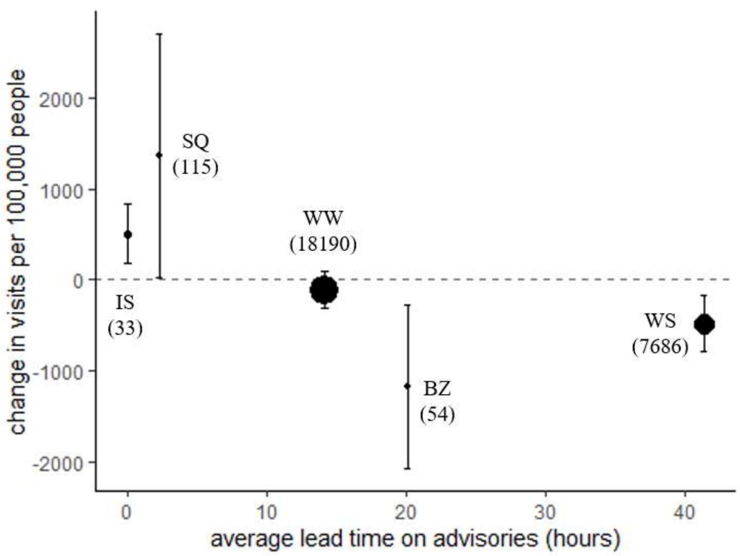
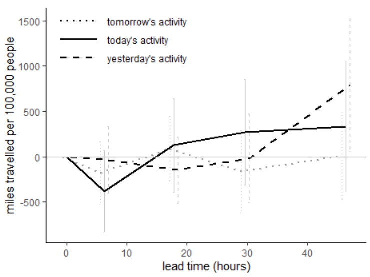


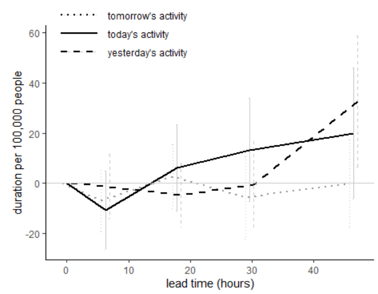
Figure B.3: Effect of advisory event type on visits by average lead time

Notes: The figure plots the estimated effect of the five advisory event types on visits per 100,000 people based on the regression results in Column 6 of Table 3. The dependent variable is all visits per 100,000 people. The markers with whiskers plot the estimated effect (y-axis) of the five advisory event types on visits per 100,000 people average lead time (x-axis) on each type of advisory event. The whiskers plot the associated 95% confidence interval. The marker size is proportional to the number of observations (in parenthesis next to the marker) for each event type (written next to the marker). The five event types are Blizzard (BZ), ice rain (IS), snow squall (SQ), winter storm (WS), and severe winter weather (WW). Standard Errors are clustered at WFO-date level.

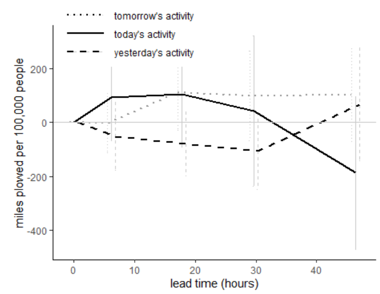
Figure C.4: Regression result- effect of lead time on visits and crashes



