EFFECTS OF ADVERSE WINTER WEATHER ON DRIVERS IN HIGH RISK AGE

GROUPS: STATEWIDE ANALYSIS

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ABSTRACT:

3 Using new state-level data our research shows that young (<19) and older (65+) drivers are significantly overrepresented in crashes during winter road conditions. Drivers in Maine are, on 4 5 average, involved in 93 crashes per day, about one crash per 10,000 drivers. The daily number of crashes varies with many factors, including two that are the focus of this study: temperature and 6 7 snowfall. Winter-maintenance activities also influence safety and mobility and are costly. Maine spent \$98 million in 2008-2009 on winter road maintenance efforts to improve safety and 8 mobility. In order to efficiently allocate winter road maintenance resources, managers and policy 9 makers need to understand the relationship between road safety and varying levels of adverse 10 winter weather. Our analysis improves on past studies by exploring the relationship between 11 winter weather and vehicle crashes for different age groups on a state level rather than a national 12 level where it is more difficult to control for confounding variables. The methodology advances 13 past efforts by employing a model allowing for greater heterogeneity and using more detailed 14 weather, traffic volume and crash data. Results indicate that young drivers have the highest crash 15 16 risk with below freezing temperature and mid-levels of daily snowfall amongst all age groups. Crash risk is also shown to increase for young drivers by 13% on Fridays with trace amounts of 17 snowfall. 18 19

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21 INTRODUCTION

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23 The US Federal Highway Administration (Pisano et al. 2008) estimates that 673,000 people are injured and 7,400 people are killed each year in weather-related crashes. According to their 24 25 estimates, the average economic cost per crash is roughly \$14,100 (inflation adjusted to the year 2000) giving an annual cost of around \$22 billion dollars for weather-related crashes, and nearly 26 double that figure if including unreported crashes (Pisano et al. 2008). With 24% of all weather-27 related crashes occurring on snowy, slushy or icy pavements, winter crash costs for northern US 28 states are high. Researchers at the University of Maine estimate an annual average economic cost 29 of \$1.5 billion from crashes in Maine. Additionally, in direct costs, the state spends \$98 million 30 31 dollars annually on winter road maintenance efforts to improve safety and mobility (MCSPC 32 2010).

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34 Increases in crash rates for young and older drivers are an immediate road safety concern. In the State of Maine, drivers ages 16 to 18, and older than 65, contribute to a small percentage 35 of the annual traffic volume but account for a greater percentage of crashes and fatalities than all 36 other drivers. Young drivers alone account for 13% of registered drivers but 30% of drivers 37 38 involved in crashes (MTSC 2004). Many studies have considered the impact of age on vehicle crashes (Zhang et al. 2003; Bèdard et al. 2001; Massie et al. 1994), but only one has analyzed the 39 effect of winter weather on crashes based on driver age (Eisenberg and Warner 2005). With 40 41 crash risks increasing for all drivers during adverse winter weather, it is important to understand how these high-risk age groups are affected by such conditions. Responses of older drivers to 42 winter weather are especially relevant in Maine where the average age is the highest of any state 43 44 in the U.S. (U.S. Census 2010). This analysis departs from past studies by exploring the

45 relationship between winter weather and vehicle crashes for different age groups on a state level

1 rather than a national level where it is more difficult to control for confounding variables. The

2 methodology improves upon past efforts by employing a model allowing for greater

- 3 heterogeneity and using more detailed weather, traffic volume and crash data. Results differ
- 4 substantially from past efforts and give a clearer understanding to this serious issue.
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6 This is the first study estimating the effect of winter weather on road safety for an entire 7 state using statewide traffic volume data which is superior to annual estimates. Although there 8 are benefits to a less aggregated scale, such as the road segment level, statewide results can be 9 very useful in policy making that affects the entire state. In addition, due to a state's inherent 10 heterogeneity, this study is able to capture how winter weather affects crashes in rural and urban 11 settings with differing road classes and weather events.

