Wireless Alerts for Flash Flood Warnings and the Impact on Car Accidents

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Abstract
Wireless alerts delivered through mobile phones are a recent innovation in regulatory efforts toward preparation for extreme weather events including flash floods. In this article, we use difference-in-differences models of the number of car accidents from days with government issued alerts for flash flood events in Virginia. We find that wireless alert messages for flash flood warnings reduced car accidents by 15.9% relative to the counterfactual with non-wireless alert protocols. We also use a regression discontinuity model to analyze hourly traffic volume data immediately before and after a flash flood warning message is issued. We find that traffic volume is reduced by 3.1% immediately following the issuance of a wireless alert relative to before the alert. These results imply that wireless alert messages effectively reduce exposure to hazards associated with extreme weather.

Keywords: wireless alerts, extreme weather, hazard mitigation

Nearly every community in the United States is periodically threatened by extreme weather events including hurricanes, tornadoes and flash floods. The National Weather Service (NWS) actively monitors weather events as they develop and in the case of an imminent threat, issues emergency alerts to affected areas. To complement existing warning protocols, the Wireless Emergency Alert (WEA) system was adopted nationally in the US in June 2012. They issue warnings directly to mobile devices in case of national emergency, extreme weather and AMBER alerts. Wireless messages in cases of extreme weather aim to mitigate potential risk for individuals facing life-threatening exposure to inclement weather. The purpose of this article is to study the effect of WEA messages for extreme weather on daily car traffic conditions based on a sample of flash flood events from counties located in Virginia between 2011 and 2013. We evaluate hazard mitigation outcomes in response to WEA messages through an empirical examination of car accidents and assess mechanisms for hazard mitigation through an analysis of traffic volume patterns following WEA messages.

The growth of mobile phone usage has changed how people communicate and altered the global economy. The United Nations (UN) estimates that mobile phones have spread faster than any other technology in world history (UN 2010). Previous research has examined the impact of access to mobile phones on microeconomic development outcomes. This includes studies of the impact of mobile phones on markets for fish (Abraham 2006; Jensen 2007), agriculture (Chowdhury and Wolf 2003; Muto and Yamano 2009; Aker 2010) and textiles (Chowdhury and Wolf 2003; Jagun, Heeks, and Whalley 2008). These studies suggest that access to mobile phones reduces costs of communication and price dispersion, improving both consumer and producer welfare in the process. Phones can also change the mode of communication between governments and citizens. In case of an emergency for extreme weather or other hazard events,

government agencies in the US and other developed nations traditionally rely on conventional media sources, including television and radio, to distribute warning messages. With the advent and near ubiquity of mobile devices, governments can now send tailored and geographically explicit warning messages directly to individuals with the highest risk of exposure to dangerous weather conditions or other hazards.

Previous research has assessed the human impacts from natural hazards and adaptive behavior to mitigate these impacts. Gallagher (2014) shows that flood insurance take-up to mitigate property risk spikes immediately after a flood event, including in non-flooded communities in the same television media market. Hurricanes also convey new information to homeowners on perceived flood risks, which differentially reduces residential property values in floodplain areas in directly damaged regions and even "near miss" undamaged regions (Hallstrom and Smith 2005; Carbone, Hallstrom, and Smith 2006). Interestingly this effect diminishes within several years after the event (Bin and Landry 2013). After a hurricane event, heterogeneity in household response to floods is found across income and racial groups, including migration out of flood prone areas, building structures less vulnerable to flood damage, and purchasing insurance (Smith et al. 2006). Adaptation strategies have been analyzed in response to other hazards, including substitution in building choice to mitigate tornado risk (Sutter and Poitras 2010) and change in preference for more fire resistant housing attributes to mitigate wildfire risk (Donovan, Champ, and Butry 2007).

An important distinction exists between this prior literature on adaptation strategies and our analysis on how the WEA system affects driving outcomes. The WEA system provides real-time information on the spatial and temporal variation in hazardous conditions, which is important for analyzing driving outcomes. Meanwhile, the prior literature focuses primarily on

the effects of hazards on housing markets and outcomes. Because housing is located at fixed spatial locations, the prior literature has emphasized the release of hazard information via conventional sources such as television and radio (Bernknopf, Brookshire, and Thayer 1990; Gallagher 2014) or educational campaigns (Smith, Desvousges, and Payne 1995) where the effect on housing markets and outcomes are likely to occur over the span of years rather than hours. This contrasts sharply with the timely information provided via mobile alerts to warn drivers of flash flood risk. Driving conditions are often adversely and rapidly affected by extreme weather events. Many studies have found weather conditions such as precipitation and poor visibility to be significant determinants in predicting car accident outcomes (Brijs, Karlis and Wets 2008; Jung, Quin and Noyce 2010). However, no previous research has evaluated the effect of emergency weather alert protocols on hazard mitigation outcomes such as automobile collisions or other observed traffic patterns.

This study uses a panel database of daily car accidents from all counties located in Virginia in the years 2011 to 2013. The econometric model is a Poisson model of the daily count of car accidents at the county level, and we identify the effect of WEA messages based on difference-in-differences (DD) variation. For flash flood alerts, the NWS categorizes alerts into either flash flood warnings or watches that are issued at the county level. A flash flood warning indicates that a flash flood event is occurring, imminent, or highly likely. A flash flood watch generally indicates weather conditions that may develop into a flash flood event but the occurrence is neither imminent nor certain.[1] A non-wireless alert was issued for flash flood warnings during the pre-WEA period (July 2011 – June 2012), whereas a WEA message was issued for warnings in the post-WEA period (July 2012 – December 2013). A non-wireless alert was issued for flash flood watches during the entire study period. Hence, the treatment group

includes all counties that received a WEA message for a flash flood warning during the post-WEA period. The control group consists of all counties that received a non-wireless flash flood warning in the pre-WEA period, as well as all counties that received a non-wireless alert for a flash flood watch during either the pre- or post-WEA period. Other control variables used to estimate car accident counts include time of day the alert was issued, weather related variables for daily precipitation and average wind speed, day of the week, as well as fixed effects at the county and month-by-year level.

We also assess potential mechanisms for reductions in car accidents due to WEA messages utilizing hourly traffic volume at monitoring stations from counties that received flash flood warnings during the pre-WEA and post-WEA periods. Using a regression discontinuity (RD) approach, we identify the effect of WEA messages on traffic volume from the hours immediately before and after the issuance of an alert. We control for trends in traffic volume at each monitoring station by time of day and utilize a local linear regression control function to account for the impact of inclement weather and other time-varying traffic volume trends in the neighborhood of the discontinuity.

Our analysis highlights several main conclusions. On average, car accidents are elevated in both the pre- and post-WEA periods for counties receiving a flash flood warning relative to those receiving a flash flood watch. This is consistent with the hypothesis that flash flood warnings are issued primarily on days with more car accidents due to extreme weather conditions. We find that WEA messages for flash flood warnings had a statistically significant reduction of 15.9% in the rate of car accidents per day on average relative to the counterfactual when issued a non-wireless warning. Based on estimates of the average car accident cost from the National Highway Traffic Safety Administration (NHTSA), WEA messages resulted in an

expected reduction in the cost of car accidents by $2.7 million in Virginia during the post-WEA period. We also find changes in driving behavior in response to WEA messages from the investigation of traffic volume patterns. At the boundary, we estimate that WEA messages lead to a statistically significant reduction of approximately 3.1% of cars travelling per hour immediately after the alert, relative to the traffic volume before the alert. These results suggest that at least some individuals respond to WEA messages by delaying or canceling travel plans during extreme weather periods. Thus, observed reductions in car accidents may be due in part to reduced traffic volume following the issuance of a WEA message.

This study makes several important contributions to the literature. This is the first study to empirically examine the effect of mobile emergency alerting protocols on car accidents or other hazard mitigating behaviors. We utilize a difference-in-differences natural experimental design to isolate the effect of WEA messages on car accident outcomes. This study design helps to eliminate bias from several potential sources, including correlation between severe weather trends and days with flash flood warnings as well as changes in weather and other trends from the pre-WEA to the post-WEA period. WEA is currently one of only a handful of nationally operated systems designed to deliver geographically explicit emergency alert messages to mobile devices. Results of this analysis suggest that wireless messages for extreme weather successfully reduce the number of car accidents compared to existing non-wireless protocols. The US experience with WEA implementation may serve as an example to other countries and municipalities considering the adoption of similar mobile warning systems.

The remainder of this article is organized as follows. In the next section, we provide an overview of WEA policy adoption as well as the study area chosen for this analysis. Next, we describe the econometric model and data used to estimate the effect of WEA messages on car

accident outcomes. This is followed by the empirical results and several robustness checks. We then present an analysis of potential mechanisms for car accident reductions using traffic volume data. We conclude with some summary remarks as well as implications for future research.

I. Policy Overview and Study Setting

The WEA system was established throughout the United States on June 29, 2012 and is designed to warn citizens of potential and imminent threats by issuing an alert to WEA capable cellphones through mobile carrier networks. WEA capable cellphones include most smartphones, which as of 2013 the majority (56%) of Americans own (Smith 2013). All WEA enabled smartphones may receive an alert unless the subscriber has specifically opted out of alerts. The WEA system is operated by several coordinating federal agencies including the NWS, Federal Emergency Management Agency (FEMA), Federal Communications Commission (FCC), and Department of Homeland Security (DHS). WEA protocol may issue warnings, typically at the county level, related to extreme weather events, local emergency, AMBER alerts or presidential alerts during a national emergency.

Emergency messages in case of extreme weather are primarily the responsibility of the NWS, which is a component of the National Oceanic and Atmospheric Administration (NOAA). The NWS distributes non-wireless emergency alerts through NOAA Weather Radio, local news broadcast, and the Emergency Alert System on radio and television. In addition, local governments may have their own emergency alert systems such as outdoor sirens as well as email and mobile alerts delivered to subscribing residents. However, all other local systems for emergency weather alerts that are distributed through mobile devices are strictly opt-in systems, requiring the individual to subscribe to receive weather updates.