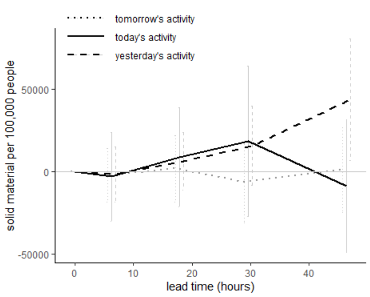
(a) Effect on distance travelled



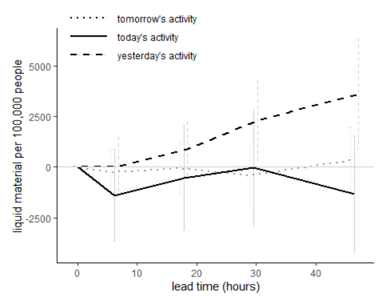
(b) Effect on operating duration



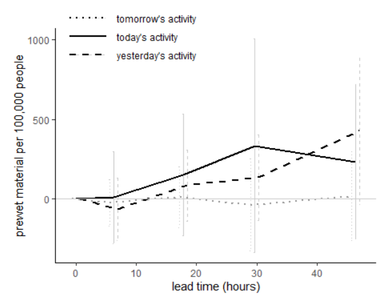
(c) Effect on distance plowed



(d) Effect on solid material applied



(e) Effect on liquid material applied



(f) Effect on prewet material applied

Notes: The figures plot the estimated effect of advisory lead time on road treatment activities that are performed on the current (solid line), previous (dotted gray line), and the next day (dashed black line) of the advisory. The estimations are based on specification similar to that in Equation 4. The dependent variables for specifications in Panel A–F are distance travelled by snowplows, operating duration of plows, distance plowed, solid material applied, liquid material applied, and prewet material applied, respectively, per 100,000 people. The markers with whiskers plot the estimated effect (y-axis) of advisory lead time (in hours on x-axis) on the corresponding road treatment activity. The whiskers plot the associated 95% confidence interval. The key variables of interest are the four indicator variables that capture which lead time bin, $b \in \{(0,12], (12\text{-}24], (24\text{-}36], >36\}$, the advisory lead time falls in. The regressions include county-year-month fixed effects. Additional controls included for advisory event type, advisory event issuance time, and current, previous, and next day's weather, day of week, workday, and week of year effects. All regressions are weighted by county population. Standard Errors are clustered at WFO-date level.

D Sample Winter Weather Advisory

Figure D.5: Sample winter weather advisory text message

```
635
WWUS43 KMKX 042053
WSWMKX

URGENT - WINTER WEATHER MESSAGE
National Weather Service Milwaukee/Sullivan WI
253 PM CST Mon Feb 4 2019

...FREEZING RAIN, SLEET AND SNOW EXPECTED TUESDAY NIGHT...

.A wintry mix will quickly overspread southern Wisconsin Tuesday
evening, tapering off or ending by sunrise on Wednesday.
Precipitation amounts won't be especially high, but it is the
likelihood of freezing rain and sleet that raises concern for a
hazardous impact to motorists Tuesday night, possibly stretching
into the Wednesday morning commute.

Ice accumulations of around 1/10 of an inch are expected, mainly
east and south of Madison. Temperatures will be in the 20s Tuesday
night.

WIZ046-047-051-052-056>060-062>072-050500-
/O.NEW.KMKX.WW.Y.0006.190206T0000Z-190206T1200Z/
Marquette-Green Lake-Fond Du Lac-Sheboygan-Sauk-Columbia-Dodge-
Washington-Ozaukee-Iowa-Dane-Jefferson-Waukesha-Milwaukee-
Lafayette-Green-Rock-Walworth-Racine-Kenosha-
Including the cities of Montello, Westfield, Oxford, Neshkoro,
Endeavor, Berlin, Princeton, Markesan, Fond Du Lac, Plymouth,
Sheboygan Falls, Howards Grove, Oostburg, Baraboo, Reedsburg,
Prairie Du Sac, Sauk City, Portage, Columbus, Lake Wisconsin,
Lodi, Beaver Dam, Waupun, Mayville, West Bend, Germantown,
Hartford, Mequon, Cedarburg, Grafton, Dodgeville, Mineral Point,
Barneveld, Madison, Watertown, Fort Atkinson, Jefferson,
Waukesha, Brookfield, New Berlin, Menomonee Falls, Muskego,
West Allis, Wauwatosa, Greenfield, Franklin, Oak Creek,
South Milwaukee, Cudahy, Darlington, Shullsburg, Benton, Belmont,
Argyle, Blanchardville, Monroe, Brodhead, Janesville, Beloit,
Whitewater, Delavan, Elkhorn, Lake Geneva, East Troy, Racine,
and Kenosha
253 PM CST Mon Feb 4 2019

...WINTER WEATHER ADVISORY IN EFFECT FROM 6 PM TUESDAY TO 6 AM
CST WEDNESDAY...

* WHAT...A mixture of freezing rain, sleet and snow is expected.
  Sleet and snow is the main concern west of Madison, while
  freezing rain and sleet expected to the east and south of
  Madison. The freezing rain could result in ice accumulations of
  around 1/10 of an inch, especially across far southeast
  Wisconsin.

* WHERE...Portions of east central, south central and southeast
  Wisconsin.

* WHEN...From 6 PM Tuesday to 6 AM CST Wednesday.

* ADDITIONAL DETAILS...Plan on slippery road conditions. The
  hazardous conditions could impact the Tuesday evening and
  Wednesday morning commute.

PRECAUTIONARY/PREPAREDNESS ACTIONS...

A Winter Weather Advisory means that periods of snow, sleet or
freezing rain will cause travel difficulties. Expect slippery
roads and limited visibilities, and use caution while driving.

The latest road conditions for the state you are calling from can
be obtained by calling 5 1 1.

&&

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Notes: The figure shows a winter weather advisory issued by the Milwaukee weather forecast office on February 4, 2019. The advisory shows the time of issuance, the nature and severity of the forecasted winter event, a description of the potential risk to people, the timing of the winter event, and a list of counties and cities the advisory is issued for.