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13 LITERATURE REVIEW

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15 Vehicle crashes and decreased mobility during winter months impose large costs on society and are the main motivation for any winter road maintenance program (Andrey 2003; Hanbali 1994; 16 17 Maze 2007). The relationships between varying types of adverse winter weather, varying levels of winter roadway maintenance, and road safety are central to allocating winter road 18 maintenance resources efficiently. Understanding these relationships grows with increasing costs 19 20 of salt and other snow and ice-control materials. Additionally, road salt has been found to be highly corrosive to metal and may cause substantial damages to vehicles. Therefore, controlling 21 the amount of salt on the road can decrease the costs from corrosion and possibly reduce rusty 22 brake lines, which is a safety hazard (MCSPC 2010). 23

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In an extensive literature review, adverse weather has been shown to increase the risk and incidence of a vehicle crash occurring (Knapp 2000; Norrman et al. 2000; Eisenberg and Warner 27 2005; Qin 2006; Datla 2008;). On average, adverse weather is associated with 7,000 fatalities, 800,000 injuries and 1.5 million vehicular crashes in the United States annually (Eisenberg and Warner 2005). Specifically, a meta-analysis found that the probability of a crash occurring increases by up to 420% during heavy snow events and, on average, by 169% with light snow (Qin 2008).

32 Eisenberg and Warner (2005) conducted the first analysis on the safety effects of winter weather, specifically snowfall, on drivers of different age groups. Using a national model looking 33 at crashes in the US, Eisenberg and Warner found that elderly (ages 65+) and young (less than 34 18) drivers experience a decrease in fatality numbers during days with adverse winter weather, 35 while the middle age group showed a slight increase. These results are useful as a starting point, 36 but their methodology has many shortfalls that are improved upon in the current analysis. 37 Specifically, Eisenberg and Warner do not include an exposure measurement sufficient enough 38 to account for traffic volume reduction due to winter weather. Additionally, by employing a 39 model on a national scale, state and regional heterogeneity such as differences in driver behavior 40 cannot be completely accounted for. It is important to note that the authors do include state fixed 41 effects to account for this issue but do not provide any figures describing their success. Lastly, 42 the authors choose to concentrate only on fatal crashes and do not provide any insight on how 43

- 1 winter weather affects other severity level crashes with drivers of different age groups. This
- 2 analysis uses statewide daily traffic volume measurements to estimate the relationship between
- 3 winter weather and crashes across driver age for the state of Maine.
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5 METHODS

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7 Data Sources

8 Crash data was provided by the Maine Department of Transportation (MaineDOT) and was

9 derived from all police reported crashes in the state for the years 2000 to 2007. Crashes that have

10 estimated damages of over \$1,000 and/or personal injury are required to be reported to the

11 police. Therefore, this analysis does not include minor property-damage-only crashes.

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Traffic counts, also provided by MaineDOT, were obtained from 27 Automatic Traffic Counters (ATC) throughout the state. Count locations were chosen based on functional road class (Interstate, State Highway, Rural and Urban Arterial) and geographic location (Augusta, Bangor, Caribou, Farmington, Portland) to ensure that each road type and each state region were accounted for. Overall, each functional class is represented in the five regions for the years 2000 to 2007.

Daily snowfall and temperature values were collected from five weather stations
throughout the state. Data from the five stations were averaged to find statewide daily values for
snow and temperature.

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24 Explanatory Variable Processing

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The output measure in question is the reported number of vehicle crashes in a given 24-hour period. Crash data, weather and exposure variables are grouped into daily levels for the years 2000 to 2007, a total of over 2900 days. Although the scope of this study is to model the relationship between winter weather and vehicle crashes, all days of the year are included in the model to control for trends in crashes not related to winter weather conditions.

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32 Traffic Volume Variables

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Hourly traffic counts from each site were summed up into daily totals. Then the average daily flow was calculated for each site. Actual daily counts were then divided by the average for that site to measure the per-day variation in traffic volume, as a proportion of the average. These proportions from each site were then averaged over all sites, creating a value measuring the variation in traffic statewide.