Protocols for WEA messages are in addition to existing NWS procedures for emergency weather alerts, which did not otherwise change after WEA introduction. WEA messages may be issued in case of tsunami, hurricane, dust storm, extreme wind and flash flood. When a storm system develops into an imminent threat, the NWS will nominate an alert for WEA message. This recommendation is then passed on to the DHS and then to mobile carriers for distribution to mobile devices.[2] All individuals located within affected areas with a WEA capable cellphone will receive an alert unless the individual has opted out of WEA messages. WEA messages are less than 90 characters in length and are designed to warn citizens of the nature of the weather emergency and the area affected as well as to advise individuals of appropriate precautionary behavior. WEA alerts are reserved only for the most severe weather conditions, so as an example, WEA messages are distributed when a storm is upgraded to flash flood warning status but are never issued in cases of flash flood watch.

The WEA program is intended to provide an integrated and flexible system to alert American people in case of emergency or other hazards to public safety. Several countries either have adopted or are experimenting with the adoption of wireless protocols for extreme weather events, natural disasters such as earthquakes and tsunamis, and geopolitical violence. This includes systems currently being developed by countries in the European Union as well as wireless alert systems already established in Japan, Chile and Israel.[3] By distributing messages through mobile phone networks, government regulators hope to communicate directly with individuals facing the greatest exposure to risk and encourage appropriate hazard mitigating behavior. In cases of extreme weather conditions, such as a flash flood, one of the principle aims of WEA messages are to encourage safer driving behavior during severe weather periods. Flash floods often entail elevated levels of precipitation that may directly imperil driving conditions. In

addition, one of the greatest hazards posed by flash flood result from roadways deluged with excess rainfall, since as little as two feet of water can carry away most automobiles.[4] WEA messages signify that extreme weather conditions are imminent or ongoing and the purpose is to allow individuals time to seek cover and avoid driving during these periods. With enough warning, WEA messages may help to prevent increases in automobile collisions, injuries and fatalities that often accompany extreme weather events.

The Commonwealth of Virginia is the study region used to analyze the effect of the WEA system on the rate of car accidents. There are a total of 134 counties and independent cities in Virginia. Climatic conditions in Virginia are generally temperate but with warm and humid summer months. Severe weather most often occurs due to large thunderstorms, which may occasionally develop into flash floods. Typically, any weather event that is elevated to flash flood warning status will trigger the dissemination of a WEA message. However, the distribution of WEA events was hampered for much of 2012 due to software malfunction and scheduled system maintenance. As a result, after July 2012, there exist several instances of weather events that triggered non-wireless NWS warnings for flash flood that were not recorded as receiving a WEA message. Unfortunately, software malfunction impacted both the dissemination of WEA messages and the recording of WEA events. It is therefore impossible to determine the exact reason why WEA messages were not recorded in these cases. For this reason, in subsequent analyses, we drop any observations from counties that were recorded as receiving a NWS warning in the post-WEA period that lack a record of receiving a corresponding WEA message. This amounts to a total of 86 county-day flash flood events in the post-WEA period. Table I summarizes the county-day flash flood warnings and flash flood watches in Virginia during the pre-WEA period (July 2011 – June 2012) and post-WEA period (July 2012 – December 2013).

During the study period between July 2011 and December 2013 there were 133 days and 1,850 county-day events with extreme weather alerts for flash flood warnings or watches. Flash flood warnings represent approximately 26% of all flash flood alerts issued. The incidence rate of flash flood warning was similar in the pre- and post-WEA periods. There were approximately 0.11 flash flood warnings per county per month in the pre-WEA period and 0.13 during the post-WEA period. There were a total of 226 county-day flash flood events with a WEA message. Since the program inception in July 2012, WEA messages have been distributed relatively evenly across Virginia. Figure A1 displays the frequency of WEA messages by county in Virginia from July 2012 to December 2013. WEA messages have been issued in 80% of counties, with a mean of 2.01 alerts per county over this time period. Albemarle County received a total of 11 WEA messages, the most recorded by any county in the sample.

II. Econometric Model of Daily Car Accidents

In this section, we develop an econometric model to evaluate the effect of the WEA system on the number of daily car accidents at the county level. The daily count of car accidents are observed for each county that received either a non-wireless flash flood warning in the pre-WEA period or a wireless flash flood warning in the post-WEA period. We also observe car accidents in control counties that received a non-wireless alert for a flash flood watch, but did not also receive a wireless or non-wireless warning. Car accidents that occurred on other days without a flash flood warning or watch are not considered. In this way, estimated model parameters and unobserved daily heterogeneity in weather conditions are all specific to counties on days with conditions that may generate either a flash flood warning or watch.

The econometric model is a Poisson model of daily car accident counts, clustered by date to account for correlation in daily storm-level heterogeneity between counties and to allow for

overdispersion (Cameron and Trivedi 2005).[5] Let $Y_{it} \in \mathbb{N}^{+}$ be the observed number of car accidents for county i in period t. Let W_{it} be a binary variable for a flash flood warning, taking on a value of one if county i received either a wireless or non-wireless warning for a flash flood in period t and is equal to zero otherwise. Let τ be a post-regulatory dummy that takes on a value of one for all periods after the introduction of the WEA system. Let $\mathbf{X_{it}}$ be a vector of other control variables such as time of day the alert was issued and day of the week, as well as weather related variables for daily precipitation and average wind speed. Daily precipitation is included as a cubic polynomial to control for the potential nonlinear effects of extreme weather conditions on daily car accidents. The variable $\mathbf{C_i}$ is a vector of fixed effects at the county level. Let $\mathbf{M_t}$ represent fixed effects at the month-by-year level, where one month-by-year level fixed effect is omitted from each of the pre-WEA and post-WEA periods. The probability that $Y_{it} = y$ is represented as

(1)

$$\Pr\left[Y_{it} = y\right] = \frac{e^{-\exp\left(W_{it}\beta_1 + \tau\beta_2 + W_{it}\tau\beta_3 + \mathbf{\Omega_{it}}\alpha\right)}\left(\exp\left(W_{it}\beta_1 + \tau\beta_2 + W_{it}\tau\beta_3 + \mathbf{\Omega_{it}}\alpha\right)\right)^{y}}{y!}$$

where $\mathbf{\Omega_{it}}\alpha = \mathbf{X_{it}}\alpha_1 + \mathbf{C_i}\alpha_2 + \mathbf{M_t}\alpha_3$.

The effect of the WEA system in Equation 1 is identified based on DD variation to compare the daily number of car accidents in treatment counties that received a WEA message for flash flood warning in the post-WEA period to the counties in the control group that either receive a non-wireless warning in the pre-WEA period or a non-wireless watch during either the pre-WEA or post-WEA period. The parameter β_1 accounts for baseline differences in car accident trends in flash flood warning and watch counties. The overall difference between flash

flood warning conditions compared to flash flood watch conditions are captured by the combined effect of β_1 as well as other variables including precipitation and wind. The parameter β_2 captures changes in car accident trends and extreme weather conditions during the post-WEA period relative to the pre-WEA period. As noted above, we have included month-by-year fixed effects dropping a single month from the pre-WEA and post-WEA periods respectively. Hence, the parameter for β_2 and the constant term are estimated relative to the baseline months omitted from the model and are used to control for temporally changing patterns in car accident rates but do not have an important economic interpretation. Finally, the effect of the WEA system is identified in Equation 1 based on the interaction parameter β_3, which accounts for spatial and temporal heterogeneity in which counties are selected for WEA messages. However, as Ai and Norton (2003) and Puhani (2012) note, sign and significance of parameters for interaction terms from nonlinear models cannot be interpreted directly. For this reason, we emphasize the importance of marginal effects for interpreting the impact of WEA messages on the count of daily car accidents.

Marginal effects are calculated for all estimated parameters in the model. For the control variables, let $x_{it}^k \in \mathbf{X_{it}}$ and $\alpha_1^k \in \alpha_1$, such that Equation 2 represents the marginal effect of covariate *k* on the daily number of car accidents

$$\frac{\partial E\left[Y_{it}\right]}{\partial x_{it}^k} = \alpha_1^k \exp\left(W_{it}\beta_1 + \tau\beta_2 + W_{it}\tau\beta_3 + \mathbf{\Omega_{it}}\alpha\right). \tag{2}$$

For interaction terms, the formulation of marginal effects is slightly more complicated. In a linear regression, estimates from DD models are recovered through the assumption of additive separability of the conditional expectation function. In a nonlinear model, cross-group

differences between counties and over time need not be equal (Puhani 2012). Instead, the treatment effect of WEA messages on the treated group is recovered as the difference between the observed outcome with a WEA message, Y_{it}, to the counterfactual potential outcome without a WEA message, Y_{it}^{0}. The conditional expectation for the observed number of car accidents is

(3) $$E\left[Y_{it} \mid W_{it} = 1, \tau = 1\right] = \exp\left(\beta_1 + \beta_2 + \beta_3 + \mathbf{\Omega_{it}}\alpha\right).$$

Although the counterfactual outcome without a WEA message cannot be directly observed, Y_{it}^{0} can be estimated using parameters from Equation 1 (Puhani 2012). The conditional expectation for the counterfactual number of car accidents without a WEA message is

(4) $$E\left[Y_{it}^{0} \mid W_{it} = 1, \tau = 1\right] = \exp\left(\beta_1 + \beta_2 + \mathbf{\Omega_{it}}\alpha\right).$$

The difference between Equations 3 and 4 represents the estimated treatment effect of WEA messages on daily car accidents

(5) $$E\left[Y_{it} \mid W_{it} = 1, \tau = 1\right] - E\left[Y_{it}^{0} \mid W_{it} = 1, \tau = 1\right] =$$

$$\exp\left(\beta_1 + \beta_2 + \beta_3 + \mathbf{\Omega_{it}}\alpha\right) - \exp\left(\beta_1 + \beta_2 + \mathbf{\Omega_{it}}\alpha\right).$$

Estimates from Equation 5 may be interpreted as the effect that the introduction of the WEA system had on the daily number of car accidents in flash flood warning counties relative to the counterfactual for only a non-wireless warning being issued. Because the exponential function is strictly monotonic, the treatment effect of WEA messages in Equation 5 has the same sign as the estimated parameter β_3, though significance of these terms may differ (Puhani 2012). We hypothesize that the treatment effect in Equation 5 is negative, indicating that WEA messages tend to reduce the incidence of car accidents by conveying new information regarding the imminent threat of extreme weather relative to a non-wireless warning. For instance, individuals that received a WEA message may be more likely to delay travel and avoid roadways

during extreme weather periods, thereby reducing car accidents. Alternatively, car accidents may be reduced because individuals are more likely to adopt precautionary driving behaviors in response to WEA messages, such as defensive driving techniques and reduced speed.

