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Accident Analysis and Prevention xxx (2003) xxx–xxx

ACCIDENT ANALYSIS & PREVENTION

www.elsevier.com/locate/aap

The mixed effects of precipitation on traffic crashes

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Abstract

Purpose: This paper investigates the relationship between precipitation and traffic crashes in the US during the period 1975–2000. Traffic crashes represent the leading cause of death and injury for young adults in the US, and the ninth leading cause of death for the overall population. Prior studies have found that precipitation raises the risk of traffic crashes significantly.

Methods: A negative binomial regression approach is employed. Two different units of analysis are examined: state–months and state–days. The sample includes all 48 contiguous states.

Results: A surprising *negative* and significant relationship between monthly precipitation and monthly fatal crashes is found. However, in the daily level analysis, a strong *positive* relationship is estimated, as in prior studies. The source of the contrasting results appears to be a substantial negative lagged effect of precipitation across days within a state–month. In other words, if it rained a lot yesterday, then on average, today there are fewer crashes. Additional analysis shows that the risk imposed by precipitation increases dramatically as the time since last precipitation increases. For example, 1 cm of precipitation increases the fatal crash rate for a state–day by about 3% if exactly 2 days have passed since the last precipitation and by about 9% if more than 20 days have passed. This basic pattern holds for non-fatal crashes as well.

Conclusions: The lagged effects of precipitation across days may be explained by the clearing of oil that accumulates on roads during dry periods or by the conditioning of people to drive more safely in wet conditions. Either way, policy interventions that prepare drivers more adequately for the risks of precipitation following dry periods are likely to be beneficial.

Keywords: Precipitation; Traffic crashes; Fatal crashes; Rain; Lagged effects

1. Introduction

The point of departure for this study is a surprising empirical result: in a typical state–month pair in the US from 1975 to 2000, increased precipitation is associated with *reduced* fatal traffic crashes. More precisely, an additional 10 cm of rain in a state–month is associated with a 3.7% decrease in the fatal crash rate. The estimate is derived from a negative binomial regression using a panel of state–month observations and including year and (state $\times$ month) fixed effects, and is statistically significant at a high confidence level ($Z = 8.1$).

This result appears to contradict a substantial body of research, which consistently finds that precipitation *increases* traffic crashes. Several studies, in fact, conclude that crashes increase during rainfall by 100% or more (Brodsky and Hakkert, 1988; Bertness, 1980; NTSB, 1980; Sherretz and Farhar, 1978), while others find more moderate (but still statistically significant) increases (Andreescu and Frost, 1998; Fridstrom et al., 1995; Andrey and Yagar, 1993; Andrey and Olley, 1990). Of two studies that focus specifically on *fatal* traffic crashes, one finds an increase in the crash rate of over 100% during rainy conditions (Brodsky and Hakkert, 1988), and the other finds an increase in one country (Denmark) and no significant change in two other countries (Norway and Sweden) (Fridstrom et al., 1995).

A closer inspection of the data in the present study shows how the estimated negative association between precipitation and fatal crashes can be reconciled with the literature described earlier. First, when the regression analysis is conducted with the state–day, rather than the state–month, as the unit of observation, the association between precipitation and fatal crashes is estimated to be *positive* and significant, as in the literature. Second, for a given day in a given state, lagged precipitation, i.e. precipitation that fell in the state in recent days, is shown to reduce fatal crash rates on the current day substantially. This result explains why more precipitation in a typical state–*month* leads to *fewer* fatal crashes, while at the same time more precipitation in a typical state–*day* leads to *more* fatal crashes.

The vast number of state–day observations in the sample (over 455,000) allow for a detailed examination of these lagged effects. It is found that the more days that have passed

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0001-4575/$ – see front matter © 2003 Elsevier Ltd. All rights reserved.
doi:10.1016/S0001-4575(03)00085-X

since precipitation has fallen in a state, the more dangerous precipitation is in terms of accidents. For example, if only 2 days have passed since the last precipitation, 1 cm of precipitation is estimated to increase the incidence of fatal crashes by 3%, whereas if 21 or more days have passed, 1 cm of precipitation is estimated to increase the incidence by 9%.

Non-fatal crash data are also analyzed for a subset of the sample period for which data are available, 17 states during 1990–1999. Compared to fatal crash rates, non-fatal crash rates are increased more by a given amount of precipitation. This difference can presumably be explained by the fact that people drive more slowly in wet conditions and therefore crashes on average tend to be less serious. Like fatal crashes, non-fatal crashes exhibit lagged precipitation effects.

The policy implications for the results of this study are not as evident as they might be in, say, an analysis of traffic safety laws. However, there are some clear reasons why it is important to understand the relationship between precipitation and crashes. One reason is to improve our ability to design appropriate laws and recommendations for driving in wet conditions. Examples of possible interventions include lower speed limits during wet conditions, as in France, for example, or electronic roadside warning signs during these conditions. Electronic warning signs in particular could provide a flexible means to emphasize the increased danger of precipitation that follows drought periods.

2. Relevant literature

Prior studies of the relationship between precipitation and traffic crashes have employed a variety of methods and data sources, but the results have been nearly universal. Table 1 provides an overview of several such studies. In each case, precipitation has been estimated to increase overall traffic crashes (Andreescu and Frost, 1998; Andrey and Yagar, 1993; Andrey and Olley, 1990; Bertness, 1980; Brodsky and Hakkert, 1988; Fridstrom et al., 1995; NTSB, 1980; Sherretz and Farhar, 1978). As for fatal crashes in particular, one study finds a strong increasing effect of precipitation (Brodsky and Hakkert, 1988) and another finds an increasing effect in one country (Denmark) but no effect in two others (Norway and Sweden) (Fridstrom et al., 1995).

The most common method used in the above studies is the "matched-pair approach". The basic idea of this method is to compare the crash rate during time periods with precipitation to the rate during comparable time periods (e.g. same day of week and same time of day, but 1 week later) without precipitation. In one study, the time unit of analysis is an entire day (Bertness, 1980), and in other studies they are smaller units ("rain events" within days) (Andrey and Olley, 1990; Andrey and Yagar, 1993; Sherretz and Farhar, 1978). Another method used in the studies is a regression approach. This is the approach used in the present study. Crash rates are regressed on precipitation amounts during the specified unit of time (Andreescu and Frost, 1998; Fridstrom et al., 1995). Next, Brodsky and Hakkert (1988) and the NTSB (1980) use what they call a "wet pavement index" method. This method compares the proportion of crashes reported to occur on wet pavement to the proportion of overall time that the pavement is wet. The amount of time the pavement is wet is estimated using hourly rainfall data and assumptions about drying time. Brodsky and Hakkert also use what they call a "difference in means" approach. They define days as rainy or non-rainy, and compare the mean number of crashes on rainy days to the mean on non-rainy days. Rainy days are defined as those days in which at least one crash in the sample area is reported by police to have happened during rainy conditions. Finally, one other approach looks at crash severity ratios (Edwards, 1998; Bertness, 1980; Sherretz and Farhar, 1978). This approach compares the severity mix of crashes (e.g. average number of injuries per crash) during rain to the severity mix during dry weather. Note that the severity mix approach is informative about only relative frequencies of different types of crashes, not absolute frequencies.