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40 Statewide daily measurements of traffic volume are not available for all roads in Maine. 41 Nonetheless, accounting for traffic volume variations has been proven necessary to measure 42 properly the increased or decreased crash risk (Fridstrøm 1995). This is especially important in 43 Maine due to fluctuating winter and tourist seasons. The state of the economy, amount of rain in 44 a summer, the day of the week, and amount of snow in a winter all contribute to increases or 45 decreases in traffic volume. In order to account for variation not accounted for in the exposure

- 1 measure, indicator variables were created for each day of the week as well as every month. Also,
- 2 a "high volume" indicator variable equals 1 if the month is April October, noting months with
- 3 higher traffic volume due to increased tourism.
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Weather Variables

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7 Temperature and snowfall do not have a linear relationship with crashes. Figures 1 and 2 show

- 8 how crashes are distributed for daily average temperatures and snowfall in Maine. We can see
- 9 that the highest daily crash numbers occur at temperatures below but near 32 degrees Fahrenheit.
- 10 When temperatures fluctuate above and below freezing there is a greater occurrence of ice and
- 11 slippery road conditions that result in more crashes (Evans 2004). Daily totals decrease when
- 12 temperatures drop well below freezing. This distribution does not account for daily traffic
- volumes and therefore, it is difficult to tell if the crash risk actually decreases or this is a factor of
- 14 people driving less in severe weather.
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FIGURE 1 Distribution of Daily Crash totals across Mean Daily Temperatures



FIGURE 2 Distribution of Daily Crash Totals across Average Daily Snowfall (in.)

The incidence of crashes per day seems to be increasing when snowfall amounts increase from trace amounts to around one inch. For greater snowfalls than one inch, there seems to be a fairly constant average number of crashes per day (Figure 2). It is understood that daily measures of snowfall may be misleading due to the potential of snowfall occurring late at night or other times when few people are on the road, but it was decided that the sample size is large enough so that daily snow totals are an accurate proxy for level of snow on the road.

In order to account for the variations in crash numbers, indicator variables are used for 11 12 temperature and snow fall. The "Near32" variable is equal to 1 when the maximum temperature was above freezing and the minimum temperature was below freezing. In addition to "Near32," 13 14 variables "Maxbelow32" and "Maxbelow25" were created to capture the different relationships between temperature and crashes. For snowfall, four separate indicator variables are employed 15 16 that are separated based on the daily snowfall depth starting from 0.01 to 0.10 inches and going as high as greater than 1 inch. These variables are noted in the model as "Trace Snow," "Mid 17 18 Snow," and "Heavy Snow." The variables "No Snow" and "Minabove35" variables are used as a baseline and their regression parameters are assumed to be zero. 19

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Organizing the weather variables in this fashion has many benefits. First, splitting up
 these essentially "grouped" variables into individual categories allows for a more detailed
 analysis of snow, temperature and crashes. Secondly, because the variables are binomial in

1 nature, the resulting regression coefficients can be interpreted as the discrete change on crash

- 2 numbers from a certain temperature range or level of snowfall on daily crash totals (Agresti
- 2007). Although the creation of more variables increases the amount of variance that can be
 explained and increases the precision, the model may suffer with lower degrees of freedom
- 5 (Griffiths 1993).
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8 DATA ANALYSIS

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10 Model

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Previous research reviewed above used a standard version of the negative binomial regression (NB) to model the association between winter weather and crash frequencies based on age (Eisenberg and Warner 2005). The analysis in this paper uses both the standard version as well as a generalized version (GNB) that is becoming more common in crash modeling literature

16 (Miauo 1994). The two models are compared for best fit.