Equation 1 allows for heterogeneity in which counties are selected for WEA treatment across space as well as baseline differences in the incidence of car accidents over time. The primary identifying assumption in Equation 5 is that controlling for other observables, there are no unobservable factors that impact the incidence of car accidents on days with WEA messages that are not common to either flash flood watch days or days with flash flood warnings in the pre-WEA period. In robustness checks discussed in the results section, we test the sensitivity of the results to this assumption by running several falsification tests. We conduct a temporal falsification test using observations from the pre-WEA period (July 2011 – June 2012) with false treatment beginning in January 2012. We also conduct a falsification test using data from the post-WEA period (July 2012 – December 2013) with false treatment in July 2013. These falsification tests are used to check for differential time trends in car accident patterns between flash flood warning and watch counties that may confound estimates of the effect of WEA messages on car accident rates. To test for unobserved spatial heterogeneity in which counties were selected for WEA messages, we also conduct a spatial falsification test. In this model we compare car accident outcomes in counties that share a border with a county that was issued a WEA message or non-wireless flash flood warning to counties that share a border only with a flash flood watch county.

III. Available Data

Data used for this study are collected from two primary sources: emergency alert data from NOAA and traffic outcome data from the Virginia Department of Transportation (VDOT).

NOAA maintains an online daily log of all WEA messages issued since program inception.[6] Using these data, we collect information on the location and time of WEA messages for flash flood warnings issued between July 2012 and December 2013 in Virginia. We also collect county-level data on all non-wireless flash flood warnings and watches from NOAA's Interactive Products Database. Data for historical flash flood warnings are available from 1986 to the present. However, information on historical flash flood watches only exists since July 2011, which is the reason that the pre-WEA period spans July 2011 to June 2012 in our empirical analysis. For both wireless and non-wireless events, alert logs contain information on the time the alert was issued, locations affected, and type of weather event.

We acquired car accident data from VDOT, which collects information on the location and date for each car accident that occurs on public roads and highways in Virginia. Using these data we determine the total number of car accidents for each day between 2011 and 2013 and for all counties and independent cities in Virginia. Once aggregated to the county level, we merge the car accident database with the data on NOAA emergency alerts issued by county and by day. The outcome variable for this analysis is the daily count of car accidents per county. To allow sufficient time for alerting protocols to impact car crash patterns, if an emergency alert was issued after 10pm, we use accident totals from the day following the alert.[7] We also determine the number of licensed drivers per county, in hundreds of thousands, based on data provided by VDOT from 2012.

To explain daily incidence of car accidents, we collect data for several important control variables. Table II provides summary statistics for covariates included in this analysis. The time of day the alert was issued is included as a categorical variable with six four-hour groups (12am-4am, 4am-8am, 8am-12pm, etc.), with 12am-4am serving as the baseline category. This variable

is used to capture differences in car accident patterns from alerts issued at different times of day, which may be common to both flash flood warnings and watches. In addition, we interact the dummy variable for flash flood warning status with emergency message time categories to assess the differential effect that emergency message timing has in counties that received a flash flood warning versus a flash flood watch.

Time of alert may be important to explain car crash incidence, especially as alert timing overlaps with daily commute schedules. As an example, Figure 1 displays average hourly traffic volume for weekdays and weekends based on VDOT data from 2011 to 2013. For weekdays, traffic volume peaks with morning and evening commuting traffic between 7am-9am and 4pm-7pm, respectively. On the weekends, traffic volume varies more smoothly throughout the day but reaches its highest level in the afternoon and early evening. Traffic volume is at its lowest level from approximately 12am-4am. Emergency alerts that are timed to coincide with heavier volumes of traffic that occur as the population commutes to and from work may have a greater influence on both driver behavior as well as the number of cars on the road. We also include dummy variables for the day of week, with Sunday set as the baseline, to account for cyclical patterns in traffic volume, which tends to peak during the workweek (Monday – Friday) and fall over the weekend. Month-by-year fixed effects are used to account for other unobserved sources of temporal heterogeneity such as seasonal weather patterns. We also include county specific fixed effects to control for time-invariant unobservable county characteristics such as average daily traffic volume that may also impact car accident outcomes.

To control for heterogeneous weather conditions that may impact car crash incidence, we collect data on county-level daily averages for precipitation and wind speed from historical weather station data managed by NOAA's National Climactic Data Center.[8] For each day in the

sample, we match counties to the closest neighboring active weather station collecting information on relevant weather related variables. For the vast majority of counties (85%), daily weather data are determined from weather stations located within county borders. Precipitation, measured in millimeters of rainfall per day, is expected to positively affect car crashes by decreasing road traction and visibility.[9] To account for the potential nonlinear effects of precipitation on car accidents, this variable is included as a cubic polynomial in the Poisson model. Based on previous research (Levine et al. 1995), which has generally found an insignificant relationship between wind and car accidents, we anticipate an ambiguous sign for wind speed, which is measured in meters per second.

Table III provides a summary of the average daily number of car accidents that occurred in flash flood warning and watch counties during the pre- and post-WEA periods. We report the average daily number of accidents per county as well as per 100,000 licensed drivers. The average number of car accidents is elevated in counties that received a flash flood warning relative to flash flood watch counties. Counties that received a flash flood warning averaged approximately 26% and 19% more car accidents per 100,000 licensed drivers than flash flood watch counties in the pre- and post-WEA periods, respectively. This increase in the number of car accidents is most likely due to inclement weather conditions that tend to accompany warning messages. On average, flash flood warning counties report approximately 24.1 mm of precipitation on alert days versus 10.0 mm in flash flood watch counties. Overall, there is a decrease in the number of car accidents reported in flash flood warning counties in the post-WEA versus the pre-WEA period. However, these numbers are not directly comparable because of differing populations of flash flood warning counties as well as heterogeneous weather conditions between the pre- and post-WEA periods. It is therefore necessary to examine the

econometric model of daily car crash counts developed in the following section to determine the aggregate effect of WEA messages on car crash outcomes.

IV. Results

Table IV reports the estimation results of the Poisson model of daily car accident incidence in Virginia counties clustered by date. As noted earlier, the parameter for the post-WEA dummy variable is estimated relative to the month omitted from the post-WEA period set as the baseline month. Hence, we have excluded this coefficient from reported results because it does not have an important economic interpretation similar to the estimated month-by-year fixed effects. Table V provides average marginal effects for covariates included in this analysis, which may be interpreted as the average marginal effect of a deviation in observed covariate values on the daily number of car accidents per county. Standard errors are calculated using the delta method.

Based on the estimation results in Table IV, day of the week has a significant effect on predicting car accidents. As expected, car accidents peak during the workweek when traffic volume is typically highest, and Sundays are estimated to have the lowest levels of car accidents. Precipitation has a nonlinear effect on car accidents, as indicated by the significance on these coefficients for linear and higher order polynomial terms in Table IV. Consistent with previous studies, higher levels of precipitation tend to increase the daily count of car accidents, and the average marginal effect of an increase in daily precipitation by 1 mm tends to result in a statistically significant increase of 0.02 daily car accidents (Table V).

Flash flood warning counties have more car accidents on average than flash flood watch counties, and this result is significant at the 1% level. This is consistent with the interpretation that flash flood warnings tend to coincide with the most extreme weather conditions. Thus, car accidents may be elevated on these days due to more severe weather conditions that tend to

accompany these events. The timing of flash flood alert messages is an important predictor of the expected number of car accidents. On average, days with emergency alert messages issued between 4am-8am are estimated to have an increase in car accidents, which is statistically significant at the 1% level. This may be due to the fact that alerts issued during this time immediately precede the typical morning rush hour commute. As a result, peak inclement weather conditions may arrive during the time of day with the largest number of drivers on the road, causing a spike in car accidents. Compared to flash flood watch counties, flash flood warning counties are estimated to have an average of 1.75 fewer car accidents for alerts issued between 4am-8am, and 1.47 fewer car accidents for alerts issued between 8am-12pm, which are both significant at the 1% level. The large reduction in car accidents among flash flood warning counties during this time may be due to drivers responding to the perceived severity in weather conditions by delaying their morning commute until after the most extreme weather conditions have passed. However, only 2.2% of observations and 10.4% of flash flood warnings were reported between 4am-12pm, the lowest share of any time category. Thus, the large magnitude of this effect could also be explained by some other unusual correlation of county and weather driving conditions among the small set of observations reported during these periods.

The impact of WEA messages for flash flood warnings is estimated based on the interaction of flash flood warning status and the post-WEA dummy variable. Table VI provides a breakdown of the predicted change in car accidents due to the introduction of WEA messages, calculated based on Equations 3-5. We calculate average change in car accidents overall, per 100,000 licensed drivers and as a percentage change from the total number accidents without a WEA message. We predict an average of 3.38 car accidents for flash flood warning counties with a WEA message, calculated based on Equation 3. Under the counterfactual, we predict an

average of 4.02 car accidents for flash flood warning counties without a WEA message, calculated based on Equation 4. Hence, the WEA treatment effect for flash flood warning counties is a reduction of approximately 0.64 car accidents, which is statistically significant at the 1% level. This difference corresponds to a reduction of about 15.9% compared to the predicted number of accidents without a WEA message in flash flood warning counties.

NHTSA estimates that the average cost of a car accident is approximately $22,000 in 2013 dollars (Blincoe et al., 2014).[10] In total, 764 car accidents were reported in Virginia counties that received WEA messages for flash flood warnings. Based on predictions from this model, the introduction of the WEA system resulted in an expected reduction of approximately 121 car accidents relative to the counterfactual without the WEA system. Assuming that the national average cost of car accidents applies to observations from this model, WEA messages for flash flood contributed to an expected reduction of $2.7 million in damages from car accidents in Virginia alone.

