The value of forecast improvements: evidence from advisory lead times and vehicle crashes

Anand, Vaibhav

St. John's University - Peter J. Tobin College of Business, University of Wisconsin-Madison, madison, United States

1 September 2022

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

Vaibhav Anand*

January 6, 2023

Abstract

Advances in predictive technologies are improving forecasts of risk, but do better forecasts result in better risk management? Using data on winter forecasts and vehicle crashes from 11 states in the US, I investigate the value of improvements in forecast lead times. I show that winter advisories with longer lead times reduce crashes significantly, even when they are less accurate than advisories with shorter lead times. These benefits come from both the individual and institutional response to advisory lead times. When advisories arrive earlier, people visit fewer places, and snowplow crews increase the intensity of road maintenance operations.

(JEL: Q54, Q58, H41)

*Tobin College of Business, St. John's University, email: anandv@stjohns.edu. For helpful feedback, I would like to thank Mook Bangalore, Dani Bauer, Paul Block, Carlos Iturria, Kyeonghee Kim, Derek Lemoine, Tyler Leverty, Chenyuan Liu, Anita Mukherjee, Ivan Rudik, Peng Shi, Justin Sydnor, and seminar participants at the University of Colorado Environmental and Resource Economics Workshop, WEAI annual meeting and ARIA annual meeting. I am grateful to the Highway Safety Information System (HSIS) team, the Traffic Operations and Safety (TOPS) Laboratory at UW-Madison, and the DoT of 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 technologies are improving forecasts in several areas–the outcome of an election, the spread of a contagious disease, or the location and time of the next lightning strike.[1] This is particularly true in 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. Decision makers may not pay attention to forecasts (Golman et al. 2017), choose not to act on forecasts,[2] or have insufficient means to respond to forecasts.

In this paper, I investigate if forecast improvements result in meaningful benefits to society in the context of winter weather 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. On one hand, longer lead time may allow better planning; on the other hand, getting forecasts too early may adjust expectations about risk and make the weather look less hazardous (Hoekstra et al. 2011, Weyrich et al. 2020). Further, forecast accuracy and lead times are often inversely related, which may make longer lead time forecasts to appear less reliable.

Motor vehicle crashes are a significant economic and health hazard to society.[3] Winter

[1]e.g., See https://www.nesdis.noaa.gov/news/earth-orbit-when-lightning-strikes

[2]People may not trust forecasts, or may see the advisory in a forecast as a symbolic threat to their freedom and choose not to comply (Cherry et al. 2021). Uncertainty about the benefits of risk mitigating actions may also result in inaction (Li and Peter 2021)

[3]In the US, nearly 2.5 million people get injured and 35,000 people die in more than 6 million crashes

weather results in particularly risky driving conditions and greatly increases the likelihood of a crash (Qiu and Nixon 2008). Winter advisories, issued 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 or allocate more time to drive slow, or by helping road crews to manage roads proactively. This paper examines whether longer lead times on winter advisories actually enhance the crash risk mitigation, and whether these benefits are driven by individual or institutional response.

Using a novel combination of county-date level data on winter advisories, snow forecasts, weather station observations, and vehicle crashes for 11 US states during 2008-2018, I examine whether longer lead times on winter advisories result in fewer crashes.[4] There are some potential challenges in identifying the causal effect of forecast lead time on crash risk. First, places and months that receive forecasts with longer lead time may differ in their risk from those that receive shorter lead time forecasts. Second, adverse weather with longer forecast lead time is often more severe and is likely to result in more crashes. Third, forecast accuracy and lead time are often negatively correlated. So, advisories with longer lead time may be systematically different from those with shorter lead time in their prediction accuracy. My empirical design addresses these challenges by exploiting the within county-year-month variation in lead time, controlling for the observed and forecasted weather conditions on a day. Finally, my research design uses county-date level data for winter advisories and vehicle crashes, both of which occur with reasonable frequency in my sample. This allows sufficient variation in treatment and outcome to estimate the lead time effects with reasonable statistical significance.

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every year (Bureau of Transportation Statistics 2021). In 2010 alone, the total economic cost of all vehicle crashes in the US is estimated to be 871 billion dollars (Blincoe et al. 2015).

[4]The 11 states are Illinois, Indiana, Iowa, Maine, Massachusetts, Michigan, Minnesota, New Jersey, Ohio, South Dakota, and Wisconsin.

I find that longer lead times on winter advisories result in significantly fewer crashes. An additional hour of lead time reduces daily crashes by roughly 0.5% on the same day. My preliminary calculations show that existing lead times on winter advisories result in a net reduction of nearly 10 crashes per 100,000 people annually. These crash reductions result in annual economic savings of nearly 150 million USD in my sample of 11 US states.[5] To give a sense of magnitude, these savings are about 15% of the annual budget of the National Weather Service and about 3% of the annual budget for the entire meteorological services and research of the US federal government.

My analysis also provides insights into the trade-off between advisory lead time and accuracy of the underlying snow forecasts. First, the effect of advisory lead time on crash risk is robust to controlling for snow forecast accuracy. This is meaningful since advisories with longer lead times are associated with greater error in the underlying snow forecasts. Second, the crash rates do not always increase with snow forecast error. When the forecast overestimates snow on a day, crashes increase on the same and previous day, but decrease on the next day.[6] Third, the crash rates are more sensitive to the advisory lead time than to the snow forecast accuracy. While the 25th and 75th percentile advisory lead times in my sample reduce crashes by around 8% and 16%, respectively, the 25th and 75th percentile overestimation (or underestimation) errors in snow forecast affect crashes by less than 4% and 5%, respectively.

I examine two potential mechanisms that may explain the effect of advisory lead time on crash rates. First, using the mobile phone location data from SafeGraph for the 11 states in my sample, I show that people visit fewer places on the day of the advisory when there is a longer lead time. Second, using the snowplow truck location data for the state of Iowa,

[5] I quantify the dollar value of these benefits using the economic cost estimates of vehicle crashes from Blincoe et al. (2015), which estimate the economic cost of vehicle crashes in the US, accounting for both the direct and indirect economic costs (e.g., lost productivity and congestion costs) of crashes to society.

[6] Similarly, when the forecast underestimates snow on a day, crashes decrease on the same and previous day, but increase on the next day. I discuss the potential explanations for these in the results section.

I show that road maintenance activities increase with lead time for the same as well as the previous day of the advisory. These results suggest that the value of longer lead times may come from both the individual and institutional risk mitigation efforts.

This paper, to the best of my knowledge, provides the first empirical evidence that receiving forecast earlier results in better risk management.[7] Existing literature provides evidence that improvements in forecast accuracy are valuable. Martinez (2020) and Molina and Rudik (2022) examine hurricane forecasts to show that benefits from receiving accurate forecasts outweigh costs of improvements. Rosenzweig and Udry (2019) and Shrader (2020) 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, my paper shows that there is value to getting forecasts earlier. This paper also provides the first empirical evidence on the nature of trade-off between forecast lead time and accuracy. I show that in the context of winter weather and vehicle crashes, risk outcomes are more sensitive to the advisory lead time than to the accuracy of underlying forecasts.

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 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

[7] 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). One exception is an empirical study by Simmons and Sutter (2008), which suggests that, conditional on receiving a tornado warning, longer lead times do not reduce tornado related injuries or fatalities.

institutions can and do use short-run weather forecasts 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 daily temperature reduce mortality risk. My paper complements this literature, and provides 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. 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 (DeAngelo and Hansen, 2014; Gallagher and Fisher, 2020). In a related study, Ferris and Newburn (2017) show that wireless alerts for flash floods reduce road accidents in Virginia. My paper extends this literature by examining the role of advisory lead times in reducing weather related crash risk.

There are some limitations to this study. First, this paper aims to quantify the economic benefits of longer lead times of winter advisories, given the existing weather forecasting technologies. It does not 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.[8]. Third, although this paper shows that both the number of visits by individuals and activities by road crews contribute to the reduction in crashes, it does not quantify the extent to which the two mechanisms might lead to those effects. Further, there are likely other actions taken by people and

[8]Minor crashes that result in property damage below a certain threshold might not be reported. I discuss this limitation in some detail in sections 2 and A.4

organizations, which I do not examine, that may explain some reduction in crash risk due to longer lead times. This paper, however, provides the first evidence that longer lead times on weather advisories can really enable some of these mechanisms. 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 empirical strategy. Section 3 presents the main results. Section 4 discusses two potential mechanisms. Section 5 estimates the economic benefit of longer lead times from reduced crash risk. Section 6 discusses the robustness of main results. Section 7 concludes.