Previous studies have also found some evidence that the effect of precipitation that follows a prolonged dry period is especially dangerous. Fridstrom et al. (1995) find that the first snowfall of the winter causes more crashes than would be expected simply by the amount of snowfall. Brodsky and Hakkert (1988) find evidence suggesting that in Israel rain increases crashes more during November and March, when rain tends be more sporadic, than it does during the rainy winter season. These issues are explored in detail in the analysis of the present study.

3. Methods and data

The estimation method used throughout this study is a negative binomial regression, which is a generalized version of the Poisson regression. Robust standard errors allow for clustering by state. The negative binomial regression can be expressed in terms of the Poisson regression in the following way:

$$C_{st} \sim \text{Poisson}(\mu_{st}),$$

$$\text{where } \mu_{st} = \mathrm{e}^{X_{st}\beta+\text{offset}_{st}u_{st}} \text{ and } \mathrm{e}^{u_{st}} \sim \text{gamma}\left(\frac{1}{\alpha}, \frac{1}{\alpha}\right)$$

where C_{st} refers to the crash count for a given observation, subscripted by state and time. X_{st} includes the independent variables of interest, most notably the amount of precipitation (in cm). While the focus of attention in this study is on precipitation in general, snowfall and snow depth are also included in X_{st}. In addition, X_{st} includes a vector of dummy variables representing fixed effects for each year as well as each state–month combination. To be clear, the latter would include, for example, dummies for California–January, California–February, etc. The purpose of including these fixed effects is to purge confounding (i.e. non-causal) relationships between precipitation and crashes from the estimated coefficients on the precipitation variables.

Table 1
Summary of studies on effects of precipitation on traffic crashes

Author (year)	Sample	Method	Key findings
Edwards (1998)	England and Wales, 1980–1990	Compare severity mix of crashes during rain to severity mix during dry weather (weather conditions per police reports for crashes)	(A) For rainy weather, the fatal:injury-only:non-injury crash ratio is 18:227:755 (B) For dry weather, the ratio is 21:235:744
Andreescu and Frost (1998)	Montreal, 1990–1992	Estimate correlation between daily precipitation amount and daily number of crashes	(A) Significant rainfall-crashes correlation ($r = 0.27$) (B) Significant snowfall-crashes correlation ($r = 0.48$)
Fridstrom et al. (1995)	Denmark, Finland, Norway, Sweden, 1973–1987	Generalized Poisson regression to estimate contributions of various factors, including weather, to monthly crash rates by county or province	(A) Injury crash rate: in all four countries rainfall increases it, snowfall decreases it (B) Fatal crash rate: rainfall increases it in Denmark, is insignificant in Norway and Sweden, and not recorded for Finland; snowfall decreases it in Denmark, Norway, and Sweden
Andrey and Yagar (1993)	Calgary and Edmonton, 1979–1983	Matched-pair approach: compare "rain events" to comparable time periods without rain on different week	(A) Relative risk of crash during rain is 1.7 (B) Relative risk returns to normal (1.0) within 1 h after rain event
Andrey and Olley (1990)	Edmonton, 1983	Matched-pair approach (as in Andrey and Yagar, 1993)	Relative risk of crash during rain is 1.6 (CI 1.3–1.9)
Brodsky and Hakkert (1988)	Israel 1979–1981, and eastern US (DE, DC, MD, VA) 1983–1984	(1) Difference in means: rainy vs. dry days (2) "Wet pavement index": compare percent of crashes reported to occur on wet pavement to percent of overall time pavement is wet (estimated using hourly rainfall data)	(A) Injury accidents (Israel): relative risk during rain of 2.2 (method 1) or about 6 (method 2) (B) Fatal crashes (US): relative risk during rain of 2.18 (method 1) or 3.75 (method 2) (C) In Israel, relative risk during rain highest during months with sporadic rain
NTSB (1980)	US 1975–1978	"Wet pavement index" (see earlier)	Relative risk for fatal crashes on wet pavement is about 4
Bertness (1980)	Chicago and NW Indiana, 1976–1978	Matched-pair approach: compare rainy days vs. non-rainy days 1 week later or earlier	(A) Rainy days had about twice as many crashes as non-rainy (B) Crash severity (average number of injuries per accident) increased with rain in rural areas, but not in urban areas
Sherretz and Farhar (1978)	St. Louis area, summertime, 1971–1975	Matched-pair approach (as in Andrey and Yagar, 1993)	(A) About twice as many crashes during rain events (B) Number of crashes increases linearly with rain amount (C) Rain has no effect on crash severity ratio (injuries per crash)

Note: Unless stated otherwise, the term "crash" includes all types of crashes (fatal, injury-only, non-injury).

For example, it might be the case that some states experience much greater tourism traffic during months of the year when it is not expected to rain much. Including state–month fixed effects prevents this scenario from spuriously rendering the estimated relationship between precipitation and crashes more negative.

The "offset" term refers to the amount of exposure for a given observation, i.e. the denominator when we talk about crash "rates". An estimate of vehicle miles traveled (VMT) for each state–year, published by the National Highway Transportation Safety Administration (NHTSA) is used for this purpose. Since this measure cannot account for day-to-day fluctuations in VMT within state–years, the estimated relationships between precipitation and crashes may be mediated in part by unobservable decreased traffic volume. This idea is discussed further in the context of specific results.