A. Robustness Checks

In this section, we test the robustness of previous results to a variety of alternative specifications. Although the estimation results allow for heterogeneity in which counties are selected for WEA messages and flash flood warnings, the estimates may be confounded if diverging car accident trends exist between flash flood warning and watch counties over time. We conduct temporal falsification tests to examine the sensitivity of the results to unobserved time trends, such as better vehicle technology that improves traction control over time. Specifically, we use data from the pre-WEA period (July 2011 – June 2012) with hypothetical WEA treatment occurring in January 2012. Poisson model coefficients are reported in Table A1 in the appendix, with marginal effects for the false WEA treatment effect reported in Table A2. Based on these results,

there is no significant difference in the effect of flash flood warnings after false treatment (January 2012 – June 2012) as compared to the period before (July 2011 – December 2011).[11] Similarly, we conduct a temporal falsification test using data from the post-WEA period (July 2012 – December 2013) with false treatment in July 2013. Poisson model results and false WEA treatment effects are reported in Tables A3 and A4, respectively. We find no significant difference in the effect of wireless alerts during the post-WEA period.

Previous results may also be biased, for instance, if regulators routinely and non-randomly target flash flood warnings to specific areas of the state, or if these warning protocols significantly changed after the introduction of the WEA system. In Table A5 we conduct a spatial falsification exercise to test the sensitivity of the results to unobserved sources of spatial heterogeneity. In Table A6 we provide marginal effects for false WEA treatment. In this estimation we include observations from the pre- and post-WEA periods from untreated counties that share a border with a flash flood warning county, as well as untreated counties that exclusively border flash flood watch counties. Untreated counties that border areas that received flash flood warnings are considered false-treatment observations and counties that border flash flood watch counties are considered false-control observations. Based on these results, we find no significant differences in car accident patterns between flash flood warning and watch counties in this spatial falsification test.

Another potential issue that deserves further attention is the suitability of flash flood watch counties as the control group. For instance, if the population becomes accustomed to receiving WEA alerts during flash floods, this could potentially make individuals in flash flood watch counties even less attentive because they are issued a non-wireless alert but did not receive a WEA message. This could bias our estimate of the treatment effect away from zero.[12] To

examine this issue, we conduct a falsification test comparing the observations issued non-wireless alerts for a flash flood watch to those observations from other days during the entire study period with at least a moderate amount of rainfall (greater than 5mm) but that did not receive any flash flood alert (no warning or watch). Assuming that the individual response to non-wireless alerting protocols are constant over time, we should expect no significant change in the car accident rate for flash flood watch counties (false treatment group) compared to those counties without any alert. The Poisson model and treatment effects for post-WEA flash flood watch impacts are reported in Tables A7 and A8, respectively. Based on these results, we find no statistically significant changes in the accident rate for flash flood watch counties over time.

Additionally, we analyze the sensitivity of the estimated WEA treatment effects for several more parsimonious model specifications. The model specifications range from the most parsimonious model that has only the basic DD terms with county and month-by-year fixed effects to other models that progressively include additional controls on time of alert, day of the week, and weather related variables. The estimation results and WEA treatment effects are reported in Tables A9 and A10, respectively. The WEA treatment effect for the most parsimonious model is estimated as a reduction of 0.522 car accidents (or 13.4%). This is similar in sign and magnitude to the treatment effect of 0.639 car accidents (or 15.9%) for the primary model specification in Table VI, though not significant in part due to the larger standard errors in the parsimonious model without additional controls. The WEA treatment effects for the other parsimonious models have similar magnitude ranging from a reduction of 0.463 to 0.608 car accidents (or 12.0% to 15.2%).

We also further examine the robustness of the estimation results and WEA treatment effect for several alternative model specifications on the precipitation variables. Our primary

model specification in Table IV uses the cubic specification on daily precipitation since all three coefficients for the linear, quadratic, and cubic polynomial terms are statistically significant. Additionally, we estimate the model using a quadratic specification on precipitation, which is reported in Table A11. The WEA treatment effect for this quadratic model in Table A12 is estimated to be a reduction of 0.683 car accidents (or 16.8%), which is statistically significant and similar in magnitude to the treatment effect in Table VI. We also performed a robustness check that dropped outlier observations with exceptionally high daily precipitation greater than 100 mm. The estimation results are reported in Table A13, and the WEA treatment effect in Table A14 is estimated to be a reduction of 0.577 car accidents (or 14.4%). Additionally, the estimation results and WEA treatment effect are robust to the model specification using discretized decile categorical ranges for precipitation.

The primary identifying assumption for the WEA treatment effect is that the introduction of the WEA system is the only time varying policy that may differentially affect car accident rates in flash flood warning counties relative to flash flood watch counties. However, better vehicle technology over time (e.g., improvements in anti-lock braking technology) may affect the vehicle response to inclement weather, such that for the same amount of precipitation there are fewer accidents in the post-WEA period relative to the pre-WEA period. For this reason, we estimate the Poisson model that includes interaction terms between the post-WEA period and the cubic polynomial terms for precipitation (Table A15). A joint F-test for the exclusion of all post-WEA interactions with precipitation is not significant at the 10% level. The WEA treatment effect in Table A16 is estimated as a reduction of 0.669 car accidents (or 16.5%) and is statistically significant. Moreover, we estimate the Poisson model that includes interaction terms between the post-WEA period and all the control variables on alert time of day, day of week,

precipitation and wind speed (Table A17). The joint F-test for exclusion of all post-WEA interactions is not significant at the 10% level, suggesting the effect of precipitation and other control variables did not change significantly over time. The WEA treatment effect in Table A18 is estimated to be a reduction of 0.645 car accidents (or 16.0%), which is reasonably similar to the treatment effect of 0.639 car accidents (or 15.9%) in the primary model specification.

In the main estimation results in Table IV, we cluster by date to account for correlation in storm severity along with other daily varying car accident trends between counties. However, correlation may also exist between observations within the same county over time. To account for serial correlation in observations over time, we estimate an alternative fixed effect Poisson model of the daily count of car accidents with fixed effects and clustering at the county level. Unfortunately, average marginal effects are impossible to interpret from fixed effect Poisson models due to the exclusion of the fixed effects from the conditional expectation function. As an alternative, Table A19 provides the incident rate ratios (IRRs) for covariates from this model. Statistical significance for covariates is determined based on the deviation of the IRR from one. IRRs can be interpreted as the multiplicative effect of covariates from the baseline and the deviation of the IRR from one indicates the percentage change in the number of car accidents due to a marginal increase in the covariate of interest. Significance levels of covariates from Table A19 are little changed from those of Table IV. In addition, Table A19 suggests a reduction in the number of car accidents due to WEA messages that is comparable in magnitude and significance to results of Tables IV and VI.

In Table A20 we estimate a linear model with county-level fixed effects, which is two-way clustered at the date and county level and includes all variables from Table IV. Two-way clustered standard errors are calculated using the formulation proposed by Cameron, Gelbach

and Miller (2011). Coefficients for covariates from linear models may be interpreted directly as marginal effects. The distribution of count data on the number of car accidents is highly non-normal and includes some observations with zero car accidents, which is the reason the Poisson model is the preferred model specification. Based on Table A20, we find that WEA messages for flash flood create a reduction of 0.82 daily car accidents on average, which is significant at the 1% level. This result is similar in magnitude to the predicted reduction in car accidents from the main model specification in Table VI.

In addition to the models discussed above, we estimated the Poisson model that dropped observations corresponding to days on national holidays and major non-holidays (e.g., Super Bowl) that may have unusually high traffic volume and accident rates. These results are reported in Tables A21 and A22, in the appendix, and are qualitatively the same as results from Tables IV and VI. We also estimate a county fixed effect Poisson model using observations from all counties on all days from July 2011 to December 2013, including those days without an alert for either a flash flood warning or watch. In other robustness checks for the model estimation, we repeat results of Tables IV-VI but drop the months July 2013 – December 2013 to provide symmetric pre- and post-WEA time windows. We also estimate a model including additional intercepts for alert time with twelve two-hour time blocks (i.e., 12am-2am, 2am-4am, etc.). Results of these alternative models are available on request and conclusions from these models conform to those reported in Tables V and VI.

V. Mechanisms for Car Accident Reduction

In this section, we address potential mechanisms for car accident reductions due to WEA messages for flash flood warnings. There are two non-mutually exclusive hypotheses that may explain the observed reductions in car accidents. One explanation is that individuals who receive

a WEA message abandon or delay their travel plans until after the severe weather period has elapsed. Another explanation is that, in response to WEA messages, drivers adopt defensive driving behaviors that help reduce their chances of being involved in a car accident. Whereas the latter hypothesis could be discerned by analyzing individual behavioral outcomes, the former hypothesis is testable through an analysis of traffic volume data on days with WEA messages.

Reductions in traffic volume may decrease hazard exposure to individuals who opt to avoid driving and may also result in spillover benefits to other drivers by reducing congestion externalities during severe weather periods. We use an RD model to assess the effect of WEA messages on traffic volume. We compare traffic volume in the hours immediately before and after the issuance of a WEA flash flood warning during the post-WEA period (July 2012 – December 2013). Similarly, we separately analyze traffic volume before and after the issuance of a non-wireless flash flood warning during the pre-WEA period (July 2011 – June 2012). Based on the RD approach and assuming that commuting patterns and other weather trends vary in a predictable manner throughout the day, flash flood warning treatment is as good as randomly assigned in the neighborhood of the discontinuity (Lee and Lemieux 2010). Under the hypothesis that WEA messages impact an individual's driving decisions, we may expect that traffic volume decreases immediately following the issuance of a WEA message.

The econometric model used for this analysis is estimated as follows. Let V_{iqdh} be the number of cars per hour for traffic monitoring station i in quarter q (e.g., July 2012 – September 2012), on day of the week d and hour h. Let $\overline{V}_{iqh}$ represent the average number of cars per hour at station i for the quarter q, which is calculated separately for each hour of the day and for each day of the week. $\overline{V}_{iqh}$ is calculated based on an average of n_q observations per quarter, typically about 13, as this is the approximate number of weeks per quarter such that

$\overline{V}_{iqh} = \sum_{d \in q} \frac{V_{iqdh}}{n_q}$. As demonstrated in Figure 1, traffic volume tends to follow a predictable daily pattern due to daily commuting schedules. Therefore, we construct the dependent variable

$$\tilde{V}_{idh} = V_{iqdh} - \overline{V}_{iqh} \tag{6}$$

that represents traffic volume net average hourly and station specific quarterly trends and controls for the influence of cyclical commuting patterns on traffic volume. Positive values of $\tilde{V}_{idh}$ indicate above trend traffic volume and negative values indicate below trend volume. Deviations in traffic volume from mean trends may be due to extreme weather conditions, weather alerting protocols, or other unobserved sources of heterogeneity.