2 Data and Empirical Strategy

2.1 Data

This paper uses a novel combination of four data sets: data on weather advisories issued by the National Weather Service (NWS), 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 daily forecasts of snow from the National Digital Forecast Database (NDFD).

2.1.1 Weather Advisory Data

I obtain the data on the winter advisories from the archive database maintained by the Iowa Environmental Mesonet (IEM) of Iowa State University. This dataset provides information on geographic coverage, timing, and other details for all winter advisories issued since November 2005.

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. 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.

The archive database provides the time an advisory is issued by the local WFO, the name of the WFO, 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. Figure E.4 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. 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. Section A.1 provides more details on lead time calculation.

2.1.2 Snow Forecast Data

I obtain historical daily snow forecast data from the National Digital Forecast Database (NDFD) for years 2008-2018.[9] The NDFD data provide gridded forecasts of snow generated by the WFOs and Weather Prediction Center (WPC). These quantitative forecasts are used by the local WFO as a basis to issue winter weather advisories. These forecasts are publicly available on the NWS website, and are also used by third party agencies to create various forecast products distributed via TV, internet, mobile apps, and social media. I use these gridded forecasts to calculate the county level snow forecasts for each date in my sample. Section A.2 provides further details on this calculation. For a county-date in my sample, I

[9]The earliest digital forecasts of snow are available from 2008 onward.

construct a snow forecast variable that measures the forecasted value of daily snow over the next 24 hours in advance. I also construct the corresponding forecast error as the difference between the forecasted snow and actual snow reported. A negative (positive) forecast error denotes that the forecast underestimates (overestimates) the snowfall on that day.

2.1.3 Daily weather observations

I obtain daily snowfall amount, rainfall amount, and minimum 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. For each county, I estimate the daily accumulated snowfall, accumulated rainfall, and minimum temperature recorded by aggregating the weather monitor readings. 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. Section A.3 provides further details.

2.1.4 Vehicle Crash Data

Vehicle crash data is assembled using detailed police accident reports maintained by the Department of Transportation (DoT) of each state. 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. Section A.4 discusses the collection process and some limitations of using the crash data.

2.1.5 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 2008-2018. For each county and date, I construct the following variables: total number of crashes, total snow accumulation, total rain accumulation, minimum temperature observed, indicator for whether a winter advisory is active, advisory lead time in hours, type of forecasted event, hour when advisory is issued, and the level of snow forecast. I create additional variables to account for whether a day is a workday or a holiday in that county. 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.

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 1,914,367 county-date observations across 734 counties from 11 states. Of the total observations, 92,537 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). The empirical design compares days that receive longer lead time advisory with days that receive shorter lead time advisory.

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, I control 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 in estimating the effect of lead time is that advisories with different lead time may also differ in their prediction severity and accuracy. Figure 3 shows that both the amount of snow forecast over the next 24 hours (Panel A) and the root-mean-square error (RMSE) in the forecast (Panel B) increase with lead time.[10] I also examine the direction of forecast error by lead time. I define overestimation (underestimation) error as when snow forecast exceeds (falls short of) the reported snow by more than half of an inch. Panel C and D show that both the overestimation and underestimation errors increase with lead time; overestimation error more so. These forecasts of snow are also publicly available through various sources. So, it is plausible that people and institutions respond to the winter advisories as well as the underlying forecasts. In order to address any potential bias in my estimates, I control for the underlying snow forecast in my specifications. [11]

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

[10]Forecast error is measured by subtracting the reported snow from forecasted snow.

[11]A winter advisory message usually provide both the qualitative and quantitative description of the forecasted weather conditions, such as the forecasted amount of snow (for an example, see Figure E.4 in appendix). However, in my data on winter weather advisories, I do not observe this textual descriptive message. Rather, in this paper, I use the underlying quantitative forecasts on snow on which the advisories are based. These quantitative forecasts are the same forecasts which are generated by the WFO, and used as a basis to issue winter weather advisories.

following:

$$\begin{aligned} Crash_{ct} = \psi Advisory_{ct} + \beta Leadtime_{ct} + \eta ForecastError_{ct} + \\ \boldsymbol{\gamma_{t-1}} \mathbb{W}_{c,t-1} + \boldsymbol{\gamma_t} \mathbb{W}_{ct} + \boldsymbol{\gamma_{t+1}} \mathbb{W}_{c,t+1} + \boldsymbol{\lambda} \mathbb{X}_{ct} + \Phi_{cym} + \epsilon_{ct} \end{aligned} \tag{1}$$

where $Crash_{ct}$ is the number of crashes per 100,000 people in county c on date t. $Advisory_{ct}$ is an indicator variable which is 1 if there is a winter advisory issued on date t for county c, else it is 0. $Leadtime_{ct}$, the key variable of interest, is the lead time of the advisory on date t in county c in hours. When no advisory is active for a county-date, the lead time variable is set equal to 0. So, $Advisory_{ct}$ captures the effect of an advisory issued with zero lead time. $Leadtime_{ct}$ captures the effect of an additional hour of lead time on crash risk. $ForecastError_{ct}$ is the snow forecast error in centimeters measured as the observed snow subtracted from the forecasted snow in county c on date t. So, a positive (negative) error means that the snow forecast overestimates (underestimates) the actual snowfall. In some specifications, I also include the square of lead time and forecast error variables to capture their potentially nonlinear relationship with crash risk.

$\mathbb{W}_{ct}$ includes the non-parametric functional forms of observed snow, rain, and minimum temperature (following Barreca et al. (2016)), and their mutual interactions for county c on date t. Specifically, $\mathbb{W}_{ct}$ is defined as:

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

where $snowbin_{ct}$, $rainbin_{ct}$ and $tempbin_{ct}$ 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 t 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}. $\mathbb{W}_{ct}$ also includes two interacted sets of snow and rain with temperature to account for the effect of precipitation through temperature. I also include $\mathbb{W}_{c,t-1}$ and $\mathbb{W}_{c,t+1}$, 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.[12]

$\mathbb{X}_{ct}$ 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 t. I control for the effects of holidays by including an indicator variable $Workday$ which is 1 if the date t is a workday in county c, else it is 0. 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 t falls in, as defined in ISO 8601. 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.

My specification includes 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 takes one of the seven values based on the event type for which the advisory is issued for.[13] Second, I also control for the time of weather advisory issuance. The nature of an advisory as well as

[12]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.

[13]When no advisory is issues, the variable takes the value 'NoAdv'.

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 change their travel plans to earlier or later dates. For example, after receiving a snow storm advisory for the next day, people may travel the same day to purchase groceries and other necessities before the storm. 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:

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

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

Another interpretation of the coefficients on variables $Leadtime_{c,t-1}$, $Leadtime_{c,t}$, and $Leadtime_{c,t+1}$ is that they capture the effect of an additional hour of lead time of advisory active for date t on crashes that occur on date $t+1$, t, and $t-1$, respectively. So, β_{-1}, the coefficient on $Leadtime_{c,t-1}$, captures the effect of today's advisory lead-time on crashes that will occur tomorrow, and β_{+1}, the coefficient on $Leadtime_{c,t+1}$, 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 forecasted and realized weather, 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 forecasted and observed severity of weather, within a county-year-month, the remaining 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 act 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 subjective decisions of human forecasters are unlikely to be correlated with the other unexplained factors affecting the crash risk, within a county-year-month, after controlling for the forecasted and observed weather.[14]

3 Effect of Advisory Lead time on Crash Risk

3.1 Descriptive Analysis

Figure 4 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 line plots the average crashes by realized snow for those county-dates that receive winter advisory with zero lead time. The black long-dashed line plots the average crashes for those county-dates that receive advisory with lead time between 0 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

[14] 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.

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. However, the descriptive evidence in Figure 4 uses the variation in lead time and crashes across all counties and months. It also does not control for the effects of forecasted or realized weather conditions, except realized snow. In the next section, I estimate the effect of lead time on crash risk using the fixed effect specification in Equation 1 that uses the variation within a county-year-month and controls for various factors that may affect crash risk.