The parameter α represents an indicator of the degree of overdispersion (or possibly underdispersion) in the data relative to a Poisson distribution. A Poisson distribution is

Table 2
Descriptions of key variables

Variable name	Mean	S.D.	Sample spanned	N	Source	Note
Monthly						
Fatal crash count	68.22	67.8	48 States, 1975–2000	14976	i	
Injury crash count	6865	4607	17 States, 1990–1999	1968	ii	a
Property damage only crash count	11622	8189	17 States, 1990–1999	1968	ii	a
Total precipitation (cm)	7.753	5.126	48 States, 1975–2000	14091	iii	b
Total snowfall (cm)	6.670	13.92	48 States, 1975–2000	14091	iii	b
Average snow depth (cm)	2.417	7.271	48 States, 1975–2000	14091	iii	b
Daily						
Fatal crash count	2.241	2.790	48 States, 1975–2000	455856	i	
Injury crash count	225.3	161.1	17 States, 1990–1999	59894	ii	a
Property damage only crash count	382.0	294.8	17 States, 1990–1999	59894	ii	a
Total precipitation (cm)	0.247	0.570	48 States, 1975–2000	429381	iii	b
Total snowfall (cm)	0.221	1.128	48 States, 1975–2000	429253	iii	b
Average snow depth (cm)	2.387	7.732	48 States, 1975–2000	428332	iii	b

Sources: (i) Fatal Accident Reporting System, National Highway Transportation Administration; (ii) State Crash Data System, National Highway Transportation Administration; (iii) Cooperative Summary of the Day, National Climactic Data Center. *Notes*: (a) 17 states have monthly non-fatal crash data for 1990–1999, with the following six state–years (72 obs) missing: GA–1999, NC–1990, NC–1991, WA–1997, WA–1998 and WA–1999; the 17 states are CA, FL, GA, IL, IN, KS, MD, MI, MO, NC, NM, OH, PA, TX, UT, VA, and WA; (b) weather data are missing for some state–days (and therefore state–months) because only data from weather stations that recorded measures at 6:00 p.m. were used. See Section 3 in the text for a discussion of this issue.

described by the special case, where α is 0. In all regressions in this study, likelihood ratio tests reject that α equals 0 with very high degrees of statistical confidence ($P < 0.001$). The results of these tests are not reported but are available on request.

For ease of interpretation and comparability, the estimated coefficients for all results are presented as proportional changes in incidence rate. Thus, the coefficients answer the question, for a one unit change in the independent variable, what is the predicted proportional change in crashes per VMT? For example, a coefficient of 0.05 for the precipitation variable is interpreted to mean that an increase of 1 cm of precipitation is associated with a 5% increase in the crash rate.

Table 2 summarizes the variables used for the monthly and daily analyses, respectively. The source for all crash data is NHTSA in the US Department of Transportation. The fatal crash data are calculated from the Fatal Accident Reporting System (FARS), and the non-fatal crash data, divided into injury crashes and property damage only crashes, are from the State Data System (SDS). FARS data are available for all states and DC for 1975–2000, while SDS data are available for 17 states for 1990–1999.[1] The present study, however, is limited to the 48 continental states, and therefore excludes FARS data for Alaska, Hawaii, and DC. As mentioned earlier, VMT data are taken from NHTSA's *Highway Statistics* publications (NHTSA, 1975–2000, 1990–1999). The measure is computed for each state–year using a combination of fuel consumption, roadway type, and vehicle type data.

The FARS data, which are the primary focus of this study, represent a complete census of all fatal crashes in the US and are collected in a thorough and highly standardized process. The SDS data, on the other hand, are reported by the states to NHTSA and may reflect some differences in reporting procedures across states or over time. However, this caveat is unlikely to introduce any problem other than random noise for the purposes of the estimations, because the fixed effects can largely account for such reporting discrepancies. The coefficients for the non-fatal crash regressions will be biased, however, if reporting practices vary systematically *within* states as a function of the level of daily (or monthly) precipitation. For example, if non-fatal crashes are less likely to be reported on rainy days, perhaps because people do not want to wait in the rain for police to arrive, then the coefficients would be biased downwards.

Weather data are derived from the National Climactic Data Center's "Cooperative Summary of the Day (TD3200) Database" (NCDC, 1975–2000), which is a database containing daily weather measures from over 20,000 weather stations in the US. For some stations, the period of record extends back to the 1850s, but for this analysis only the years 1975–2000 are used. The measures used are total precipitation, total snowfall, and average snow depth. All three are measured in cm. Weather station level data are averaged in order to create state-level measures. In this averaging, weather stations are weighted in proportion to the geographical area of the division within states that they represent.[2]

[1] Seventeen states are included in the SDS for 1990–1999: CA, FL, GA, IL, IN, KS, MD, MI, MO, NC, NM, OH, PA, TX, UT, VA, and WA. However, the following six state–years are missing: GA–1999, NC–1990, NC–1991, WA–1997, WA–1998 and WA–1999.

[2] For weather data purposes, each state is divided into anywhere between 1 and 10 divisions. In creating the statewide measures, weather station level data are first averaged within divisions. Then the division level data are averaged within states, with the divisional weights in proportion to geographical area.

Table 3
Monthly regressions of crash rates on precipitation

	Model			
	1	2	3	4
Method: negative binomial regressions; unit of observation: state–month				
Dependent variable	Fatal crash count	Non-fatal injury crash count	Property damage only crash count	Total crash count
Exposure measure	Annual VMT	Annual VMT	Annual VMT	Annual VMT
Sample	48 States, 1975–2000	17 States, 1990–1999	17 States, 1990–1999	17 States, 1990–1999
Number of observations	14091	1966	1966	1966
Precipitation (cm)	−0.0038 (−8.12)	0.0025 (3.85)	0.0058 (4.12)	0.0043 (5.17)
Snowfall (cm)	−0.0006 (−1.34)	0.0014 (2.68)	0.0022 (2.24)	0.0020 (2.58)
Average snow depth (cm)	−0.0064 (−5.38)	−0.0015 (−1.28)	0.0045 (5.25)	0.0022 (1.98)
Year fixed effects	Yes	Yes	Yes	Yes
(State × month) fixed effects	Yes	Yes	Yes	Yes

Notes: (1) coefficients reported are proportional changes in incidence rates for one unit changes in the independent variables; (2) corresponding *Z*-statistics are in parentheses.