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18 The NB model, a generalized version of the Poisson regression is widely used because 19 the restricting assumption in Poisson models of the variance and mean being equal. This 20 assumption does not often hold true and the NB model, which allows for extra variation or 21 "dispersion" from the mean in the form of a dispersion parameter, is used instead. This extra 22 parameter allows for extra variance from the mean that occurs because of unexplained 23 heterogeneity in the model and/or omitted variables (Cameron and Trivedi 2001). The standard 24 model is shown below:

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$Y_i \sim NB(\mu_i, \theta)$

- $\mu_i = \exp(\beta_0 + \beta_k X_{ik} + Exposure_i)$
- In this study, Y_i = actual observed total number of crashes for each individual day i, and 28 θ is an over-dispersion parameter that equals 0 if Poisson. Additionally, μ_i is the predicted daily 29 crash total which is a function of explanatory variables X_{ik} and regression coefficients β_k for 30 each k variable. Exposure refers to the amount of exposure in a given observation, which in this 31 case is the traffic volume value previously discussed. In this standard version of the NB, θ is 32 33 assumed to be a constant that is estimated in the modeling process. This assumption is restricting because variation in the number of crashes per day can change dramatically with weather 34 conditions, driver behavior and other factors. If this extra variation does exist, the model faces 35 potential bias and inflation or deflation of the standard errors on the regression coefficients. A 36 generalized version of the NB model can then be used that relaxes the assumption of a constant 37 over-dispersion parameter by making it a function of its covariates \mathbf{z}_{j} and respective regression 38 estimators γ_k . The functional form of the GNB model is as follows: 39 40

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$$Y_i \sim NB(\mu_i, \theta)$$

$$\mu_i = \exp(\beta_0 + \beta_k X_{ik} + Exposure_i)$$

$$\ln(\theta) = \mathbf{z}_j \gamma$$

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The Generalized Negative Binomial (GNB) model allows dispersion to vary across each observation (Cameron and Trivedi 2001). This functional form seems most appropriate for this analysis with the use of statewide data and varying levels of traffic volume on roads for given weather events.

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Following a method similar to Hermans et al. (2006), the Akaike Information Criterion
(AIC) value is used as a comparison of best fit. Other measurements of goodness of fit, such as
R-squared have been proven inappropriate for the NB models (Hermans 2006; Miauo 1996). To
calculate AIC values, the following equation is used:

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13 $AIC_i = -2(LL_i) + 2K_i$

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where *LL* is the log likelihood and *K* equals the number of parameters for model *i*. With the lowest AIC value the results indicate that the GNB model is the best fit for the data. Allowing the dispersion parameter to vary does indeed capture more of the variation in the model compared to the standard NB with constant over-dispersion. This result is also shown in estimation results where variables are found to be significant in explaining the variation of the dispersion parameter, proving that it does indeed vary and should not be assumed constant in this analysis.

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23 Interaction Terms

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25 Without the use of interaction terms, regression parameters show only the effect of the individual

variable on crash numbers, but do not allow for interpretation of a combined effect of multiple

variables interacting. For example, the coefficient on the snow variable describes the effect of

snow on crashes while assuming all other variables are held constant at their means. This

relationship can potentially change for different temperature ranges and days of the week, and

the combined effect cannot be captured by simply adding or multiplying the individual

coefficients. Therefore, interaction terms combining temperature, snowfall and days of the week

- are included to estimate these combined effects.
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34 Age Classification

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36 The increase in crash risk for young drivers can be attributed to speeding, driving under the

influence of alcohol or drugs, and overall inexperience, while older drivers may experience more

crashes due to poor eyesight, delayed reaction time, and other physical impediments (MTSC

2004). To analyze the effect of adverse winter weather on drivers of different age groups, daily

40 crashes are filtered for older (ages 65+), younger (ages less than 19) and "mid-age" (ages 19 to

41 65) drivers. In addition to an encompassing model with all drivers, three separate models are

42 estimated using the high risk age groups as the response variable.