Let $c_{idh} = h - \theta_{id}$ be a running variable, where $\theta_{id} \in \mathbb{R}^{+}$ represents the time of day that the alert was issued. Let E_{idh} be a dummy variable that takes on a value of one for all hours after a flash flood warning (i.e., $c_{idh} > 0$). The type of alert is designated as $\mathrm{T} \in \{0,1\}$; where $\mathrm{T} = 1$ indicates a wireless flash flood warning from the post-WEA period and $\mathrm{T} = 0$ indicates a non-wireless flash flood warning from the pre-WEA period. Let μ_{id} be fixed effects at the station-by-day level and ε_{idh} be a disturbance term clustered at the traffic monitoring station level. Equation 7 is used to predict the effect of wireless and non-wireless alerts on traffic volume

$$\tilde{V}^{\mathrm{T}}_{idh} = E^{\mathrm{T}}_{idh}\lambda^{\mathrm{T}} + f^{\mathrm{T}}\left(c^{\mathrm{T}}_{idh}\right) + \mu^{\mathrm{T}}_{id} + \varepsilon^{\mathrm{T}}_{idh} \ , \tag{7}$$

$$\text{where } h^{-} \le c^{\mathrm{T}}_{idh} \le h^{+} \text{ and } \mathrm{T} \in \{0,1\}.$$

Equation 7 is estimated separately for post-WEA and pre-WEA flash flood warnings. Given the emphasis on the WEA program, our primary interest is the estimate on λ^{1} representing the

average treatment effect on the treated (ATT) for wireless alerts in the post-WEA period. We hypothesize that the estimate of the ATT for wireless alert λ^1 is negative, indicating a decrease in traffic volume immediately after the issuance of a wireless alert in the post-WEA period. We also expect that the estimated ATT for non-wireless alerts λ^0 is negative; however, we expect it to have lower magnitude assuming that WEA messages contribute to greater adoption of hazard mitigating behavior than would occur using non-wireless alert protocols.

We also include fixed effects at the station-by-day level to de-mean the regression of any unrelated trends in traffic volume that are common to the traffic monitoring station on days when flash flood warnings are issued. The variables h^- and h^+ represent the bandwidth of the data used. The function $f^{\mathrm{T}}\left(c_{idh}^{\mathrm{T}}\right)$ is the control function and is included to capture unobservable trends in traffic volume such as the effect of inclement weather, which may differ on the left hand side versus right hand side of the discontinuity (i.e., before and after the alert). However, for purposes of identification these baseline trends in traffic volume are assumed to vary smoothly in the region of the discontinuity.

Traffic volume for this analysis is reported in hourly increments and is based on continuous traffic monitoring station data provided by VDOT. There are a total of 435 traffic monitoring stations in Virginia, located in 92 out of 134 counties in the state. The locations of these stations are displayed in Figure A2 in the appendix. Monitoring stations tend to be concentrated primarily near large urban centers, such as Virginia Beach and Richmond, as well as along interstates and highways. The sample consists of hourly traffic volume from the day of alert for stations located in counties that received either a pre-WEA or post-WEA flash flood warning. We also use data from days without any flash flood warnings to control for the

influence of daily commuting patterns on traffic volume, following the method described in Equation 6.

Table VII lists the average hourly traffic volume reported as the number of cars per hour and deviation in hourly traffic volume from the quarterly station level trends for days with post-WEA messages. Average traffic volume trends follow a pattern consistent with the weekday commuting patterns displayed in Figure 1 and typically peak in the morning and afternoon and are at the lowest during nighttime hours. On average, the deviations in traffic volume are below station level hourly trends in the post-WEA period. Previous research has found that traffic volume tends to decrease in response to increased precipitation (Keay and Simmonds 2005). Thus, the negative deviations in traffic volume below the average station level hourly trends may be due in part to the arrival of extreme weather conditions. Average hourly traffic volume and the deviation in hourly traffic volume for the pre-WEA period are reported in Table A23 in the appendix.

The running variable for this analysis is hours from the issuance of a flash flood warning, which may take a value in the interval -12 to 12. Negative values indicate hours prior to the alert and positive values indicate hours afterward. We adjust the running variable to account for the minute within the hour that the alert was issued. Thirty minutes past the hour is treated as the zero point for the discontinuity. As an example, for a flash flood warning issued precisely at 8:20am, the value of the running variable for the periods of 7-8am and 9-10am would be -0.83 and 1.17, respectively. This is due to the fact that the period 7-8am is closer, on average, to the boundary than the period 9-10am. In the primary specification, we also drop any hour during which a flash flood warning was issued if the alert was sent after the 15th minute and before the 45th minute of the hour.[13] For instance, from the previous example, we would drop the hour 8-

9am. This is due to the fact that a substantial share of the hour occurred before as well as after the alert was issued and its inclusion would tend to attenuate the ATT estimates near the boundary.

To estimate the effect of WEA messages on traffic volume, we use a non-parametric, local linear regression discontinuity model. The dependent variable is the number of cars per hour, net quarterly station specific trends by day of week and hour of day, as explained in Equation 6. We proceed by first de-meaning the data of average station-by-day fixed effects. Then we use these residuals to fit a local linear regression of the running variable using a triangular kernel function and optimal bandwidth calculated based on the method in Imbens and Kalyanaraman (2012). We calculate the local Wald estimate of the impact of flash flood warning alerts on hourly traffic volume and cluster standard errors at the traffic monitoring station level.

A. Traffic Volume Results

Table VIII reports the estimation results of several alternative RD models for the impact of WEA messages on traffic volume. For each model, we report the estimated ATT for wireless alerts issued during the post-WEA period. Model 1 is estimated based on Equations 6 and 7 and includes observations from alerts issued during all times of day. Model 2 excludes station-by-day fixed effects but is otherwise identical to Model 1. Additionally, we conduct falsification tests using data from the day immediately prior to flash flood warnings (Model 3) and data from counties neighboring wireless flash flood warning counties (Model 4). These falsification models are estimated with the same model specification used in Model 1. Assuming that the RD method is valid for Model 1, we should expect no significant RD effect in either Model 3 or 4.

In Model 1, traffic volume in the post-WEA period decreases significantly immediately after a WEA flash flood warning compared to before the warning. Specifically, we find that

WEA messages reduced traffic volume by approximately 29 cars per hour, which is statistically significant at the 1% level (Table VIII). This supports the hypothesis that WEA messages help contribute to reductions in traffic volume by encouraging individuals to delay or cancel travel during severe weather periods. An average of 947 cars per hour were recorded during the hour WEA messages were sent, meaning that the reduction of 29 cars per hour as predicted in Model 1 represents a decrease in traffic volume of 3.1%. The reduction in traffic volume has the direct effect of reducing the number of drivers exposed to hazardous flash flood conditions. Additionally, it has the indirect effect of reducing congestion for the drivers remaining on the road, and this reduction in the congestion externality is expected to further reduce the likelihood of a car accident during severe weather periods. We report the estimated ATT for non-wireless flash flood warnings issued during the pre-WEA period in Table A24 in the appendix. The estimated ATT for non-wireless alerts is positive but not statistically significant, suggesting that non-wireless alerts have little or no effect on traffic volume in the pre-WEA period.

Figure 2 provides a graphical representation of the effect of wireless alert messages in the post-WEA period based on the local linear regression estimated in Model 1. Traffic volume is represented on the vertical axis, after controlling for average hourly traffic volume trends and using station-by-day fixed effects. Hours from alert is listed on the horizontal axis. The vertical line in the middle of Figure 2 represents the time the alert was issued. Observations to the left of the vertical line occurred prior to the issuance of an alert, and observations to the right occurred after the alert. Traffic volume is decreasing in the hours prior to the issuance of a wireless alert during the post-WEA period. At the discontinuity, there is a sharp decrease in traffic volume, and in the hours after the WEA message is sent, traffic volume gradually rises back to pre-alert

levels. We also provide a graphical representation of the effect of non-wireless alert messages in the pre-WEA period in Figure A3 in the appendix.

To test sensitivity of the control function to unobserved trends in traffic volume, we conduct temporal falsification tests in Model 3 reported in Table VIII. Model 3 uses data from the day immediately preceding the issuance of flash flood warnings and is estimated with the same specification as Model 1.[14] There is no evidence of a statistically significant false treatment effect for WEA messages. Figure A4 in the appendix provides a graphical representation of control functions from Model 3. Finally, in Model 4 we conduct a falsification test using data from neighboring counties that did not receive a wireless flash flood warning. Figure A5 provides a graph of the control functions from this model. The graph of the control functions for neighboring counties looks similar to Figure 2, and at the boundary, we find a significant reduction in traffic volume, though this effect is less than half the size predicted for flash flood warning counties. This result may be likely caused by spillover impacts of WEA warning protocols to other neighboring counties from individuals crossing county borders after receiving an alert.

VI. Concluding Remarks

The WEA system is among the only emergency message systems in the world that distributes geographically explicit emergency messages directly to mobile devices on a strictly opt-out basis. This allows regulators to send tailored emergency messages directly to individuals in harm's way and suggest hazard mitigating behaviors to minimize their exposure to risk. In this article, we investigate the impact of WEA messages for flash floods on car accident outcomes and traffic volume in Virginia between 2011 and 2013. The empirical analysis suggests that

WEA messages significantly reduce the number of car accidents by 15.9% during flash flood warning conditions relative to the counterfactual when non-wireless warnings are issued.