An important detail in the context of daily analyses is the fact that the daily weather data are not necessarily recorded by calendar day, i.e. from midnight to midnight. In fact, by far the most common time of day for collecting data in the sample is 6:00 p.m. About 45% of weather stations in the sample collected data at this time, with the next most common times being 6:00, 7:00, and 8:00 a.m. (about 25% of stations combined). As a result of this pattern, 6:00 p.m. is used in the present study as the beginning of a day. This poses no problem for the fatal crash data, for which the hour of occurrence is known for each individual crash. The non-fatal crash data, on the other hand, are only available by calendar day. Since there is relatively little daily weather data that is recorded at midnight, the non-fatal crash data are simply matched to the weather data that use 6:00 p.m. (of the previous day) as the starting time for each day. Thus, 6 h of each day do not match appropriately. It is not obvious what direction the bias in the estimates will be, if any. However, it is clear that any estimated lagged effects for $t = -1$ (the previous day) must be viewed with skepticism.[3]

4. Analysis using monthly data

Results for the monthly negative binomial regressions are reported in Table 3. The first column shows the result mentioned at the outset of this paper: precipitation is associated with a reduction in fatal crashes (3.73% per 10 cm of precipitation).[4] It is interesting to see that snowfall, as distinguished from precipitation in general, also appears to reduce fatal crashes, although the coefficient is not statistically significant at the 90% level. Also, the average snow depth has a clear negative association with fatal crashes, which is consistent with findings in Fridstrom et al. (1995).

Comparison of the results for non-fatal crashes (columns 2 and 3) to those for fatal crashes reveals a distinct pattern. As the severity of crashes falls (from fatal, to injury, to property damage only), the associations between crashes and all three weather measures become more positive. This observation fits with the idea that people drive more slowly in bad weather conditions (Edwards, 1999), and therefore the crash mix becomes less severe. Also, snow depth may lessen the severity of many crashes by preventing cars from going off the road. The number of total crashes (the sum of the three severity types) has a positive coefficient on all three weather variables, reflecting the fact that less serious crashes constitute the vast majority of all crashes, as can be seen in Table 2.

How can we explain the relatively large negative coefficient for precipitation in the fatal crash regression in Table 3? Before turning to an investigation of daily data and lagged effects, it is reasonable to consider a handful of straightforward explanations. First, perhaps there are simply fewer vehicles on the road during wet conditions and therefore less exposure to risk. Indeed, other studies have found some reduction in traffic volume due to precipitation; for example, Doherty et al. (1993) and Codling (1974) both find about a 2% decrease in traffic volume during rain. However, some

[3] One final issue with the weather data is the fact that, by restricting attention to measures collected at 6:00 p.m., one does not have data from all divisions in all states for days in the sample. Thus, statewide measures no longer represent all divisions within the states in all cases. Again, it is not clear which direction the bias would go, if any, for the estimates. One would expect that there is no systematic relationship between which stations collect measures at 6:00 p.m. and how precipitation affects crashes near those stations. In this case, we would simply have a source of random measurement error that would bias the coefficients towards finding no "effects." In any case, this issue is addressed by re-estimating regressions with the subsample of state–days for which all divisions are represented. As expected, the results are unchanged in each case.

[4] Note that, given how the regression is specified and the coefficients reported, the predicted proportional change in the incident rate, for a given change in x, Δx, is calculated as $e^{\Delta x \hat{B}}$. So in this case, the predicted proportional change is $e^{10(-0.0038)} = 0.9627$, or a 3.73% decrease. Note that simply multiplying 10 by the coefficient −0.0038 yields a reasonable approximation, a 3.8% decrease. This shortcut will be used henceforth when making statements about the magnitude of predicted effects.

simple calculations demonstrate that this degree of traffic volume reduction cannot account for the size of the coefficient on precipitation in the first column of Table 3. This can be seen as follows. The estimates from the above two studies imply that, over the course of a month, traffic volume would fall by 2% if it rained constantly. Assuming that traffic volume is roughly proportional to exposure to fatal crash risk, one would then expect a 2% reduction in fatal crashes due to reduced traffic volume. However, recall that the result in Table 3 equates to a 3.73% reduction in fatal crashes per 10 cm of precipitation in a month. Consider that 10 cm of rain typically falls over the course of a handful of hours, and is therefore a tiny fraction of the precipitation that would fall during a month of *constant* precipitation. Thus, one can calculate that the estimated effect in the present study is about two orders of magnitude greater than that implied by the traffic volume argument above.

Table 4
State-by-state monthly regressions of fatal crash rates on precipitation

State	Precipitation		Snowfall		Snow depth	
	B	*Z*	*B*	*Z*	*B*	*Z*
AL	−0.006	−4.16	0.000	−0.02	−0.070	−0.36
AR	−0.005	−2.65	0.001	0.11	−0.066	−1.36
AZ	−0.006	−1.59	−0.003	−0.89	0.009	0.69
CA	−0.001	−1.40	0.000	0.06	−0.010	−1.30
CO	−0.016	−2.30	−0.002	−1.71	−0.005	−2.60
CT	0.001	0.27	−0.003	−0.75	−0.014	−1.57
DE	−0.008	−1.38	−0.005	−0.64	0.012	0.27
FL	0.000	−0.33	−37.65	−2.20	4775	2.19
GA	0.000	0.15	−0.002	−0.10	−0.206	−0.36
IA	−0.004	−1.37	−0.001	0.72	−0.012	−3.51
ID	−0.031	−3.50	0.002	1.46	−0.008	−3.02
IL	−0.006	−3.56	−0.002	−1.45	−0.013	−3.83
IN	−0.003	−1.65	0.001	0.68	−0.026	−5.63
KS	−0.008	−2.42	0.005	1.56	−0.064	4.88
KY	−0.003	−1.85	0.008	2.66	−0.084	−5.35
LA	−0.003	−1.19	−0.121	−0.57	3.578	0.50
MA	0.001	0.25	−0.003	−1.13	−0.021	−4.59
MD	−0.003	−1.58	−0.001	−0.42	−0.013	−1.19
ME	0.000	−0.10	−0.002	−1.17	−0.009	−4.07
MI	−0.003	−1.12	0.001	1.70	−0.005	−4.12
MN	−0.007	−1.79	0.001	0.54	−0.007	−3.95
MO	−0.005	−3.06	0.000	0.02	−0.017	−2.57
MS	−0.003	−1.76	−0.016	−1.18	0.097	0.56
MT	−0.010	−1.04	0.000	−0.09	−0.016	−3.26
NC	−0.003	−2.20	−0.005	−1.15	0.010	0.19
ND	−0.019	−2.02	−0.006	−1.49	−0.006	−1.16
NE	−0.023	−3.92	0.003	1.158	−0.022	−3.05
NH	−0.009	−2.01	−0.003	−1.86	−0.003	−0.89
NJ	−0.002	−1.45	0.002	0.736	−0.024	−2.60
NM	−0.004	−0.66	−0.002	−0.54	−0.007	−0.37
NV	−0.014	−1.31	−0.002	−0.57	−0.012	−1.88
NY	−0.003	−1.43	0.000	−0.53	−0.006	−5.68
OH	−0.005	−2.91	0.000	−0.2	−0.020	−5.27
OK	−0.006	−2.91	0.008	2.595	−0.098	−3.07
OR	0.002	0.54	0.000	0.176	−0.006	−0.86
PA	−0.005	−3.26	0.000	0.571	−0.009	−4.62
RI	−0.003	−0.69	0.008	1.752	−0.049	−2.71
SC	−0.002	−1.15	−0.004	−0.38	0.041	0.37
SD	−0.014	−1.77	−0.002	−0.65	−0.015	−2.83
TN	−0.003	−1.76	−0.002	−0.4	−0.040	−0.99
TX	−0.006	−4.31	−0.003	−0.52	−0.056	−0.80
UT	−0.007	−0.67	0.002	0.781	−0.013	−1.96
VA	−0.001	−0.39	0.002	0.835	−0.026	−1.60
VT	−0.009	−1.41	−0.001	−0.58	−0.011	−3.11
WA	0.000	−0.20	−0.002	−1.85	0.003	1.34
WI	0.000	−0.05	0.001	0.499	−0.010	−5.73
WV	−0.001	−0.19	0.001	0.351	−0.017	−2.68
WY	−0.023	−1.58	0.000	0.048	−0.007	−1.57