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2 **RESULTS**

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4 Table 1 presents crash rates per age group for days with adverse winter weather as a proportion 5 to days with no snow and above freezing temperature (Baseline). On days with the maximum temperature well below freezing, crash rates for young and mid-age drivers increase by 20% and 6 10% respectively. In terms of snowfall, crash risk for mid-age drivers' increases substantially 7 8 more than for younger drivers specifically during days with snowfall greater than an inch (200%) and 85% respectively). Allowing for interactions, mid level snowfall and colder temperatures 9 seem to be most dangerous for younger drivers, where the increase in crash risk is highest for all 10 ages at temperatures near, and below freezing. Additionally, although only the mid-age group 11 shows significance, the interaction between heavy snowfall and very cold temperatures reduces 12 the crash risk compared to heavy snowfall and cold temperatures separately. This decrease in 13 risk may be attributed to drivers avoiding driving under extreme conditions, but without hourly 14 traffic volume data, this cannot be determined. However, the total effect of heavy snowfall and 15 very cold temperatures is that the crash risk for mid-age drivers increases by almost 220% and 16 17 for young drivers by 80% compared to the baseline of no snow and warm weather. 18

Young drivers have the highest increase in risk on Fridays compared to all other ages.
Trace amounts of snow alone does not appear significant for young drivers, but when combined
with the Friday indicator variable, results show a significant increase in risk. Young drivers may
be driving more than other age groups on Friday's mixed with their inexperience may be giving
this result. Traffic volume data per age group does not exist in Maine so there is no way to test
this hypothesis.

- Crash risk is shown to increase significantly for all age groups in the month of December.
 With the first major snow events occurring during this month, drivers may need time to adjust to
 the winter conditions, and this effect does not differ by age. This result is supported in past
 research (Fridstrøm and Ingebrigsten 1991; Eisenberg 2005).
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Perhaps the most surprising result is the lack of significance on weather variables for older drivers. On one hand, this result may be derived from older drivers deciding not to drive during winter weather events since the exposure term used does not differentiate miles driven by age group. On the other hand, the positive sign on each weather variable, indicating more crashes are to be expected with heavy snow and colder temperatures, follows what is to be expected. In addition, the risk for older drivers increases with more snow and colder temperatures, in a similar fashion as for all other ages, indicating that a possible relationship does exist.

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1 TABLE 1 Age Specific Winter Weather Crash Rates

Variable	All Drivers IRR	Younger	Older Drivers	Mid-age Drivers
	(P-value)	Drivers IRR	IRR	IRR
		(P-value)	(P-value)	(P-value)
Baseline		1.00	1.00	1.00
Near32	1.06 (0.00)	0.99 (0.87)	1.04 (0.24)	1.08 (0.00)
Maxbelow25	1.12 (0.02)	1.19 (0.01)	1.12 (0.13)	1.10 (0.05)
Maxbelow32	1.11 (0.01)	1.08 (0.22)	1.11 (0.13)	1.12 (0.01)
Trace Snow	1.05 (0.12)	1.06 (0.31)	1.05 (0.41)	1.06 (0.08)
Mid Snow	1.26 (0.00)	1.12 (0.14)	1.03 (0.70)	1.34 (0.00)
Heavy Snow	2.64 (0.00)	1.86 (0.02)	1.37 (0.23)	3.03 (0.00)
Sunday	0.79 (0.00)	0.78 (0.00)	0.62 (0.00)	0.83 (0.00)
Monday	0.98 (0.16)	0.96 (0.07)	0.95 (0.05)	1.00 (0.84)
Tuesday	1.00 (0.78)	0.98 (0.45)	0.98 (0.45)	1.02 (0.20)
Thursday	1.03 (0.05)	1.02 (0.45)	0.99 (0.95)	1.04 (0.01)
Friday	1.11 (0.00)	1.17 (0.00)	1.00 (0.85)	1.13 (0.00)
Saturday	0.96 (0.01)	0.97 (0.24)	0.82 (0.00)	0.99 (0.70)
December	1.29 (0.00)	1.25 (0.00)	1.28 (0.00)	1.29 (0.00)
High Volume	1.08 (0.00)	1.17 (0.00)	1.19 (0.00)	1.04 (0.02)
Near32*Trace Snow	0.99 (0.71)	0.98 (0.70)	0.91 (0.16)	0.99 (0.75)
Near32*Mid Snow	1.21 (0.00)	1.29 (0.00)	1.05 (0.60)	1.21 (0.00)
Near32*Heavy Snow	0.84 (0.48)	1.00 (0.99)	0.95 (0.85)	0.81(0.39)
Maxbelow32*Trace	1.02 (0.68)	1.03 (0.77)	1.02 (0.76)	1.01 (0.82)
Snow				
Maxbelow32*Mid	1.28 (0.00)	1.33 (0.01)	1.09 (0.45)	1.29 (0.00)
Snow				
Maxbelow32*Heavy	0.86 (0.55)	1.06 (0.83)	0.99 (0.97)	0.83 (0.44)
Snow				
Maxbelow25*Trace	0.96 (0.61)	0.97 (0.77)	0.87 (0.19)	0.97 (0.71)
Snow				
Maxbelow25*Mid	0.85 (0.05)	0.90 (0.32)	1.02 (0.79)	0.82 (0.02)
Snow				
Maxbelow25*Heavy	0.92 (0.42)	0.82 (0.10)	0.84 (0.17)	0.95 (0.63)
Snow				
Sunday*Trace Snow	1.02 (0.69)	1.01 (0.93)	1.01 (0.91)	1.02 (0.68)
Sunday*Mid Snow	0.94 (0.32)	1.03 (0.70)	1.04 (0.61)	0.90 (0.13)
Sunday*Heavy Snow	1.22 (0.03)	1.19 (0.09)	1.01 (0.91)	1.22 (0.04)
Friday*Trace Snow	1.07 (0.16)	1.13 (0.06)	1.02 (0.77)	1.07 (0.22)
Friday*Mid Snow	0.93 (0.19)	0.96 (0.57)	0.98 (0.81)	0.91 (0.15)
Friday*Heavy Snow	1.00 (0.99)	0.94 (0.53)	0.97 (0.78)	1.01 (0.93)
Saturday*Trace Snow	1.01 (0.76)	1.08 (0.18)	0.87 (0.05)	1.01 (0.76)
Saturday*Mid Snow	0.87 (0.05)	0.92 (0.29)	0.89 (0.19)	0.86 (0.03)
Saturday*Heavy Snow	1.02 (0.82)	1.09 (0.40)	0.78 (0.04)	1.02 (0.86)