3.2 Fixed Effects Analysis

Table 1 Columns 1–2 present the results from estimating Equation 1. Columns 3–4 present the results from estimating Equation 2. All specifications include controls for realized weather, snow forecasted error, advisory event type, advisory issuance time, day of week, holiday, and week number. Column 2 and 4 also include the square terms for lead time and forecast error variables to capture their nonlinear relationship with crash risk. The fully specified model in column 4 is my preferred specification. The coefficient on $Leadtime_{c,t}$ shows the effect of an additional hour of advisory lead time on vehicle crash rates on the day of the advisory. The coefficients on $Leadtime_{c,t-1}$ and $Leadtime_{c,t+1}$ 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. Similarly, the coefficient on $ForecastError_{c,t}$ shows the effect of overestimating the snowfall by 1 cm on crash risk on the day of the advisory.

The coefficient on $leadtime_{c,t}$ is negative and statistically significant at 1% level across all specifications. These coefficients suggest that an additional hour of lead time reduces crashes by 0.032–0.054 per 100,000 people on the same day the advisory is active. The coefficient on the non-linear term $leadtime^2_{c,t}$ is positive but small, which suggests a relatively negative linear relationship between advisory lead time and crash risk on the same day. Accounting for the small non-linear effect of lead time, a one standard deviation increase in lead time, i.e., an increase of 17.6 hours, reduces crashes by 0.56–0.83 per 100,000 people on the same day the advisory is active. Given the average crash rate of 11.1 crashes per 100,000 people on days with an active advisory, an increase in the advisory lead time by one standard deviation reduces crashes on the same day by 5.1%–7.6%.

The coefficients on $leadtime_{c,t+1}$ and $leadtime^2_{c,t+1}$ in Column 4 are also economically and statistically significant. The negative and positive sign of the coefficients on the linear and nonlinear terms, respectively, suggest a convex relationship between advisory lead time and crash risk on a day prior to the advisory. The coefficients suggest that a smaller increase in lead time (i.e., less than 30 hours) decreases the crash rate on the previous day of the advisory, while a larger increase in lead time may increase the crash rate.[15] The coefficient on $leadtime_{c,t-1}$ are small and not statistically significant, suggesting that advisory lead time do not have meaningful effect on crash risk on a day after the advisory.

The coefficients on $ForecastError_{c,t}$ and $ForecastError_{c,t+1}$ are positive, whereas the coefficient on $ForecastError_{c,t-1}$ is negative. This means that when snow forecasts overestimate the actual snow by a centimeter, crash risk increases on the previous and the current day by roughly 0.023 and 0.028 respectively, but decreases on the next day by 0.045. Similarly, when snow forecasts underestimate the actual snow, crash risk increases on the previous and the current day but decreases on the next day. Before I discuss the potential economic intuitions behind these results, I plot the estimated effects obtained using a flexible functional form of earlier specification that captures the non-linear relationship of lead time and forecast error with crash risk.

Figure 5 and Figure 6 plot the estimated effects of lead time and forecast error, respectively, on crash risk by including a flexible discretized functional form of the lead time and

[15]The coefficients on $leadtime_{c,t+1}$ and $leadtime^2_{c,t+1}$ are -0.018 and 0.0006. Equating $-0.018Leadtime_{c,t+1} + 0.0006Leadtime^2_{c,t+1} = 0$ gives a cut-off value of 30 hours, beyond which the increase in lead time will increase the crash risk on the previous day.

forecast error variables in the main specification. Specifically, the figure plots the results from estimating the Equation B.1, which is discussed in appendix B. In Figure 5, the markers with gray whiskers plot the estimated effect of lead time (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. Similarly, Figure 6 plots the effect of forecast error on crash risk.

Figure 5 provides two insights. First, it shows that the effect of lead time on crash risk for the same day is close to linear. As lead time increases, crash risk for the same day decreases. The effect of lead time on crash rate reduction 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. This suggests that individuals and institutions can use the additional lead time on advisory to take meaningful actions to reduce crash risk. Second, the plot shows that the effect of longer lead time on the previous day's crash risk is non-linear. As the advisory lead time increases from zero to around 30 hours, the crash rate on the previous day decreases marginally. As lead time increases beyond 30 hours, the crash rate on the previous day increases. It is likely that longer lead times allow people to reschedule some discretionary travelling activities (such as shopping) to the prior day. I will discuss this in some detail in the section on mechanisms.

The effect of snow forecast errors on crash risk is somewhat non-intuitive, as plotted in Figure 6. The figure shows that, holding fixed the advisory lead time, as snow forecast error increases from negative (underestimation) to positive (overestimation), crashes on the same day and the previous day increase, whereas the crashes on the next day decrease. I list some likely reasons for these results. First, people and institutions may respond to overestimated forecasts by undertaking a higher degree of mitigating actions, and vice versa. This may result in unusually more commuter traffic the previous day, and more snowplow and road maintenance traffic the same day. Second, some commuters may choose to drive themselves or use cab services during the day when the forecast snow level is higher. Third, due to increased road maintenance on the current day, there may be fewer crashes the next day, when roads have likely less snow accumulation from the previous day's snow. These factors, holding fixed the lead time, may increase the crash risk for the previous and current day, while decreasing it for the next day. In the next section on mechanisms, I provide some limited evidence for these reasons.

Overall, my results show that crash rate decreases with lead time, but it can both increase or decrease with forecast error. However, the magnitude of the effect of forecast error is smaller compared to that of the effect of advisory lead time. While a lead time of more than 48 hours can reduce crashes by up to 2.96 per 100,000 people, a forecast error of nearly 2 inches changes crashes by less than 0.5 per 100,000 people. Given that forecast accuracy and lead time are negatively correlated, a natural question is whether we can use these results to comment on the overall trade-off between lead time and accuracy? The results suggest that knowing early about a snowstorm is more effective in crash risk mitigation than knowing accurately about the snowstorm severity. However, my analysis is limited to show how advisory lead time and underlying forecast accuracy, resulting from the existing forecasting technology, affect crash risk. This analysis neither aims to suggest nor provides guidance on the optimal level of lead time and accuracy in weather forecasts.

4 Mechanisms

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 due to reduced road traffic. When advisories arrive earlier, people may get sufficient time to change travel plans and consequently visit fewer places outside home. Similarly, businesses and schools may decide to close. Specifically, using mobile phone location data from SafeGraph, I examine whether longer lead times reduce outside-home visits by people. The second potential mechanism is that longer lead times 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.

4.1 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 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 2018 for the 11 states in my sample.[16] Using the latitude and longitude location data of a smartphone, SafeGraph determines the 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 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 263,965 county-date observations from 739 counties for the 11 states.

To estimate the effect of lead time on visits, I estimate the following fixed-effects specification, which is similar to the one in equation 2.

$$\begin{aligned} visits_{ct} = & \sum_{i=-1}^{1} \beta_i Leadtime_{c,t+i} + \sum_{i=-1}^{1} \eta_i ForecastError_{c,t+i} + \sum_{i=-1}^{1} \psi_i Advisory_{c,t+i} \\ + & \quad \boldsymbol{\gamma_{t-1}} \mathbb{W}_{c,t-1} + \boldsymbol{\gamma_t} \mathbb{W}_{ct} + \boldsymbol{\gamma_{t+1}} \mathbb{W}_{c,t+1} + \boldsymbol{\lambda} \mathbb{X}_{ct} + \Phi_{cym} + \epsilon_{ct} \end{aligned} \tag{3}$$

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

$visits_{ct}$ is the total visits to all POIs by unique visitors per 100,000 people in county c on date t. The rest of the variable definitions remain the same as described for equation 2 in section 2.2. The coefficients on $Leadtime_{c,t-1}$, $Leadtime_{c,t}$, and $Leadtime_{c,t+1}$ can be interpreted as the estimates of change in visits per 100,000 people in county c on the next day, current day, and the previous day, respectively, of the advisory due to an additional hour of lead time of an advisory active on date t. Similarly, the coefficients on $ForecastError_{c,t-1}$, $ForecastError_{c,t}$, and $ForecastError_{c,t+1}$ can be interpreted as the estimates of change in visits per 100,000 people in county c on the next day, current day, and the previous day, respectively, of the forecast due to an additional overestimation error of 1 cm in snow forecast for date t.