Notes: (1) these are the results of 48 separate regressions, 1 per state; (2) the method is negative binomial regression, with exposure proxied by annual VMT; (3) coefficients (denoted by *B*) reported are proportional changes in incidence rates for one unit changes in the independent variables; (4) *Z*-statistics (denoted by *Z*) are next to corresponding coefficients.

Another possibility is that the negative relationship between fatal crashes and monthly precipitation is driven by a particular segment of the sample, such as a particular region of the country, time period, age group, or type of crash (e.g. drunk driving, or ones that involve pedestrians or cyclists). The analysis is repeated for subsets of the sample broken down along these dimensions, and in all cases the negative coefficient remains. For example, Table 4 shows regression results for each separate state. The estimated coefficient on precipitation is negative for all but 4 of the 48 states (CT, GA, MA, and OR), and these four positive coefficients are not statistically different from zero. Of the 48 negative coefficients, 21 are statistically different from zero at the 90% confidence level. Regression results for the other sample subsets (time period, age group, etc.) are available on request.

5. Analysis using daily data

The daily version of the monthly analysis in Table 3 is shown in Table 5. The same basic pattern across crash severity levels is evident, but now the coefficients for precipitation and snowfall are positive and significant for fatal crashes. The daily results are more aligned with those of the literature than the monthly results are. An increase of 1 cm of precipitation is associated with a 1.15% increase in the fatal crash rate, and an additional 1 cm of snow corresponds to a 0.9% increase. Snow depth, on the other hand, continues to be associated with fewer fatal crashes (0.84% decrease for 1 cm).

With the large amount of data in the sample, there is an opportunity to look more closely at the relationships between the weather variables and crash rates. For example, rather than specifying the weather variables as linear terms, one can construct categorical dummy variables corresponding to various intervals. This approach is taken in Table 6. For example, precipitation is broken into the following intervals (in cm): (i) $x = 0$ (none); (ii) $0 < x \leq 0.5$ (very light); (iii) $0.5 < x \leq 1$ (light); (iv) $1 < x \leq 2$ (medium); (v) $2 < x \leq 5$ (heavy); (vi) $5 < x$ (very heavy). The intervals defined for snowfall and snow depth are similarly defined, as shown in the table. In the regressions, the omitted category for each weather measure is $x = 0$ (none).

Table 5
Daily regressions of crash rates on precipitation

	Model			
	1	2	3	4
Method: negative binomial regressions; unit of observation: state–day				
Dependent variable	Fatal crash count	Non-fatal injury crash count	Property damage only crash count	Total crash count
Exposure measure	Annual VMT	Annual VMT	Annual VMT	Annual VMT
Sample	48 States, 1975–2000	17 States, 1990–1999	17 States, 1990–1999	17 States, 1990–1999
Number of observations	427824	59764	59764	59764
Precipitation (cm)	−0.0115 (3.15)	0.1082 (9.94)	0.1224 (10.41)	0.1150 (10.62)
Snowfall (cm)	0.0090 (2.74)	0.0356 (4.87)	0.0580 (6.01)	0.0505 (5.23)
Average snow depth (cm)	−0.0084 (−6.49)	−0.0001 (−0.11)	0.0063 (3.62)	0.0041 (2.56)
Year fixed effects	Yes	Yes	Yes	Yes
(State × month) fixed effects	Yes	Yes	Yes	Yes

Notes: (1) coefficients reported are proportional changes in incidence rates for one unit changes in the independent variables; (2) corresponding *Z*-statistics are in parentheses.

The results show some striking patterns. First, very light precipitation ($0 < x \leq 0.5$) is associated with a 1.1% decrease in the fatal crash rate. In fact, only substantial precipitation (heavy or very heavy) is associated with an increase in the fatal crash rate. A possible explanation is that light precipitation alerts drivers to be more careful without posing a significant risk. Meanwhile, all levels of precipitation predict increases in non-fatal crashes, whether injury or property damage only. Second, snowfall shows an upside down U-relationship with respect to crash rates. Crash rates appear to peak around the medium level of snow, and actually decrease in very heavy snowfall. This fact is not sur-