Marginal effects of the GNB model for all drivers are given in Table 2. To facilitate 1 interpretation, the beta coefficients for the variables "Minabove32", "Nosnow", and 2 "Wednesday" are set to 0. This allows each marginal effect to be interpreted as the increase or 3 decrease of daily crashes compared to a Wednesday with no snow and a mild temperature. The 4 average daily crash total reflects these normalized conditions and shows that there are 5 approximately 93 crashes per "average" day without any winter weather, or large variation in 6 traffic volume. The statistically significant marginal effects can be interpreted as adding or 7 subtracting from the base value. For example, when the daily maximum temperature is below 8 9 freezing, and traffic volume not affected, there will be approximately 10 additional accidents statewide, or 104 crashes on average. Similarly, the greatest effect on crashes from snow occurs 10 on days with accumulation greater than 1 inch, where we should expect 144 more crashes, an 11 increase of over 150% from an "average" day. 12

13 In addition, the interaction terms show the combined effect of temperature, snowfall, and 14 days of the week. These results tell us that with temperatures near freezing and trace amounts of snow, we should expect more crashes than near freezing and trace amounts of snow by 15 themselves would give. On the other hand, when temperatures are well below freezing and 16 17 snowfall is between .01 to 1 inches, shown in the "Maxbelow25" interaction term, crashes are shown to decrease. This result may appear to contradict past studies that have shown increases in 18 crash rates under such conditions (Qin 2006), but it is more likely that the negative sign reflects a 19 drop in reported crashes due to slower driver speeds and less severe crashes (fewer crashes 20 21 costing more than USD1000).

Other factors that may be contributing to the variation in crashes, but are not included in this analysis, are time of day of snowfall, and the fact that drunk driving may vary with some variable such as season rather than just with weekday and month. Overall, we conclude that adverse weather, specifically snowfall and colder temperatures, lead to a greater number of crashes.