Columns 1 of Table 2 presents the regression results for the specification in equation 3. The figures in bracket are standard errors clustered at WFO-date level. All specifications include county-year-month fixed effects. Column 1 shows that the coefficient on $Leadtime_{ct}$ is negative and statistically significant at the 1% level. The coefficient means that for an additional hour of lead time on advisory active for county c on date t, the visits fall by 0.19%.[17]

I also estimate the effect of lead time on visits to different categories of POIs using the specification in equation 3. Column 2–6 of Table 2 present the estimates of lead time effect on visits to POIs categorized as retail, leisure, commercial, education, and health, respectively. These estimates show 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 -0.17% to -0.26% for different types of visits. This suggests that longer lead time may result in change of travel plans by people or change in hours of operations by businesses on the day of the advisory, and subsequently reduce crash risk on that day.

The coefficients on $leadtime_{c,t-1}$ and $leadtime_{c,t+1}$ are positive for retail, leisure, and

[17]The coefficient in column 1 is -9.57. The mean visits on days with advisory are 5,020. So, the percentage change is $9.57/5020 \times 100$.

commercial categories of visits. These type of visits are often discretionary and may be more likely to be moved to another day given a longer lead time. However, the coefficients on $leadtime_{c,t-1}$ and $leadtime_{c,t+1}$ are negative or close to zero for education and health related visits, which are often not discretionary. This suggests that additional lead time on advisories may shift some discretionary visits to the previous or the next day, consequently shifting the crash risk as well.

The coefficient on $ForecastError_{c,t}$ is negative for all type of visits. The estimates show that an additional centimeter of overestimation in snow forecast reduces all type of visits by 0.3%, but reduces commercial visits by 0.5%, and education and health visits by nearly 1%. This suggests that institutional decision-making may be more sensitive to snow forecast magnitude compared to individual decision-making, who may be more sensitive to lead time. For example, higher levels of snow forecasts may be more relevant to schools, health care establishments, and commercial institutions in their decision to change their working hours in anticipation of adverse weather. Although these estimates suggest that visits on the current day fall with forecast error, the results in Table 1 show that crashes on the current day increase with forecast error. This means that it may be the choice of transportation, concentration of traffic within a limited period, or the increase in road maintenance vehicles on the road that likely increases the crash risk on the day of the advisory. The coefficient on $ForecastError_{c,t-1}$ is negative for all visits, suggesting that all types of visits fall with forecast error the next day. The coefficient on $ForecastError_{c,t+1}$ is negative for all visits except education and health, suggesting that all discretionary visits increase and non-discretionary visits decrease on the previous day with forecast error.

Although the results in Table 2 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 2 show that an additional hour of lead time reduces crashes by 0.36% and visits by 0.19% 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 nearly 2% on a day with winter advisory. My estimate from Table C.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 10 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.

4.2 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.[18] These institutions often use specialized in-house systems to obtain information on weather and road conditions. 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 whether 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

[18]In general, county highway departments maintain state and national highways, and Department of Transportation (DoT) maintains the local roads.

October 2014 to December 2018.[19] This dataset provides detailed location and operation level data for snowplows collected using the Automated Vehicle Location (AVL) system. The AVL system continuously tracks and stores the location, speed, direction, plow position, and application rate of any solid or liquid material for a snow plow. 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 2

$$\begin{aligned} activity_{ct} = &\sum_{i=-1}^{1} \beta_i Leadtime_{c,t+i} + \sum_{i=-1}^{1} \eta_i ForecastError_{c,t+i} + \sum_{i=-1}^{1} \psi_i Advisory_{c,t+i} \\ + &\quad \boldsymbol{\gamma_{t-1}} \mathbb{W}_{c,t-1} + \boldsymbol{\gamma_t} \mathbb{W}_{ct} + \boldsymbol{\gamma_{t+1}} \mathbb{W}_{c,t+1} + \boldsymbol{\lambda} \mathbb{X}_{ct} + \Phi_{cym} + \epsilon_{ct} \end{aligned} \tag{4}$$

$activity_{ct}$ is the measure of activity per 100,000 people in county c on date t. The rest of the variable definitions remain the same as described for equation 2 in section 2.2. I estimate a separate specification for each of the six activities listed above. The coefficients on $Leadtime_{c,t-1}$, $Leadtime_{c,t}$, and $Leadtime_{c,t+1}$ can be interpreted as the change in the road treatment activity on the next, current, and the previous day, respectively, due to an additional hour of lead time of an advisory active on date t.

Table 3 presents the regression results. Column 1 shows the estimates of the effect of lead time and forecast error 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

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

at WFO-date level. All specifications include county-year-month fixed effects.

The coefficient on $Leadtime_{c,t}$ is positive for distance and duration, which means that snow plow trucks cover 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 0.5% more distance and operate for 0.8% longer duration. The coefficient on $Leadtime_{c,t+1}$ is positive for distance, duration, and solid, liquid, and prewet material dispensing activities. This means that when advisories arrive with longer lead time, 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 1.8% more solid, 2.4% more liquid, and 2.6% 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.

The coefficient on $ForecastError_{c,t}$ is positive and statistically significant for nearly all metrics of road maintenance activities. The estimates show that, on the day of the snow forecast, for an additional centimeter of forecast overestimation error, the trucks travel 5.8% more distance, operate for 6.5% more hours, plow 9% more distance, and nearly 8%–9% more solid, brine, and prewet material. This suggests a significant increase in road maintenance activity with forecast overestimation, and likely a significant increase in the number of road maintenance vehicles on the road.

Overall, 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 0.4% on the day of the advisory or a 1% increase in anti-icing material one day prior to the advisory should reduce crashes by nearly 0.15%.

This section provides evidence that both the visits by individuals and road maintenance activities respond to advisory lead times. However, my analysis does not quantify to what extent the reduction in vehicle crashes due to longer lead times can be explained by the two mechanisms. It is likely that longer lead times allow decision-makers to undertake other risk mitigation activities, which I do not examine, that may also explain some reduction in crashes. Overall, this analysis suggests that the value of longer lead times do come from both individual and institutional risk mitigation efforts.

5 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.[20]

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 t for the observed lead time

[20] 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.

on advisories. I denote the predicted crashes by $\hat{crash}_{ct}^{obs}$. Specifically, I use the estimates from the fully specified specification in model 4 of Table 1 to calculate the predicted crashes $\hat{crash}_{ct}^{obs}$, i.e.

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

Replacing the actual lead times with zero in Equation 5 provides the estimated crashes in county c on date t, i.e. $\hat{crash}_{ct}^{zero}$, 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 positive lead time on advisory in county c on date t is

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

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,[21] and of a fatal crash is 1.4 million USD. I calculate the average cost of a single crash as the weighted

[21]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 the mix of injuries remains the same over time and geography.

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.[22] These calculations estimate the average cost of a single crash to be around 20,000 USD in 2018 dollars.[23]

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

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

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

My estimates suggest that, during 2010-2014 in the sample when data from all 11 states is available, positive lead times on winter advisories reduce roughly 10.4 crashes per 100,000 people each year. These avoided crashes result in an annual economic savings of approximately USD 150 million in my sample during this period. 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.

6 Robustness Tests

6.1 Multi-day winter advisories

A winter advisory may be valid for multiple days. In this case, 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

[22]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.

[23]17,300 USD in 2010 dollars.

time as the number of hours passed since the issuance of the advisory until the beginning of that day. However, on the second or third day of an advisory, people may have the both the benefit of a longer lead time advisory and the opportunity to experience the adverse weather during the past few days. In this section, I examine whether my estimates are unusually driven by longer lead time on multiple-day advisories. Specifically, I re-estimate my regression specifications in equation 1 by including only those county-dates that have no active advisory on the previous day.

Table 4 presents the regression estimates. Column 3 and 4 include controls for forecast errors. Column 1 and 3 include non-linear terms for lead time and forecast error variables. All specifications include the same controls and fixed effects as the specifications in Table 1. The coefficient on $Leadtime_{c,t}$ in Table 4 are consistent with those shown in Table 1.