Table 6
Daily regressions of crash rates on categorical precipitation dummies

	Model			
	1	2	3	4
Method: negative binomial regressions; unit of observation: state–day				
Dependent variable	Fatal crash count	Non-fatal injury crash count	Property damage only crash count	Total crash count
Exposure measure	Annual VMT	Annual VMT	Annual VMT	Annual VMT
Sample	48 States, 1975–2000	17 States, 1990–1999	17 States, 1990–1999	17 States, 1990–1999
Number of observations	427824	59764	59764	59764
Precipitation				
(0 cm, 0.5 cm]	−0.0114 (−2.74)	0.0652 (6.68)	0.0797 (7.79)	0.0722 (7.92)
(0.5 cm, 1 cm]	−0.0079 (−1.22)	0.1648 (11.92)	0.1822 (11.49)	0.1712 (12.58)
(1 cm, 2 cm]	0.0000 (0.00)	0.2213 (11.18)	0.2432 (12.37)	0.2307 (12.26)
(2 cm, 5 cm]	0.0351 (3.41)	0.2759 (9.39)	0.317 (11.59)	0.2952 (10.93)
(5 cm, ∞ cm]	0.1066 (3.78)	0.2819 (12.01)	0.3259 (11.35)	0.3021 (12.45)
Snowfall				
(0 cm, 1 cm]	0.0039 (0.47)	0.0717 (5.54)	0.1041 (6.55)	0.0925 (6.36)
(0.5 cm, 5 cm]	0.0743 (4.83)	0.1978 (6.21)	0.2793 (5.88)	0.2541 (5.74)
(1 cm, 10 cm]	0.1076 (3.40)	0.2435 (5.28)	0.3457 (7.30)	0.3127 (6.12)
(2 cm, 20 cm]	0.0343 (0.93)	0.2415 (3.84)	0.3582 (7.26)	0.3103 (5.02)
(5 cm, ∞ cm]	−0.2377 (−2.12)	−0.4387 (−1.85)	−0.2778 (−1.89)	0.3401 (−1.97)
Snow depth				
(0 cm, 5 cm]	−0.012 (−0.69)	0.0055 (0.34)	0.0641 (2.67)	0.0416 (1.88)
(0.5 cm, 10 cm]	−0.0915 (−3.83)	0.0225 (1.23)	0.1489 (5.75)	0.1052 (4.19)
(1 cm, 20 cm]	−0.1613 (−4.71)	0.024 (0.89)	0.1413 (3.09)	0.0879 (2.11)
(2 cm, 50 cm]	−0.2698 (−6.22)	0.0241 (−0.72)	0.1 56 (2.74)	0.0937 (1.69)
(5 cm, ∞ cm]	−0.4083 (−10.02)	0.0350 (0.30)	0.2409 (2.65)	0.1556 (1.35)
Year fixed effects	Yes	Yes	Yes	Yes
(State × month) fixed effects	Yes	Yes	Yes	Yes

Notes: (1) coefficients reported are proportional changes in incidence rates for one unit changes in the independent variables; (2) corresponding *Z*-statistics are in parentheses.

Table 7
Daily regressions of fatal crash rates on 1-day lagged precipitation

	Model	
	1	2
Method: negative binomial regression; unit of observation: state–day		
Dependent variable	Fatal crash count	Fatal crash count
Exposure measure	Annual VMT	Annual VMT
Sample	48 States, 1975–2000	48 States, 1975–2000
Number of observations	427561	427625
Precipitation (cm)	0.0183 (5.21)	0.0210 (6.12)
1-day lagged precipitation (cm)	−0.0306 (−10.21)	−0.0374 (−10.42)
(Today is dry) × (1-day lagged precipitation)		0.0221 (2.83)
Snowfall (cm)	0.0114 (3.31)	0.0091 (2.75)
1-day lagged snowfall (cm)	0.0156 (−6.74)	
Average snow depth (cm)	−0.0074 (−6.29)	−0.0083 (−6.46)
Year fixed effects	Yes	Yes
(State × month) fixed effects	Yes	Yes

Notes: (1) coefficients reported are proportional changes in incidence rates for one unit changes in the independent variables; (2) corresponding *Z*-statistics are in parentheses; (3) non-fatal crashes are not included here for reasons discussed in Section 3.

Table 8
Precipitation effect as a function of "time since last precipitation"

	Model			
	1	2	3	4
Method: negative binomial regressions; unit of observation: state–day				
Dependent variable	Fatal crash count	Non-fatal injury crash count	Property damage only crash count	Total crash count
Exposure measure	Annual VMT	Annual VMT	Annual VMT	Annual VMT
Sample	48 States, 1975–2000	17 States, 1990–1999	17 States, 1990–1999	17 States, 1990–1999
Number observations	427197	59695	59695	59695
Precipitation (cm) × (1 day since last precipitation)	0.0037 (0.89)	0.0965 (9.71)	0.1121 (9.93)	0.10 (10.27)
Precipitation (cm) × (2 days since last precipitation)	0.0372 (4.47)	0.1326 (6.03)	0.1416 (7.00)	0.1359 (6.62)
Precipitation (cm) × (3 days since last precipitation)	0.0340 (4.26)	0.1449 (6.53)	0.1560 (8.22)	0.1490 (7.57)
Precipitation (cm) × (6 days since last precipitation)	0.0593 (5 53)	0.1787 (8.97)	0.1847 (7.92)	0.1791 (8.52)
Precipitation (cm) × (7–10 days since last precipitation)	0.0598 (8.34)	0.1629 (4.55)	0.1711 (5.46)	0.1652 (5.05)
Precipitation (cm) × (11–20 days since last precipitation)	0.0744 (3.39)	0.2143 (5.99)	0.2037 (5.73)	0.2031 (5.88)
Precipitation (cm) × (21+ days since last precipitation)	0.0916 (2.68)	0.2306 (5.69)	0.2670 (6.67)	0.2530 (7.02)
Snowfall (cm)	0.0092 (2.80)	0.0352 (4.74)	0.0577 (5.91)	0.0502 (5.14)
Snow depth (cm)	0.0084 (−6.50)	0.0000 (−0.04)	0.0064 (3.65)	0.0042 (2.61)
Year fixed effects	Yes	Yes	Yes	Yes
(State × month) fixed effects	Yes	Yes	Yes	Yes

Notes: (1) coefficients reported are proportional changes in incidence rates for one unit changes in the independent variables; (2) corresponding *Z*-statistics are in parentheses.

prising considering that traffic volumes, not to mention driving speeds, are undoubtedly reduced severely during snowstorms. Third, all levels of snow depth are associated with the following: reduced fatal crash rates, increased property damage only rates, and no significant relationship with injury crash rates. In this case, the interesting pattern in the data reads from left to right in the table, rather than from up to down. As the severity of crash category declines from fatal to injury to property damage only, snow depth goes from a protective, to an insignificant, to a damaging factor.

As with the monthly results, one must keep in mind that these daily results do not control for how exposure (VMT) varies except at the state–year level. Since there are generally fewer vehicles on the road during wet conditions, as discussed earlier, then the coefficients are likely to underestimate the true relative risks faced by any given driver. However, one can repeat the simple calculations done earlier to show again that this bias is likely to be small compared to the size of the coefficients estimated.[5]

[5] The bias is probably substantial, however, if one were to focus on the relative risks of extreme precipitation conditions, during which case traffic volume is likely to be reduced by much more than the 2% estimate cited.