We also examine potential mechanisms for reductions in car accidents. Using an RD model, we analyze hourly traffic volume data immediately before and after a flash flood warning message is issued. During the post-WEA period, we find that traffic volume is reduced by approximately 3.1% immediately following the issuance of a WEA message relative to before the alert. These results suggest that some individuals respond to WEA messages by avoiding roadways during inclement weather periods, thereby directly lowering the population of drivers exposed to risk and contributing to a reduction in car accidents. Moreover, the reduction in traffic volume is expected to decrease congestion externalities, which may further reduce the likelihood of a car accident for the drivers remaining on the roadways during inclement weather.

It is important to discuss the magnitude of our main findings regarding the effects of WEA messages on the reduction of car accidents, as well as caveats and future directions for research. As noted in Smith (2013), smartphone ownership in the US is approximately 56%, though we would expect slightly higher smartphone ownership for our study population than the national average. Smartphone ownership increases with household income (Smith 2013), and Virginia residents have higher median incomes than the national average and drivers of private automobiles tend to have higher incomes than those who do not own a vehicle. Considering the estimate of a 15.9% reduction in car accidents, the reduction in traffic volume of 3.1% is an important contributing factor that may lower hazard exposure for individuals who chose to delay or cancel their travel and lower congestion externalities for the remaining drivers who do not alter their travel plans. WEA messages may also contribute to a greater adoption of defensive driving and other risk mitigating behaviors. While it would be ideal to have information on the

opt-out rates for WEA alerts, the DHS and telecom companies unfortunately do not collect individual information on who does or does not receive a WEA alert due to privacy concerns. The large magnitude of the estimated WEA treatment effect may be due in part to the newness of the WEA program during the study period, in which opt-out rate are expected to be relatively low and individuals' recent exposure to wireless alerts may increase the likelihood that they change their driving behavior. Future research would be interesting to survey individuals to acquire data on opt-out rates or analyze behavioral aspects to examine whether individuals become desensitized to the WEA alerts over time. Furthermore, the WEA system is a national program, and it would be useful to analyze the effect from WEA alerts in other regions.

For purposes of this analysis, we have focused on the reduction in car accidents as indication of overall hazard mitigation in response to WEA messages. Future research could be used to study the effect of WEA messages on other traffic outcomes such as car accident injuries and fatalities. The empirical strategy used in this analysis could easily be applied to study the effect of WEA messages on other types of extreme weather events or natural disasters, such as tornadoes, hurricanes, earthquakes, tsunamis, or wildfires. With the advent of wireless emergency message systems in the US and elsewhere around the world, there is a need to understand the effectiveness of these systems to induce adaptive behavior to mitigate the risks for a diverse set of outcomes related to reductions in traffic accidents, evacuation from natural disasters, or avoidance of other human impacts.

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Table I: Total number of flash flood alert days and county-day observations in the pre-WEA period (July, 2011 - June, 2012) and post-WEA period (July, 2012 – December, 2013)

	Pre-WEA Period		Post-WEA Period	
Alert	Days	County-Day Observations	Days	County-Day Observations
Flash Flood Warning	49	259	40	226
Flash Flood Watch	27	487	44	878
All	62	746	71	1104

Table II: Covariate summary statistics for flash flood warning and watch counties

Variables	**Mean**	**Standard Deviation**	**Min**	**Max**
WEA Period x Warning County				
WEA Period	0.5968	0.4907	0	1
Warning County	0.2622	0.4399	0	1
WEA Period x Warning County	0.1222	0.3276	0	1
Alert Time of Day				
12am - 4am	0.1022	0.3029	0	1
4am - 8am	0.1016	0.3022	0	1
8am - 12pm	0.1497	0.3569	0	1
12pm - 4pm	0.1665	0.3726	0	1
4pm - 8pm	0.3595	0.4800	0	1
8pm - 12am	0.1205	0.3257	0	1
Day of Week				
Sunday	0.1108	0.3140	0	1
Monday	0.1670	0.3731	0	1
Tuesday	0.1557	0.3626	0	1
Wednesday	0.1724	0.3779	0	1
Thursday	0.1622	0.3687	0	1
Friday	0.1341	0.3408	0	1
Saturday	0.0978	0.2972	0	1
Weather Controls				
Precipitation (mm)	13.7334	21.8326	0	181.1
Wind Speed (m/s)	1.4414	1.7595	0	9.8000
Licensed Drivers (100,000s)	0.5161	1.1024	0.0197	7.8890
County-Day Observations	1850			
Number of Days	133			

Table III: Average daily number of car accidents for flash flood warning and watch counties

	Pre-WEA Period		**Post-WEA Period**	
Number of Daily Car Accidents	**Warning**	**Watch**	**Warning**	**Watch**
Average Daily Car Accidents per County	5.247	2.563	3.381	2.897
	(9.265)	(5.844)	(7.489)	(5.777)
Car Accidents per 100,000 Licensed Drivers	6.697	5.318	7.701	6.438
	(6.877)	(6.917)	(12.450)	(7.174)

Note: Standard deviation in parentheses

Table IV: Difference-in-differences (DD) Poisson Model for daily number of car accidents

Variables	Coefficient	Standard Error
WEA Period x Warning County		
Warning County	0.3033***	0.0894
WEA Period x Warning County	-0.1732**	0.0679
Alert Time of Day[a]		
4am - 8am	0.1344***	0.0468
8am - 12pm	0.0204	0.0628
12pm - 4pm	0.0381	0.0839
4pm - 8pm	0.0379	0.0690
8pm - 12am	0.0651	0.1405
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-0.5036***	0.1569
Warning County x 8am - 12pm	-0.4663***	0.1550
Warning County x 12pm - 4pm	0.0301	0.1251
Warning County x 4pm - 8pm	0.0454	0.1044
Warning County x 8pm - 12am	-0.2286	0.1707
Day of Week		
Monday	0.3963***	0.0689
Tuesday	0.5618***	0.0844
Wednesday	0.4414***	0.0738
Thursday	0.4433***	0.0606
Friday	0.5090***	0.0680
Saturday	0.4294***	0.0860
Weather Controls		
Precipitation (mm)	0.0087***	0.0031
Precipitation^2	-1.73x10^-4**	0.68x10^-4
Precipitation^3	8.94x10^-7**	3.87x10^-7
Wind Speed (m/s)	-0.0248	0.0181
Constant	-0.2073	0.2052
Fixed Effects		
County	Yes	
Month-by-Year	Yes	
County-Day Observations	1850	
Number of Days	133	

***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

[a]Baseline time category of 12am-4am

Table V: Average marginal effects for covariates on daily number of car accidents

Variables	Marginal Effect	Standard Error
WEA Period x Warning County		
Warning County	1.1453***	0.3039
WEA Period x Warning County	-0.6392**	0.2646
Alert Time of Day[a]		
4am - 8am	0.4406***	0.1567
8am - 12pm	0.0630	0.1939
12pm - 4pm	0.1188	0.2627
4pm - 8pm	0.1182	0.2148
8pm - 12am	0.2059	0.4528
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-1.7502***	0.4862
Warning County x 8am - 12pm	-1.4711***	0.4770
Warning County x 12pm - 4pm	0.1226	0.5066
Warning County x 4pm - 8pm	0.1866	0.4214
Warning County x 8pm - 12am	-0.8436	0.6895
Day of Week		
Monday	1.0358***	0.1889
Tuesday	1.6055***	0.2630
Wednesday	1.1818***	0.1988
Thursday	1.1882***	0.1649
Friday	1.4134***	0.2052
Saturday	1.1425***	0.2473
Weather Controls		
Precipitation (mm)	0.0171***	0.0058
Wind Speed (m/s)	-0.0794	0.0577
Fixed Effects		
County	Yes	
Month-by-Year	Yes	
County-Day Observations	1850	
Number of Days	133	

***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

[a]Baseline time category of 12am-4am

Table VI: Treatment effect for WEA messages on number of daily car accidents conditional on flash flood warning status in the post-WEA period

Warning	With WEA	Without WEA	DD Treatment Effect	Per 100,000 Licensed Drivers	Percent Change
Flash Flood	3.381***	4.020***	-0.639**	-1.246**	-15.902***
	(0.124)	(0.254)	(0.265)	(0.508)	(5.710)

Note: Standard errors in parentheses.
***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Table VII: Average hourly traffic volume (number of cars per hour) for post-WEA flash flood warnings

Hour	Average Hourly Traffic Volume	Deviation From Hourly Average
12am - 1am	259	1
1am - 2am	178	-1
2am - 3am	155	0
3am - 4am	164	1
4am - 5am	266	6
5am - 6am	602	12
6am - 7am	1054	17
7am - 8am	1365	-5
8am - 9am	1383	-1
9am - 10am	1339	8
10am - 11am	1351	1
11am - 12pm	1405	11
12pm - 1pm	1487	16
1pm - 2pm	1510	-3
2pm - 3pm	1577	5
3pm - 4pm	1731	-6
4pm - 5pm	1753	-29
5pm - 6pm	1778	-36
6pm - 7pm	1489	-40
7pm - 8pm	1135	-46
8pm - 9pm	912	-29
9pm - 10pm	750	-22
10pm - 11pm	511	-14
11pm - 12am	394	-4

Note: Deviation refers to the average difference in hourly traffic volume from quarterly traffic monitoring station trends

Table VIII: Regression discontinuity models of the impact of post-WEA flash flood warnings on hourly traffic volume

	WEA Flash Flood Warning		Falsification Tests	
	(1)	**(2)**	**(3)**	**(4)**
Post-WEA	-29.02***	-30.5***	-0.39	-14.87***
	(8.78)	(8.32)	(5.18)	(5.61)
Station-Day Fixed Effects	Yes	No	Yes	Yes
Number of Stations	296	296	296	389
Observations	15892	15892	15774	53051

***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Bootstrapped standard errors in parentheses calculated based upon 1,000 bootstrapped replications.

Model 1 uses a sample of alerts from all hours of the day and includes station-by-day fixed effects. Model 2 excludes station by day fixed effects but is otherwise identical to Model 1. Models 3 and 4 present falsification tests using data from the day immediately prior to flash flood warnings and from counties neighboring flash flood warning counties, respectively.