6.2 Longer lead time and multiple advisories

A county may receive multiple winter advisories for the same date. Often, a subsequent advisory is an update on the previously issued advisory for that date. County-dates that are forecast to experience severe weather are likely to receive multiple advisories, often with longer lead time as well. A potential alternative explanation of the estimated effect of longer lead time is that it is (partly) driven by the number of advisories, rather than the longer lead time. In this section, I examine whether my estimates are consistent to excluding county-date observations that receive multiple winter advisories. Specifically, I re-estimate my regression specifications in equation 1 by dropping all county-dates that receive more than one winter advisory.

Table 5 presents the regression estimates. Column 3 and 4 include controls for forecast errors. Column 1 and 3 include non-linear terms for lead time and forecast error variables. All specifications include the same controls and fixed effects as the specifications in Table 1. The coefficient on $Leadtime_{c,t}$ in Table 5 are consistent with those shown in Table 1.

7 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 novel combination of data on winter advisories, weather forecasts, weather station observations, and vehicle crashes at the county-date level, 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. These results are robust to controlling for underlying forecast accuracy. Preliminary calculations show that longer lead times, relative to zero lead time on advisories, result in an annual reduction of nearly 10 crashes per 100,000 people. My estimates suggest that actual lead times on winter advisories have resulted in an annual economic savings of nearly 150 million dollars in the 11 states in my sample. This paper also examines two potential mechanisms that might lead to these benefits of longer lead times. I show that both the visits by individuals and road maintenance activities respond to advisory lead times. 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 such mechanisms that may explain the effect of lead times on crash risk, a natural extension of this work is to quantify the extent to which these and other mechanisms contribute to the observed effects of lead times. 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.

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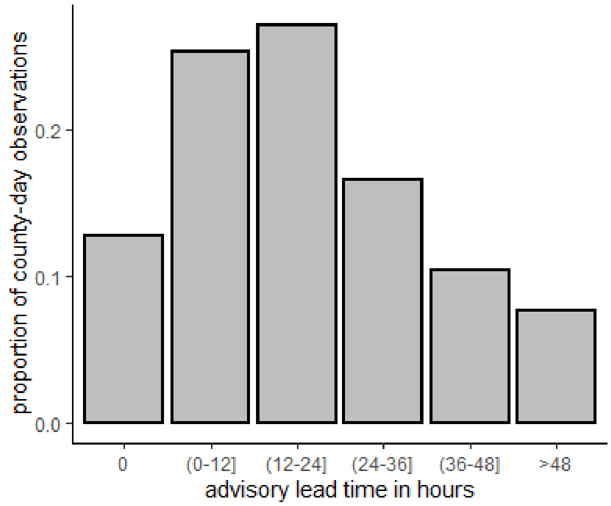
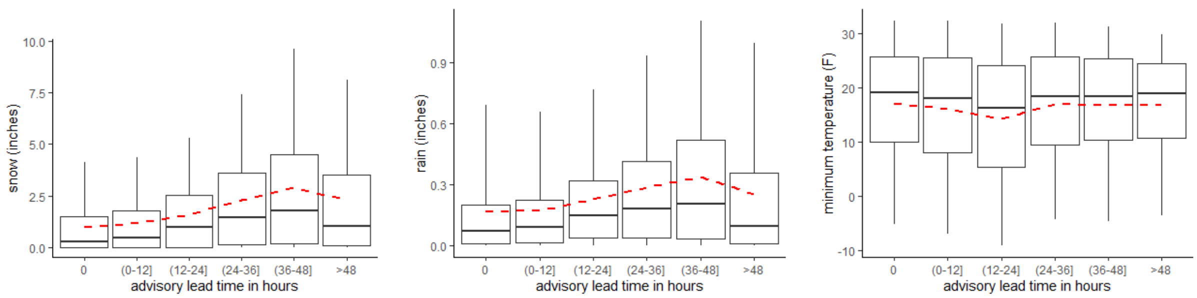
Figure 1: Distribution of Winter Advisory Lead times



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).

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



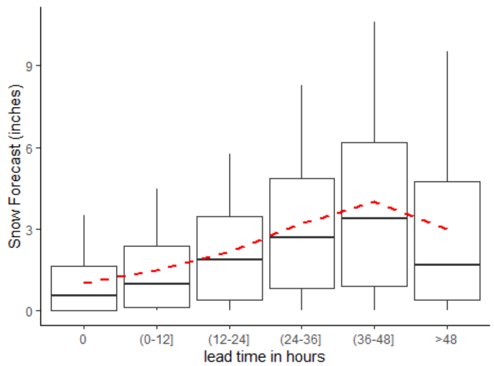
(a) Snow (inches)

(b) Rain (inches)

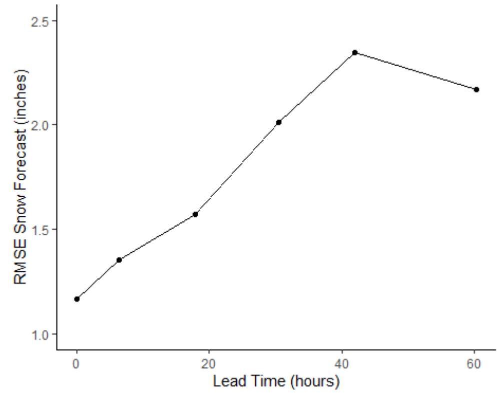
(c) Minimum temperature (F)

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.

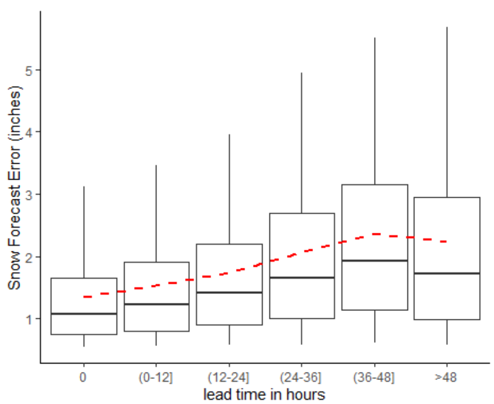
Figure 3: Snow forecast level and error by advisory lead time



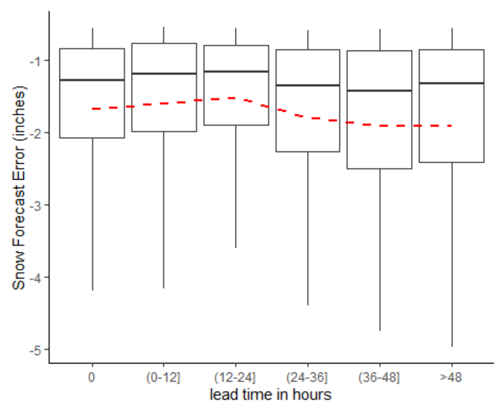
(a) Snow Forecast (inches)



(b) RMSE Snow Forecast (inches)



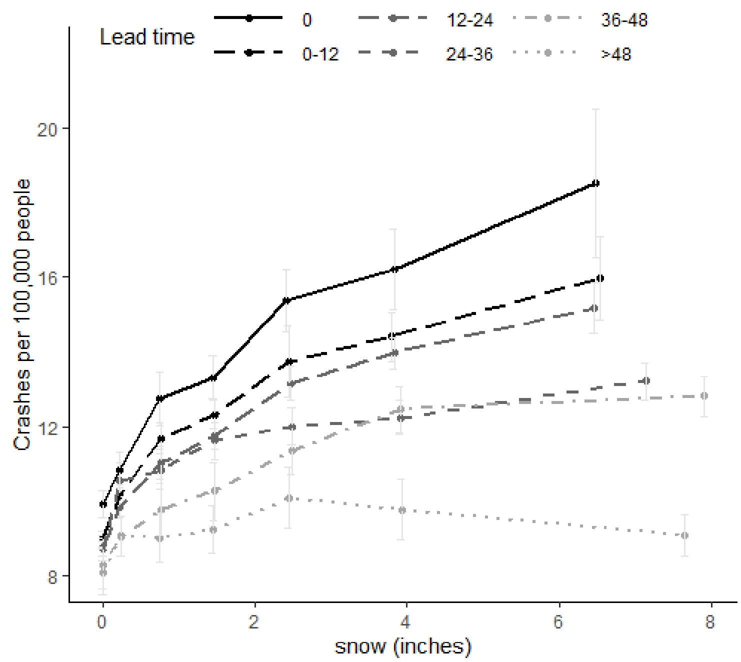
(c) Forecast Overestimation Error (inches)