6. More analysis using daily data: lagged effects

Thus far, the monthly analysis has shown a negative and significant relationship between precipitation and fatal crashes that is present not only for the whole sample (US 1975–2000) but also for a variety of subsamples. In contrast, the daily analysis has shown a positive and significant relationship between precipitation and fatal crashes, at least in a simple linear specification. One way these opposite results might be reconciled is if there are negative "spillover" effects of precipitation on crashes across days and within state–months. In other words, an increased amount of precipitation during a particular day in a state–month somehow reduces the number of fatal crashes on a different day or days within the state–month. In this scenario, the affected day or days must be in the future relative to the day with increased precipitation, because it is hard to imagine any way in which precipitation might affect the number of crashes in past days.[6] Therefore, lagged effects (day t affects day $t + x$: where $x > 0$) are the focus here. They are examined in a variety of ways, as follows.

First, simple 1-day lagged effects are analyzed. Table 7 reports the results. The analysis is only conducted for fatal crashes due to the time of day inconsistency of the non-fatal crash data with respect to the weather data (as discussed in Section 3). The regression reported in the first column of Table 7 is the same as that in the first column of Table 5, except that 1-day lagged precipitation and 1-day lagged snowfall have been added as RHS variables. The coefficients for the lagged variables are negative and significant, as hypothesized, and their magnitudes are even larger than the current day coefficients. One centimeter of precipitation on day $(t - 1)$ is associated with a 3.06% decline in the fatal crash rate on day t, whereas 1 cm of precipitation on day t is only associated with a 1.83% increase in the fatal crash rate on day t. For snowfall, the values are 1.56 and 1.14%, respectively.

Why does yesterday's precipitation predict a reduction in today's fatal crashes? One well-known mechanism involves engine oil and gasoline that accumulate on the road. When precipitation falls for the first time after an extended dry period, these oils mix with the water to create slick conditions. However, if precipitation has fallen yesterday, then today's rainfall is less hazardous, because the oils have been washed off the road recently. Even if the roads are dry today, yesterday's precipitation might have had a beneficial effect by removing oils from the road. The effect is likely to be less, however, because oils are most dangerous when they are spread all over the road by water. Another possible mechanism is that precipitation conditions drivers to be more careful in the near future. It could condition drivers to be more careful in future wet conditions, or it could even condition drivers to be more careful in all conditions.

[6] One might argue that people anticipate precipitation in future days based on weather forecasts, and this anticipation affects driving patterns. If this is the case, if anything one would think that anticipated future precipitation increases the amount of driving today and thereby increases crashes. So this scenario, even if it is true, would not help explain the contrasting monthly and daily results.

Table 9
Analysis of Table 8, by state and with fewer time intervals

State	Precipitation × (1 day since)		Precipitation × (2–5 days since)		Precipitation × (6+ days since)	
	B	*Z*	*B*	*Z*	*B*	*Z*
AL	0.017	1.80	0.048	2.55	0.100	2.92
AR	0.011	0.86	0.073	2.07	0.017	0.26
AZ	0.005	0.13	0.260	1.26	0.400	1.82
CA	0.023	2.20	−0.110	−1.68	0.076	0.79
CO	−0.170	−3.26	0.049	0.25	0.274	0.79
CT	−0.007	−0.26	0.021	0.61	0.029	0.47
DE	0.025	0.72	0.006	0.13	0.062	1.02
FL	0.014	1.80	0.016	0.74	0.015	0.56
GA	0.037	4.05	0.078	2.91	0.141	2.62
IA	−0.069	−3.07	−0.011	−0.21	0.088	0.79
ID	−0.201	−2.85	0.156	0.64	−0.679	−0.93
IL	−0.014	−1.18	0.068	2.23	0.229	2.50
IN	−0.007	−0.53	0.043	1.29	0.025	0.35
KS	−0.071	−2.95	0.030	0.95	0.040	0.66
KY	0.034	2.91	0.041	1.22	0.026	0.34
LA	0.002	0.16	−0.010	−0.36	−0.042	−0.75
MA	−0.017	−0.70	0.146	0.79	−0.350	−0.54
MD	0.012	0.88	0.119	4.24	0.138	2.50
ME	−0.055	−1.75	0.030	−0.65	−0.274	−1.98
MI	0.024	1.38	0.088	1.77	0.136	0.45
MN	−0.049	−2.07	−0.118	−1.97	−0.044	−0.26
MO	−0.018	−1.51	0.048	1.97	0.075	1.73
MS	0.017	1.68	0.013	0.76	0.024	1.57
MT	−0.173	−2.14	−0.653	−0.61	1.624	0.90
NC	0.045	4.84	0.061	2.282	0.034	0.67
ND	−0.087	−1.13	0.200	0.655	0.466	0.27
NE	−0.064	−1.65	0.022	0.191	0.149	0.68
NH	−0.049	−1.56	0.021	0.519	−0.098	−1.02
NJ	0.021	2.00	0.020	1.258	0.095	3.87
NM	−0.120	−2.09	0.354	−0.8	0.810	1.33
NV	−0.126	−1.20	0.118	−0.27	0.180	0.19
NY	0.021	1.86	0.029	1.046	0.157	1.39
OH	−0.019	−1.61	0.048	1.811	0.064	1.13
OK	0.004	0.26	−0.041	−1.03	0.103	2.01
OR	−0.013	−0.42	0.053	0.214	−0.472	−0.58
PA	−0.015	−1.38	0.030	1.441	0.056	1.22
RI	0.032	0.93	0.034	0.739	0.074	1.04
SC	0.031	2.80	0.094	2.951	0.071	0.98
SD	−0.054	−0.90	−0.206	−0.63	0.117	0.09
TN	0.001	0.12	0.025	0.955	0.071	0.90
TX	−0.003	−0.19	0.077	0.992	0.177	1.33
UT	0.038	0.46	0.397	0.818	0.703	0.73
VA	0.020	1.66	0.127	3.656	0.070	0.82
VT	−0.060	−1.30	0.040	−0.56	0.245	2.17
WA	−0.004	−0.17	0.100	0.814	0.832	2.83
WI	−0.026	−1.36	−0.001	−0.02	0.077	0.72
WV	−0.033	−1.42	0.057	1.322	0.065	0.69
WY	−0.356	−3.08	−0.566	−1.04	1.550	1.76

Notes: (1) these are the results of 48 separate regressions, 1 per state; (2) the method is negative binomial regression, with exposure proxied by annual VMT; (3) coefficients (denoted by *B*) reported are proportional changes in incidence rates for one unit changes in the independent variables; (4) *Z*-statistics (denoted by *Z*) are next to corresponding coefficients; (5) snowfall and snow depth are controlled for, but are not shown.