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1	TABLE 2 Winter	Weather Margina	l Effects (All Ages)
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Variable	Marginal Effect	P-value	
Near32	5.48	0.00	
Maxbelow25	10.94	0.03	
Maxbelow32	10.39	0.01	
Trace Snow	4.82	0.13	
Mid Snow	23.62	0.00	
Heavy Snow	143.94	0.01	
Sunday	-20.17	0.00	
Monday	-1.81	0.15	
Tuesday	0.34	0.79	
Thursday	2.50	0.06	
Friday	10.54	0.00	
Saturday	-3.38	0.01	
December	26.04	0.00	
High Volume	7.20	0.00	
Near32*Trace Snow	-1.35	0.71	
Near32*Mid Snow	19.42	0.00	
Near32*Heavy Snow	-14.7	0.44	
Maxbelow32*Trace	2.31	0.69	
Snow			
Maxbelow32*Mid	25.90	0.01	
Snow	23.80	0.01	
Maxbelow32*Heavy	12 78	0.52	
Snow	-12.70	0.32	
Maxbelow25*Trace	-3.24	0.60	
Snow	-3.24	0.00	
Maxbelow25*Mid	-13 72	0.04	
Snow	-15.72	0.04	
Maxbelow25*Heavy	-6.91	0.41	
Snow	0.71	0.71	
Sunday*Trace Snow	1.71	0.05	
Sunday*Mid Snow	-5.67	0.31	
Sunday*Heavy Snow	20.05	0.05	
Friday*Trace Snow	6.56	0.17	
Friday*Mid Snow	-6.79	0.18	
Friday*Heavy Snow	0.08	0.99	
Saturday*Trace Snow	1.22	0.78	
Saturday*Mid Snow	-11.23	0.03	
Saturday*Heavy	1.98	0.83	
Snow			

1 **DISCUSSION**

2 Results from the age specific models show that the risk of a crash does vary per age group and weather condition. One particularly important result shows that, when allowing for interaction 3 amongst weather variables, younger drivers have the highest crash risk on days with medium 4 levels of snow and near to below freezing temperatures. Additionally, younger drivers hold the 5 6 highest risk on Fridays with medium to heavy levels of snow than all other ages. Older drivers 7 also show an increase in risk with snow, but their risk is significantly lower than other age groups, and the results appear insignificant. Although it cannot be confirmed in this analysis, our 8 hypothesis is that older drivers drive less during days with snow but their driving habits are not 9 10 affected by temperature. Planners can use this information to better allocate their resources to which age groups pose the greatest risk during such adverse winter events. 11

12 The results of the GNB model are consistent with past literature (Qin 2006) and show that colder temperatures and daily snowfall greater than an inch create dangerous driving 13 14 conditions and increase the daily crash number by up to 140%. Although our analysis does not compare the exact time of crashes in relation to the weather, we can conclude that with over 100 15 additional crashes on average occurring in adverse winter weather, there is indeed a strong 16 relationship between adverse winter weather and the number of vehicle crashes in the state of 17 18 Maine. Additionally, if using FHWA estimates, days with adverse winter weather cost the state approximately 1.5 million dollars each in additional crash costs. With the state spending 98 19 20 million dollars annually on snow and ice control, days with adverse weather account for a substantial proportion of their budget. 21

One of the main limitations of this analysis is that by using daily crash totals, we are 22 unable to fully capture the effect of weather on road safety. Without time of crash, time of 23 weather event and current traffic volume, we cannot draw definite conclusions. A similar 24 geographic limitation exists by averaging weather observations from stations across the state. 25 Maine is a diverse state geographically and extreme northern or southern weather most likely 26 skews the daily averages. It was because of this lack of data that we chose a 19 year time period 27 with over 7,091 observations in hopes of finding reliable results in a large sample size. Future 28 research should connect crashes to their closest weather station via Geographic Information 29 30 Systems (GIS)

This is the first study of its kind using comprehensive state-level data. This study provides winter road maintenance managers with a better understanding of what combinations of temperature and snow will create the most dangerous driving days allowing a better allocation of resources to such days to combat snow and ice. State-wide analysis allows state and federal planners to compare results to other snow-belt states to gain a better understanding of statespecific driving hazards.

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