(d) Forecast Underestimation Error (inches)

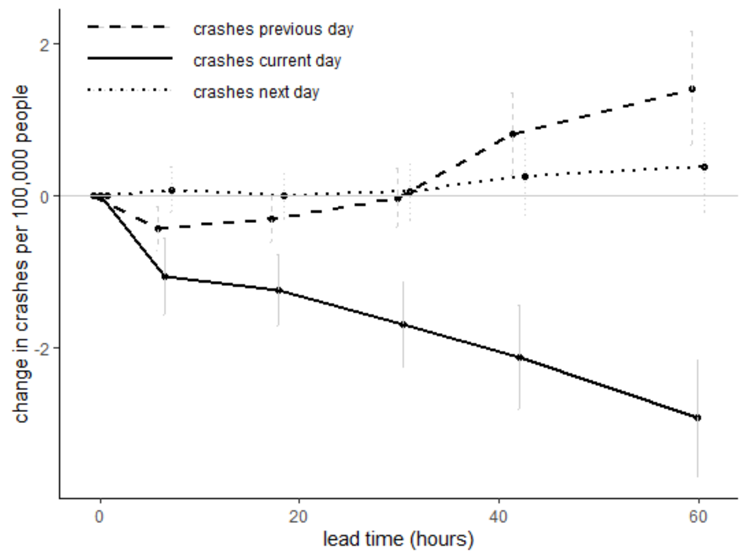
Notes: The figures show the distribution of forecasted snow (Panel A), the root mean square error (RMSE) of snow forecast (Panel B), and the distribution of forecast error when forecast overestimates (Panel C) and underestimates (Panel D) the snowfall at the county-date level by advisory lead time for the main sample. Box and whisker plot the measured variable (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.

Figure 4: Crashes per 100,000 people by snow for different advisory lead times



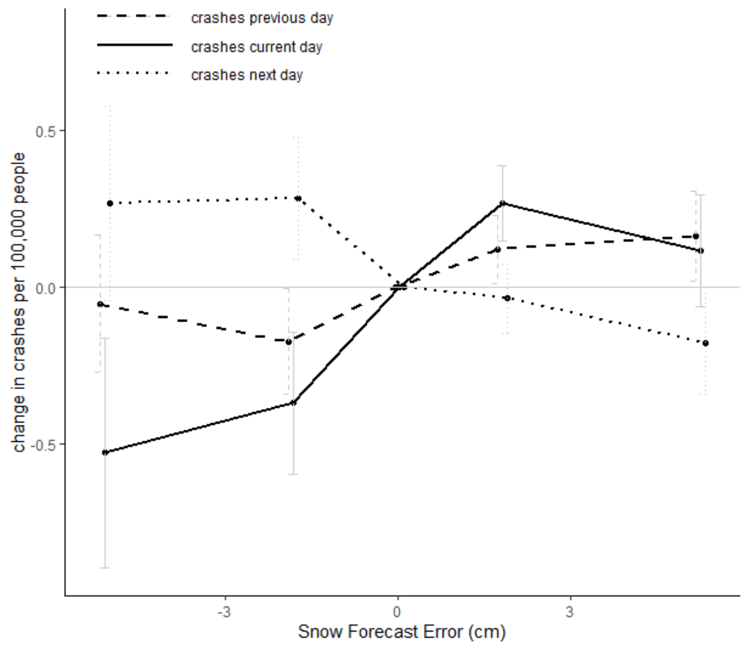
Notes: The figure shows the binned scatter plot of the average crashes per 100,000 people (x-axis) by average realized snow in inches (y-axis) within each of the six snow bins in inches, i.e., {<0.01, 0.01–0.5, 0.5–1, 1–2, 2–3, 3–5,>5}. The markers with whiskers plot the average crashes per 100,000 people 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.

Figure 5: 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 B.1. 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.

Figure 6: The effect of snow forecast error on crashes per 100,000 people



Notes: The figure plots the estimated effect of snow forecast error on crashes per 100,000 people based on estimating the Equation B.1. 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 forecast error (in cm 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 forecast error on crashes that occur on the same day the snow forecast is provided for. The dashed and dotted black lines correspond to the estimates of the effect of forecast error on crashes that occur on the previous and the next day, respectively. The x-axis coordinate of markers correspond to the average error in the corresponding error bin which are $\{$<-1.0, (-1.0,-0.5),[-0.5,0.5], (0.5,1.0], >1.0$\}$. Standard Errors are clustered at WFO-date level.

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

Dependent Variable:	crashes per 100,000 people			
	(1)	(2)	(3)	(4)
$Leadtime_{c,t}$	-0.032***	-0.054***	-0.036***	-0.053***
	(0.005)	(0.012)	(0.005)	(0.012)
$Leadtime^2_{c,t}$		0.0004**		0.0003
		(0.0002)		(0.0002)
$Leadtime_{c,t-1}$			0.006	-0.003
			(0.004)	(0.008)
$Leadtime^2_{c,t-1}$				0.0001
				(0.0001)
$Leadtime_{c,t+1}$			0.017***	-0.018*
			(0.005)	(0.009)
$Leadtime^2_{c,t+1}$				0.0006***
				(0.0002)
$ForecastError_{c,t}$	0.012	0.030*	0.013	0.027
	(0.016)	(0.017)	(0.017)	(0.018)
$ForecastError^2_{c,t}$		-0.004**		-0.004**
		(0.001)		(0.001)
$ForecastError_{c,t-1}$			-0.058***	-0.045***
			(0.013)	(0.014)
$ForecastError^2_{c,t-1}$				-0.003**
				(0.001)
$ForecastError_{c,t+1}$			0.024**	0.027**
			(0.010)	(0.011)
$ForecastError^2_{c,t+1}$				0.0006
				(0.0008)
County-Year-Month Fixed Effects	Yes	Yes	Yes	Yes
Mean Crashes (days with advisory)	10.98	10.98	10.98	10.98
Observations	1,914,367	1,914,367	1,877,166	1,877,166
R^2	0.18	0.18	0.18	0.18

Notes: The table shows the results from estimating the regression models in Equation 1 (Columns 1–2) and Equation 2 (Columns 3–4). 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. $Leadtime_{c,t}$, $Leadtime_{c,t-1}$, and $Leadtime_{c,t+1}$, the key variables of interest, are lead times (in hours) of winter advisories active on date t, $t-1$, and $t+1$. $ForecastError_{c,t+i}$ for $i = -1, 0, 1$ are snow forecast errors (in cm) for date $d + i$. Additional controls include: All specifications include controls for current, previous, and next day's weather, advisory issuance type, advisory issuance time, 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: 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						
$Leadtime_{c,t}$	-9.57***	-3.36***	-2.71***	-1.46***	-0.983	-1.02**
	(3.09)	(0.954)	(1.01)	(0.513)	(0.977)	(0.411)
$Leadtime_{c,t-1}$	1.15	0.485	0.255	0.827**	-0.496	0.017
	(2.50)	(0.669)	(0.754)	(0.405)	(0.925)	(0.348)
$Leadtime_{c,t+1}$	2.77	1.47*	1.15	0.630	-0.687	0.005
	(3.11)	(0.863)	(1.04)	(0.513)	(0.854)	(0.412)
$ForecastError_{c,t}$	-16.8	-2.32	-1.29	-3.06*	-6.05**	-4.33***
	(11.1)	(3.06)	(3.51)	(1.81)	(2.73)	(1.16)
$ForecastError_{c,t-1}$	-12.1	-2.37	-3.00	-1.88	-1.53	-3.10***
	(8.33)	(2.29)	(2.59)	(1.35)	(2.44)	(0.982)
$ForecastError_{c,t+1}$	4.47	1.66	3.79	0.608	-1.21	-0.876
	(7.97)	(2.17)	(2.41)	(1.26)	(2.13)	(1.22)
county-year-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean (days with advisory)	5,020.0	1,843.6	1,372.6	567.1	582.2	476.7
Mean (all days)	6,786.1	2,474.0	2,020.4	777.4	701.0	566.9
Observations	253,965	253,965	253,965	253,965	253,965	253,965
R^2	0.553	0.440	0.395	0.425	0.618	0.724