The discussion above suggests that yesterday's precipitation is likely to have the most beneficial effect on today's crashes if precipitation falls today, but there might still be some beneficial effect if conditions are dry today. The next set of results, shown in the second column of Table 7, looks at this issue by estimating the lagged precipitation effect as a function of today's precipitation. A dummy variable is defined that is equal to 1 if today is dry (zero precipitation) and 0 if not (positive precipitation). This dummy is interacted with the lagged precipitation variable. The interaction term is included as an independent variable. In this framework, the interpretation of the coefficients is as follows. The lagged effect of precipitation if today is dry is calculated as the sum of the two lagged coefficients ($-0.0374+0.0221 = -0.0153$). The lagged effect of precipitation if today is wet is simply the coefficient on lagged precipitation (-0.0374). Statistical tests reveal that both of these estimates are significantly different from zero. As anticipated, lagged precipitation has its most beneficial effect if today is wet. But there is still some benefit if today is dry.

To get a fuller picture of the lagged effects of precipitation, the next part of this analysis looks beyond 1-day lags to longer lags. The question is asked, what is the effect of today's precipitation on today's crash rates, given that precipitation has not fallen in the past X days? Table 8 reports the results of this analysis. Mechanically, the independent variables are constructed by interacting today's precipitation with, one at a time, a list of dummy variables that equal 1 if it has been within the specified time interval since the last precipitation and 0 otherwise. Note that these dummies are mutually exclusive; for example, if the last precipitation fell 5 days ago, then the 4–6 days dummy would equal 1 but the 3 days dummy would not equal 1 (but rather 0). Also note that the non-fatal crashes are now included in the lagged effects analysis. The reason is that the problem with the time of day inconsistency will not clearly bias the estimates as we look beyond the 1-day lag.

The results follow the expected pattern. As the number of days since the last precipitation increases, precipitation becomes relatively more dangerous. The estimates suggest that, if precipitation has fallen yesterday, then the current day's precipitation does not increase fatal crashes at all (but does increase non-fatal crashes). Comparing the situations in which precipitation last fell 2 days ago versus 21 or more days ago, one can see that in the latter situation precipitation adds nearly three times as much risk in terms of fatal crashes and nearly twice as much risk in terms of non-fatal crashes.

7. Policy lessons

What policy lessons can be drawn from the results of this study? First, the results just discussed have a clear implication: drivers are at significantly elevated risk when precipitation falls after a dry period of several days or more. As noted earlier, an appropriate policy response would be to warn drivers using electronic signs on the roadside. Electronic signs and non-electronic signs have already been used for many years to warn drivers of hazardous weather conditions, but more of these signs might be called for given the estimated magnitude of the risks. Cost–benefit studies of such signs could further address this issue. Additionally, the signs might be made more effective if they emphasize the hazard of wet conditions more when precipitation follows a dry period, rather than providing the same warning for all precipitation events. It is possible that these signs have more

Table 10
Analysis of Table 8, by time (1975–1983, 1984–1992, and 1993–2000)

	Model		
	1	2	3
Method: negative binomial regressions; unit of observation: state–day			
Dependent variable	Fatal crash count	Fatal crash count	Fatal crash count
Exposure measure	Annual VMT	Annual VMT	Annual VMT
Sample	48 States, 1975–1983	48 States, 1984–1992	48 States, 1993–2000
Number of observations	155832	146946	124419
Precipitation (cm) × (1 day since last precipitation)	−0.0034 (−0.83)	0.0148 (3.19)	0.0096 (1.49)
Precipitation (cm) × (2 days since last precipitation)	0.0663 (2.50)	0.0314 (1.86)	0.0254 (2.13)
Precipitation (cm) × (3 days since last precipitation)	0.0347 (1.52)	0.0539 (4.32)	0.0080 (0.55)
Precipitation (cm) × (4–6 days since last precipitation)	0.0823 (2.38)	0.0532 (3.99)	0.0378 (2.36)
Precipitation (cm) × (7–10 days since last precipitation)	0.0909 (2.62)	0.0872 (6.72)	0.0256 (2.88)
Precipitation (cm) × (11–20 days since last precipitation)	−0.0098 (−0.20)	0.0703 (1.32)	0.0588 (2.38)
Precipitation (cm) × (21+ days since last precipitation)	0.1330 (23.92)	0.0829 (0.62)	0.0485 (1.39)
Snowfall (cm)	−0.0056 (−1.44)	0.016 (4.22)	0.015 (4.08)
Snow depth (cm)	−0.0107 (−692)	−0.0083 (−5.79)	−0.0065 (−5.51)
Year fixed effects	Yes	Yes	Yes
(State × month) fixed effects	Yes	Yes	Yes

Notes: (1) coefficients reported are proportional changes in incidence rates for one unit changes in the independent variables; (2) corresponding Z-statistics are in parentheses.

impact per warning on driver awareness if they issue warnings less frequently. Targeting the warnings to the most dangerous situations may be most effective in reducing crashes.

Analyses of the type in this study can also be used to learn about what factors mediate traffic safety in wet conditions. For example, the effect of precipitation on traffic crashes can be estimated separately by state or by time period. One could then note which states, or time periods, appear to experience relatively less or more crashes as a result of wet conditions. Studying these differences could yield estimates of the beneficial effects of road quality projects or driver education programs that are present in certain states or time periods.

Tables 9 and 10 show regressions by state and by time period, respectively, using daily data. At a glance, it appears that some states experience greatly increased fatal crash rates in wet conditions (e.g. AZ and MD), while others are hardly affected at all (e.g. CT and IN). The analysis by time period suggests that the risk of fatal crashes due to wet conditions has diminished some from the first period (1975–1983) to the second (1984–1992) to the third (1993–2000). Further research could determine why these effects differ across states and over time.

Another productive strategy for informing policies may be to focus on one particular intervention, such as a road quality improvement project in a state. The relationship between precipitation and crashes could be compared before and after the intervention. This type of analysis could also be applied to the electronic signs discussed above or to lower speed limits for wet conditions in order to evaluate the effectiveness of such policy devices.

Acknowledgements

I thank the National Institute of Mental Health for funding support during the time of this research, through its Mental Health Services and Financing Postdoctoral Traineeship. I thank Jonathan Ketcham, Diane Whitmore, Kitt Carpenter, members of the Traffic Safety Center and the Health Policy Training Program seminars at University of California, Berkeley, and an anonymous reviewer for helpful comments. I thank Tom Bragan, Gary Rinehart, and Dahlia Panton at NHTSA's State Data System for their help in obtaining non-fatal crash data.

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