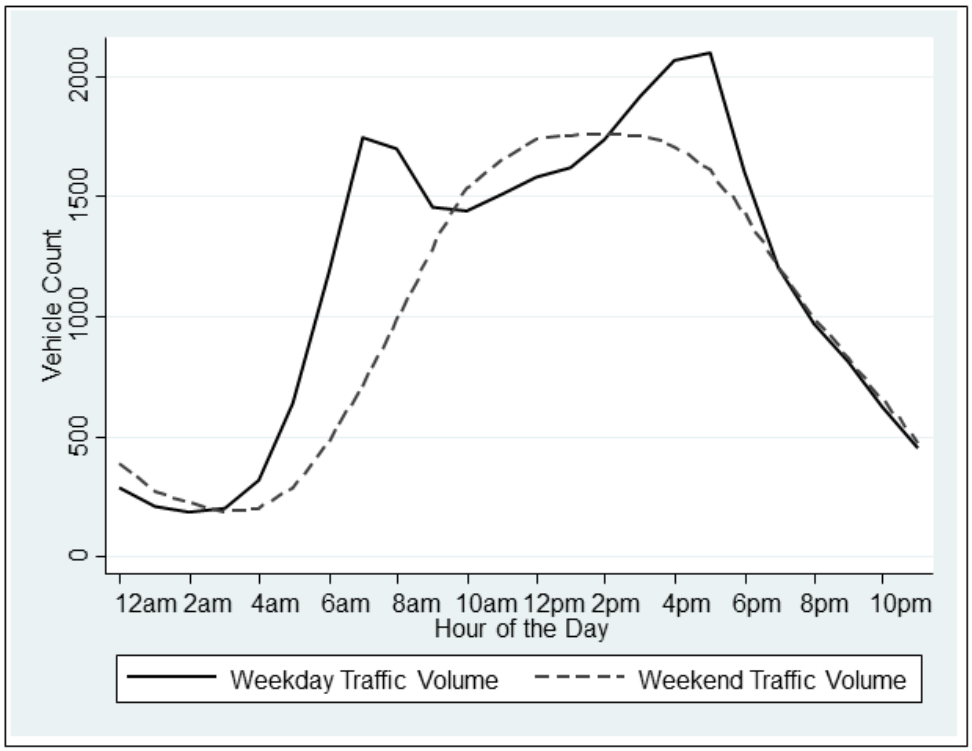
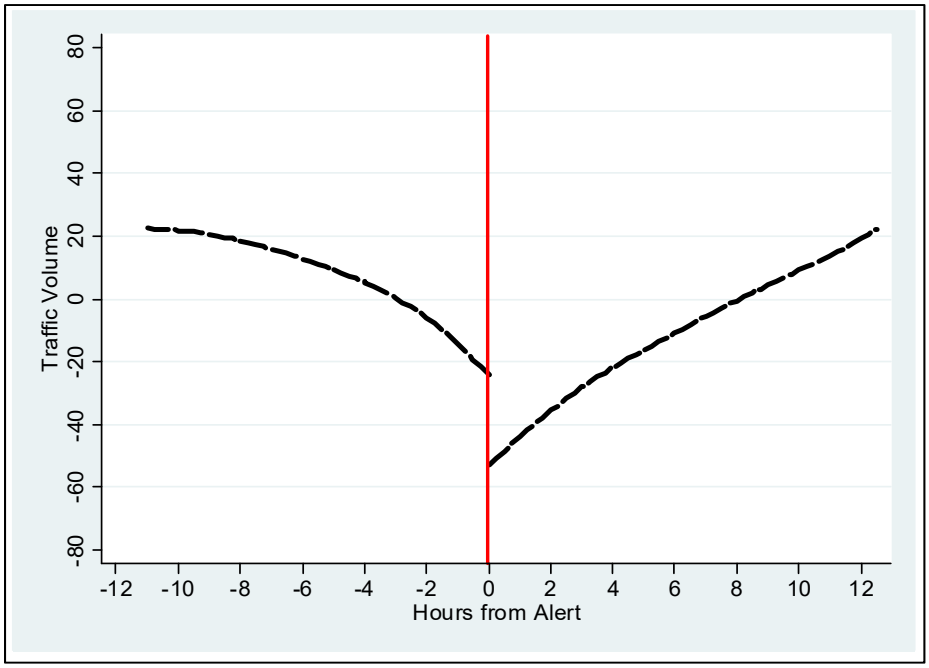


Figure 1: Average hourly traffic volume by weekday and weekend in Virginia (2011 – 2013)



Note: Deviation in traffic volume after controlling for average hourly trends using quarter-station and station-by-day fixed effects based on Model 1 specification.

Figure 2: Local linear regression on traffic volume for hours from the alert in the post-WEA periods

Appendix

Table A1. Poisson model for temporal falsification test using pre-WEA observations (July, 2011 – June, 2012) with false treatment beginning in January 2012

Variables	Coefficient	Standard Error
WEA Period x Warning County		
Warning County	0.4015***	0.1341
WEA Period x Warning County	0.0640	0.1620
Alert Time of Day[a]		
4am - 8am	0.1714*	0.0988
8am - 12pm	0.0455	0.1080
12pm - 4pm	0.1931	0.1224
4pm - 8pm	0.1528	0.1499
8pm - 12am	-0.3062	0.2981
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-0.6010***	0.1836
Warning County x 8am - 12pm	-0.3306	0.2631
Warning County x 12pm - 4pm	-0.2363	0.1874
Warning County x 4pm - 8pm	-0.1172	0.1789
Warning County x 8pm - 12am	0.1166	0.3083
Day of Week		
Monday	0.2914***	0.0755
Tuesday	0.5600***	0.1431
Wednesday	0.4384***	0.1277
Thursday	0.3460***	0.0662
Friday	0.4837***	0.1303
Saturday	0.2846**	0.1137
Weather Controls		
Precipitation (mm)	0.0059	0.0043
Precipitation^2	-19.1x10^-5**	8.10x10^-5
Precipitation^3	13.7x10^-7***	4.63x10^-7
Wind Speed (m/s)	0.0254	0.0211
Fixed Effects		
County	Yes	
Month-by-Year	Yes	
Observations	746	
Number of Days	62	

***Significant at the 1 % level
**Significance at the 5 % level
*Significance at the 10 % level
[a]Baseline time category of 12am-4am

Table A2. Pre-WEA temporal falsification test on treatment effect on number of daily car accidents

Warning	With WEA	Without WEA	DD Treatment Effect	Per 100,000 Licensed Drivers	Percent Change
Flash Flood	4.988***	4.678***	0.309	0.372	6.613
	(0.357)	(0.704)	(0.766)	(0.935)	(17.27)

Note: Standard errors in parentheses.
***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Table A3. Poisson model for temporal falsification test using post-WEA observations (July, 2012 – December, 2013) with false treatment beginning in July 2013

Variables	Coefficient	Standard Error
WEA Period x Warning County		
Warning County	-0.1042	0.1245
WEA Period x Warning County	0.1384	0.1404
Alert Time of Day[a]		
4am - 8am	0.1202	0.1174
8am - 12pm	-0.0055	0.1044
12pm - 4pm	-0.1383	0.1283
4pm - 8pm	-0.0443	0.1119
8pm - 12am	0.0064	0.1275
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-0.1894	0.2701
Warning County x 8am - 12pm	-0.5251**	0.2238
Warning County x 12pm - 4pm	0.3572*	0.2034
Warning County x 4pm - 8pm	0.2345	0.1423
Warning County x 8pm - 12am	-0.1272	0.1448
Day of Week		
Monday	0.3731***	0.1093
Tuesday	0.4914***	0.1046
Wednesday	0.3828***	0.1028
Thursday	0.4192***	0.0956
Friday	0.4976***	0.1448
Saturday	0.4504***	0.1208
Weather Controls		
Precipitation (mm)	0.0096*	0.0057
Precipitation^2	-1.77x10^-4	1.41x10^-4
Precipitation^3	7.49x10^-7	8.58x10^-7
Wind Speed (m/s)	-0.0660***	0.0213
Fixed Effects		
County	Yes	
Month-by-Year	Yes	
Observations	1104	
Number of Days	71	

***Significant at the 1 % level
**Significance at the 5 % level
*Significance at the 10 % level
[a]Baseline time category of 12am-4am

Table A4. Post-WEA temporal falsification test on treatment effect on number of daily car accidents

Warning	With WEA	Without WEA	DD Treatment Effect	Per 100,000 Licensed Drivers	Percent Change
Flash Flood	3.568***	3.107***	0.461	0.869	14.841
	(0.107)	(0.406)	(0.442)	(0.843)	(16.121)

Note: Standard errors in parentheses.
***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Table A5. Poisson model for spatial falsification test

Variables	Coefficient	Standard Error
WEA Period x Warning County		
Warning County	-0.0322	0.1112
WEA Period x Warning County	0.0742	0.1090
Alert Time of Day[a]		
4am - 8am	-0.1259	0.1043
8am - 12pm	-0.1599	0.1082
12pm - 4pm	-0.0554	0.1166
4pm - 8pm	-0.1357	0.1136
8pm - 12am	-0.2879	0.1931
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	0.1493	0.1446
Warning County x 8am - 12pm	0.0775	0.1837
Warning County x 12pm - 4pm	-0.0795	0.1939
Warning County x 4pm - 8pm	-0.0217	0.1439
Warning County x 8pm - 12am	0.1333	0.2051
Day of Week		
Monday	0.1490	0.0988
Tuesday	0.3518***	0.1090
Wednesday	0.2390**	0.1159
Thursday	0.1927*	0.1014
Friday	0.3559***	0.1010
Saturday	0.1871*	0.0959
Weather Controls		
Precipitation (mm)	0.0051**	0.0025
Precipitation^2	-1.95x10^-5	2.93x10^-5
Precipitation^3	2.52x10^-8	7.27x10^-8
Wind Speed (m/s)	0.0420**	0.0190
Fixed Effects		
County	Yes	
Month-by-Year	Yes	
Observations	1516	
Number of Days	133	

***Significant at the 1 % level

**Significance at the 5 % level

*Significance at the 10 % level

[a]Baseline time category of 12am-4am

Table A6. Spatial falsification test for treatment effect on number of daily car accidents conditional on flash flood warning in post-WEA period

Warning	With WEA	Without WEA	DD Treatment Effect	Per 100,000 Licensed Drivers	Percent Change
Flash Flood	2.348***	2.180***	0.168	0.460	7.704
	(0.086)	(0.231)	(0.239)	(0.657)	(11.739)