Notes: The table shows the results from estimating the regression models in Equation 3 with controls which are similar to those included in Column 3 of Table 1. The sample includes all county-date observations during Jan 2018–Dec 2018 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. $Leadtime_{c,t}$, $Leadtime_{c,t-1}$, and $Leadtime_{c,t+1}$, the key variables of interest, are lead times (in hours) of winter advisories active on date t, $t-1$, and $t+1$. Similarly, $ForecastError_{c,t+i}$ for $i = -1, 0, 1$ are snow forecast errors (in cm) for date $d + i$. Additional controls include: Advisory Event Type, Advisory Issuance Time, current, previous, and next day's weather, day of week, workday, and week of year fixed 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 3: 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						
$Leadtime_{c,t}$	10.2	0.533**	-3.41	165.3	-11.9	6.24
	(7.20)	(0.260)	(3.44)	(499.6)	(32.7)	(7.12)
$Leadtime_{c,t-1}$	3.91	0.174	0.868	14.2	7.24	0.519
	(5.75)	(0.207)	(2.11)	(322.2)	(21.6)	(3.66)
$Leadtime_{c,t+1}$	12.4	0.503*	-0.970	947.5**	90.2***	11.0**
	(8.02)	(0.284)	(2.60)	(446.4)	(33.1)	(5.54)
$ForecastError_{c,t}$	123.7***	4.20***	39.6***	4,624.6***	277.1***	37.8*
	(23.4)	(0.858)	(12.0)	(1,303.3)	(79.1)	(19.3)
$ForecastError_{c,t-1}$	-1.70	-0.307	0.754	-553.5	11.7	-7.77
	(16.5)	(0.599)	(6.27)	(905.0)	(48.4)	(12.0)
$ForecastError_{c,t+1}$	4.83	0.229	-6.03	-162.7	-17.9	-2.49
	(17.3)	(0.619)	(5.37)	(903.5)	(63.8)	(9.16)
County-Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep Var	2,123	64	461	51,699	3,740	425
Observations	48,120	48,120	48,120	48,120	48,120	48,120
R^2	0.42	0.45	0.26	0.30	0.18	0.10

Notes: The table shows the results from estimating the regression models in Equation 4. The sample includes all county-date observations during October 2014–December 2018 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. $Leadtime_{c,t}$, $Leadtime_{c,t-1}$, and $Leadtime_{c,t+1}$, the key variables of interest, are lead times (in hours) of winter advisories active on date t, $t-1$, and $t+1$. $ForecastError_{c,t+i}$ for $i = -1, 0, 1$ are snow forecast errors (in cm) for date $d+i$. Additional controls include: Advisory Event Type, Advisory Issuance Time, 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: The effect of advisory lead time on crash risk- Using the first day of advisory

Dependent Variable:	crashes per 100,000 people			
	(1)	(2)	(3)	(4)
$Leadtime_{c,t}$	-0.041***	-0.054***	-0.044***	-0.058***
	(0.009)	(0.019)	(0.009)	(0.019)
$Leadtime^2_{c,t}$		0.0003		0.0003
		(0.0004)		(0.0004)
$ForecastError_{c,t}$			0.038**	0.051***
			(0.017)	(0.019)
$ForecastError^2_{c,t}$				-0.003**
				(0.002)
County-Year-Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,883,426	1,883,426	1,883,426	1,883,426
R^2	0.17	0.17	0.17	0.17

Notes: The table shows the results from estimating the regression models in Equation 1 (Columns 1–2) and Equation 2 (Columns 3–4). The sample includes all county-date observations that receive as well as that do not receive a winter advisory, but have no active advisory on the previous day. The dependent variable is crashes per 100,000 people. $Leadtime_{c,t}$, $Leadtime_{c,t-1}$, and $Leadtime_{c,t+1}$, the key variables of interest, are lead times (in hours) of winter advisories active on date t, $t-1$, and $t+1$. Similarly, $ForecastError_{c,t+i}$ for $i = -1, 0, 1$ are snow forecast errors (in cm) for date $d+i$. All specifications include controls for current, previous, and next day's weather, advisory issuance type, advisory issuance time, 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 5: The effect of advisory lead time on crash risk- Using days with single advisory

Dependent Variable:	crashes per 100,000 people			
	(1)	(2)	(3)	(4)
$Leadtime_{c,t}$	-0.037***	-0.102***	-0.039***	-0.114***
	(0.008)	(0.018)	(0.008)	(0.018)
$Leadtime^2_{c,t}$		0.002***		0.002***
		(0.0004)		(0.0004)
$ForecastError_{c,t}$			0.122***	0.152***
			(0.018)	(0.019)
$ForecastError^2_{c,t}$				-0.008**
				(0.002)
County-Year-Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,883,426	1,883,426	1,883,426	1,883,426
R^2	0.17	0.17	0.17	0.17

Notes: The table shows the results from estimating the regression models in Equation 1 (Columns 1–2) and Equation 2 (Columns 3–4). The sample includes all county-date observations that receive none or only one winter advisory. The dependent variable is crashes per 100,000 people. $Leadtime_{c,t}$, $Leadtime_{c,t-1}$, and $Leadtime_{c,t+1}$, the key variables of interest, are lead times (in hours) of winter advisories active on date t, $t-1$, and $t+1$. $ForecastError_{c,t+i}$ for $i = -1, 0, 1$ are snow forecast errors (in cm) for date $d + i$. All specifications include controls for current, previous, and next day's weather, advisory issuance type, advisory issuance time, 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

A Data

A.1 Weather Advisory Data

The historical data on weather advisories issued by the NWS are digitized and maintained by the Iowa Environmental Mesonet (IEM). 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. 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.

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'.

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.[24]

A.2 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 generated by the Weather Forecast offices (WFOs) and the Weather Prediction Center (WPC). The forecasts are available with different lead times. For my purpose, I obtain the snow forecast for the next 0 to 24 hour period. However, The NDFD forecasts for snow are issued every 6 hours and are valid for the 6-hour periods. For example, a 12-hour lead time snow forecast issued at 0600 PM 01-Jan-2010 is the amount of snowfall forecasted during 0600 AM-1200 PM on 02-Jan-2010. I obtain these 6 hourly gridded data of snow forecasts in GRIB format from NDFD. 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.

I construct the 0 to 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):

Thus, the above estimated 0 to 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 01-Jan-2010. (Since 1200 UTC is 7 AM EST same day). Once I obtain this 0 to 24-hour snow forecast for each grid point, I add the forecasted amount for all the grid points that fall within a county to estimate the total forecasted snowfall in that county on a day.

[24] My results are robust to restricting the analysis to the first day of an advisory. Section 6 discusses this in detail.

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 01-Jan-2010
1800 UTC 01-Jan-2010 to 0000 UTC 02-Jan-2010	1200 UTC 01-Jan-2010
0000 UTC 02-Jan-2010 to 0600 UTC 02-Jan-2010	1200 UTC 01-Jan-2010
0600 UTC 02-Jan-2010 to 1200 UTC 02-Jan-2010	1200 UTC 01-Jan-2010

The table shows the construction of 0 to 24-hour lead-time forecast for snow using the NDFD forecasts. The forecast is what is available to an individual at 1200 UTC 01-Jan-2010 for the snow during the period 1200 UTC 01-01-2020 – 1159 UTC 01-02-2010. (1200 UTC is 7 AM EST)

A.3 Daily weather observations

I obtain daily weather observations 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 a 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 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. (2021)). 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.

A.4 Vehicle Crash Data

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 2008 to 2018.[25] These states are Illinois, Iowa, Indiana, 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. My results are robust to limiting my sample to eight states for which I have crash data for all the years during 2008-2018.

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

[25]The earliest digitized winter weather advisories are available from 2006, and the earliest digitized forecast data is available from 2008.

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 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 the 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 proactive winter road maintenance activities. So, longer lead times are likely to result in less snow accumulation on roads, enabling 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.

B Estimating the effects using a flexible functional-form

To estimate the non-linear relationship between lead time and crash risk more effectively, I re-estimate the main specification by discretizing the lead time variable in separate bins.

Specifically, I estimate the following specification:

$$Crash_{ct} = \sum_i \sum_{b \neq \{0\}} \beta_i^b Leadtime_{c,t+i}^b + \sum_i \sum_{b \neq \{0\}} \eta_i^b ForecastError_{c,t+i}^b + \sum_i \psi_i Advisory_{c,t+i}$$
$$+ \boldsymbol{\gamma_{t-1}} \mathbb{W}_{c,t-1} + \boldsymbol{\gamma_t} \mathbb{W}_{ct} + \boldsymbol{\gamma_{t+1}} \mathbb{W}_{c,t+1} + \boldsymbol{\lambda} \mathbb{X}_{ct} + \Phi_{cym} + \epsilon_{ct} \tag{B.1}$$

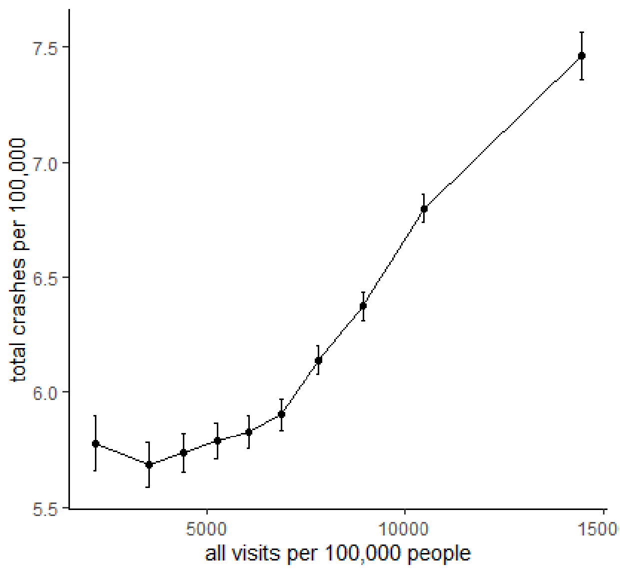
where I replace the primary variable of interest $Leadtime_{c,t+i}$ with five indicator variables $Leadtime_{c,t+i}^b$. These indicator variables capture which lead time bin, $b \in \{$(0,12], (12-24], (24-36], (36-48], >48$\}$, the advisory lead time on date $d+i$ in county c falls in. I also replace the forecast error variable $ForecastError_{c,t+i}$ with four indicator variables $ForecastError_{c,t+i}^b$. These indicator variables capture which error bin, $b \in \{$<-1.0, (-1.0,-0.5), (0.5,1.0], >1.0$\}$, the snow forecast error in inches on date $d+i$ in county c falls in. In the regression, I omit the lead time bin of exactly zero hours and the forecast error bin of $[-0.5, 0.5]$ inches. Thus, the coefficients β_i^b measure by how much the crash rate on date t changes in a county when the advisory active for date $d+i$ arrives with a lead time in bin b relative to a lead time of zero hours. The coefficients η_i^b measure by how much the crash rate on date t changes in a county when the forecast error for date $d+i$ falls in bin b relative to a forecast error within half of an inch.

C Relation between visits and vehicle crashes

C.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 C.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 C.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.

$$\begin{aligned} log(crashes)_{cd} &= \beta log(visits)_{cd} \\ &\quad + \boldsymbol{\gamma_{d-1}} \mathbb{W}_{c,d-1} + \boldsymbol{\gamma_{d}} \mathbb{W}_{cd} + \boldsymbol{\gamma_{d+1}} \mathbb{W}_{c,d+1} + \boldsymbol{\lambda} \mathbb{X}_{cd} + \Phi_{cym} + \epsilon_{cd} \end{aligned} \tag{C.2}$$

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 C.2 presents the regression estimates for equation C.2. 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 C.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 C.2. 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

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

Figure C.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.

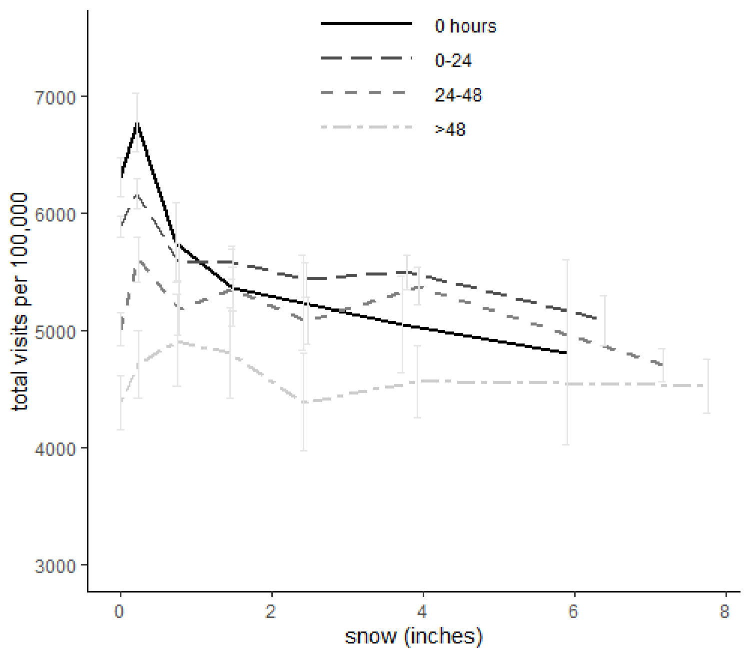


Figure C.2: Visits per 100,000 people by snow for different advisory lead times

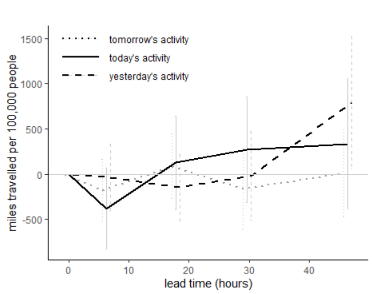
Notes: The figure shows the binned scatter plot of the average visits per 100,000 people (x-axis) for the realized average snow in inches (y-axis) within each of the six snow bins in inches, i.e., {<0.01, 0.01–0.5, 0.5–1, 1–2, 2–3, 3–5,>5}. The markers with whiskers plot the average visits per 100,000 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.

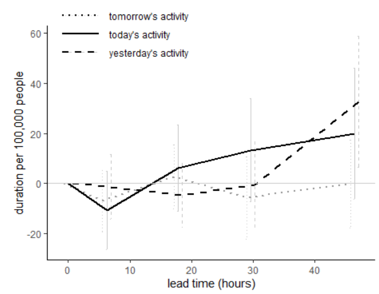
D Effect of lead time on road treatment activities

In this section, I estimate the effect of lead time on road treatment activities using a non-linear specification similar to that in equation **??** 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], (12-24], (24-36], >36$\}$, the advisory lead time on a day falls in. Figure D.3 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.

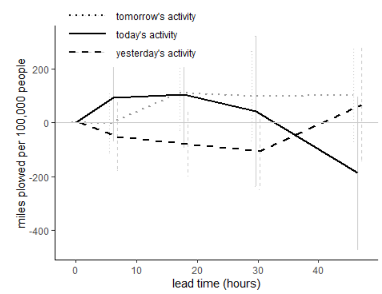
Figure D.3: Regression result- effect of lead time on visits and crashes



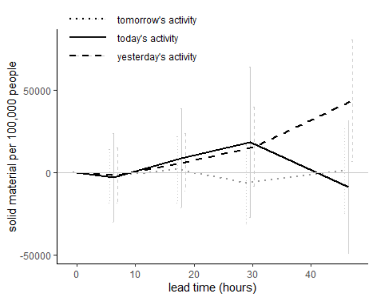
(a) Effect on distance travelled



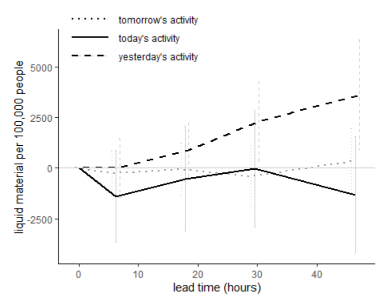
(b) Effect on operating duration



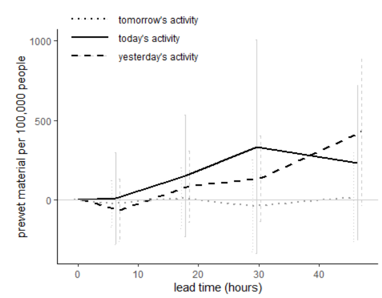
(c) Effect on distance plowed



(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 B.1. 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.

E Sample Winter Weather Advisory

Figure E.4: 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.