Note: Standard errors in parentheses.
***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Table A7. Poisson model for flash flood watch falsification test

Variables	Coefficient	Standard Error
WEA Period x Watch County		
Watch County	0.2180*	0.1243
WEA Period x Watch County	0.0797	0.0762
Alert Time of Day[a]		
4am - 8am	-0.3695**	0.1631
8am - 12pm	-0.3248***	0.1049
12pm - 4pm	-0.2022*	0.1195
4pm - 8pm	-0.1079	0.1225
8pm - 12am	-0.3560**	0.1412
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	--	--
Warning County x 8am - 12pm	--	--
Warning County x 12pm - 4pm	--	--
Warning County x 4pm - 8pm	--	--
Warning County x 8pm - 12am	--	--
Day of Week		
Monday	0.1615***	0.0364
Tuesday	0.2157***	0.0388
Wednesday	0.2645***	0.0393
Thursday	0.2305***	0.0384
Friday	0.3631***	0.0332
Saturday	0.1458***	0.0319
Weather Controls		
Precipitation (mm)	0.0053***	0.0014
Precipitation^2	-6.40x10^-5***	2.21x10^-5
Precipitation^3	2.00x10^-7***	0.71x10^-7
Wind Speed (m/s)	-0.0113*	0.0066
Fixed Effects		
County	Yes	
Month-by-Year	Yes	
Observations	24786	
Number of Days	756	

***Significant at the 1 % level

**Significance at the 5 % level

*Significance at the 10 % level

[a]Baseline time category of 12am-4am

Table A8. Flash flood watch falsification test for treatment effect on number of daily car accidents conditional on flash flood watch in post-WEA period

Warning	With WEA	Without WEA	DD Treatment Effect	Per 100,000 Licensed Drivers	Percent Change
Flash Flood	2.997***	2.768***	0.230	0.501	8.293
	(0.062)	(0.204)	(0.212)	(0.699)	(8.252)

Note: Standard errors in parentheses.
***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Table A9. Poisson model for progressively adding control variables

	Only DD Effect		**Add Time of Day**		**Add Day of Week**		**Add Weather**	
Variables	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
WEA Period x Watch County								
Watch County	0.2913***	0.0584	0.2943***	0.0519	0.2589***	0.0497	0.2369***	0.0508
WEA Period x Watch County	-0.1436	0.0981	-0.1654*	0.0900	-0.1350*	0.0768	-0.1283*	0.0744
Alert Time of Day[a]								
4am - 8am	--	--	-0.0741	0.0932	0.0076	0.0865	0.0121	0.0890
8am - 12pm	--	--	-0.1985**	0.0973	-0.0865	0.0704	-0.0461	0.0670
12pm - 4pm	--	--	-0.0433	0.0871	0.0075	0.0778	0.0132	0.0723
4pm - 8pm	--	--	-0.0838	0.0686	-0.0051	0.0596	0.0156	0.0562
8pm - 12am	--	--	-0.1881**	0.0812	-0.1487**	0.0646	-0.1197*	0.0665
Warning County x Alert Time of Day[a]								
Warning County x 4am - 8am	--	--	--	--	--	--	--	--
Warning County x 8am - 12pm	--	--	--	--	--	--	--	--
Warning County x 12pm - 4pm	--	--	--	--	--	--	--	--
Warning County x 4pm - 8pm	--	--	--	--	--	--	--	--
Warning County x 8pm - 12am	--	--	--	--	--	--	--	--
Day of Week								
Monday	--	--	--	--	0.4046***	0.0894	0.3932***	0.0811
Tuesday	--	--	--	--	0.5471***	0.0949	0.5643***	0.0881
Wednesday	--	--	--	--	0.4441***	0.0922	0.4430***	0.0844
Thursday	--	--	--	--	0.4019***	0.0774	0.4087***	0.0680
Friday	--	--	--	--	0.4969***	0.0893	0.4910***	0.0794
Saturday	--	--	--	--	0.3699***	0.0929	0.3895***	0.0907
Weather Controls								
Precipitation (mm)	--	--	--	--	--	--	0.0086***	0.0032
Precipitation^2	--	--	--	--	--	--	-17.1x10^-5**	6.96x10^-5

Precipitation^3	--	--	--	--	--	--	8.85x10^-7**	3.92x10^-7
Wind Speed (m/s)	--	--	--	--	--	--	-0.0253	0.0188
Fixed Effects								
County	Yes		Yes		Yes		Yes	
Month-by-Year	Yes		Yes		Yes		Yes	
Observations	1850		1850		1850		1850	
Number of Days	133		133		133		133	

***Significant at the 1 % level

**Significance at the 5 % level

*Significance at the 10 % level

[a]Baseline time category of 12am-4am

Table A10. Treatment effect on number of daily car accidents conditional on flash flood warning in post-WEA period, progressively adding control variables

Model specification	With WEA	Without WEA	DD Treatment Effect	Per 100,000 Licensed Drivers	Percent Change
Difference in differences	3.381***	3.903***	-0.522	-1.033	-13.377
	(0.183)	(0.326)	(0.369)	(0.727)	(8.498)
Add time of day	3.381***	3.989***	-0.608*	-1.202*	-15.248**
	(0.173)	(0.306)	(0.344)	(0.676)	(7.632)
Add day of week	3.381***	3.869***	-0.488*	-0.961*	-12.626*
	(0.141)	(0.277)	(0.290)	(0.566)	(6.707)
Add weather	3.381***	3.843***	-0.463*	-0.902*	-12.043*
	(0.138)	(0.265)	(0.279)	(0.537)	(6.540)

Note: Standard errors in parentheses.
***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Table A11. Poisson model for quadratic precipitation

Variables	Coefficient	Standard Error
WEA Period x Watch County		
Watch County	0.2998***	0.0911
WEA Period x Watch County	-0.1839***	0.0668
Alert Time of Day[a]		
4am - 8am	0.1320***	0.0466
8am - 12pm	0.0036	0.0648
12pm - 4pm	0.0267	0.0874
4pm - 8pm	0.0232	0.0708
8pm - 12am	0.0501	0.1417
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-0.4916***	0.1534
Warning County x 8am - 12pm	-0.4416***	0.1581
Warning County x 12pm - 4pm	0.0564	0.1275
Warning County x 4pm - 8pm	0.0561	0.1061
Warning County x 8pm - 12am	-0.2149	0.1729
Day of Week		
Monday	0.3984***	0.0705
Tuesday	0.5540***	0.0848
Wednesday	0.4325***	0.0750
Thursday	0.4385***	0.0626
Friday	0.5045***	0.0709
Saturday	0.4205***	0.0854
Weather Controls		
Precipitation (mm)	0.0030	0.0024
Precipitation^2	-2.106x10^-5	2.97x10^-5
Wind Speed (m/s)	-0.0281	0.0178
Fixed Effects		
County	Yes	
Month-by-Year	Yes	
Observations	1850	
Number of Days	133	

***Significant at the 1 % level

**Significance at the 5 % level

*Significance at the 10 % level

[a]Baseline time category of 12am-4am

Table A12. WEA treatment effect on number of daily car accidents conditional on flash flood warning in post-WEA period with quadratic precipitation

Warning	With WEA	Without WEA	DD Treatment Effect	Per 100,000 Licensed Drivers	Percent Change
Flash Flood	3.381***	4.063***	-0.683***	-1.332***	-16.800***
	(0.122)	(0.252)	(0.262)	(0.503)	(5.555)

Note: Standard errors in parentheses.
***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Table A13. Poisson model for dropping observations with over 100mm of daily precipitation

Variables	Coefficient	Standard Error
WEA Period x Warning County		
Warning County	0.2955***	0.0904
WEA Period x Warning County	-0.1557**	0.0693
Alert Time of Day[a]		
4am - 8am	0.1375***	0.0452
8am - 12pm	0.0265	0.0629
12pm - 4pm	0.0415	0.0842
4pm - 8pm	0.0378	0.0683
8pm - 12am	0.0739	0.1462
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-0.4869***	0.1604
Warning County x 8am - 12pm	-0.4838***	0.1558
Warning County x 12pm - 4pm	0.0185	0.1245
Warning County x 4pm - 8pm	0.0487	0.1045
Warning County x 8pm - 12am	-0.2203	0.1762
Day of Week		
Monday	0.3926***	0.0688
Tuesday	0.5564***	0.0853
Wednesday	0.4387***	0.0730
Thursday	0.4445***	0.0604
Friday	0.5071***	0.0680
Saturday	0.4282***	0.0872
Weather Controls		
Precipitation (mm)	0.0116**	0.0052
Precipitation^2	-3.07x10^-4*	1.69x10^-4
Precipitation^3	2.25x10^-6	1.39x10^-6
Wind Speed (m/s)	-0.0264	0.0180
Fixed Effects		
County	Yes	
Month-by-Year	Yes	
Observations	1832	
Number of Days	133	

***Significant at the 1 % level
**Significance at the 5 % level
*Significance at the 10 % level
[a]Baseline time category of 12am-4am

Table A14. WEA treatment effect on number of daily car accidents dropping observations with over 100mm of daily precipitation

Warning	With WEA	Without WEA	DD Treatment Effect	Per 100,000 Licensed Drivers	Percent Change
Flash Flood	3.425***	4.003***	-0.577**	-1.116**	-14.422**
	(0.125)	(0.253)	(0.269)	(0.513)	(5.931)

Note: Standard errors in parentheses.
***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Table A15. Poisson model of daily car accidents with post-WEA interaction on precipitation variables

Variables	Coefficient	Standard Error
WEA Period x Warning County		
Warning County	0.3136***	0.0820
WEA Period x Warning County	-0.1806**	0.0765
Alert Time of Day[a]		
4am - 8am	0.1461***	0.0490
8am - 12pm	0.0240	0.0589
12pm - 4pm	0.0337	0.0823
4pm - 8pm	0.0432	0.0682
8pm - 12am	0.0623	0.1351
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-0.4995***	0.1522
Warning County x 8am - 12pm	-0.4730***	0.1540
Warning County x 12pm - 4pm	0.0379	0.1245
Warning County x 4pm - 8pm	0.0421	0.1032
Warning County x 8pm - 12am	-0.2281	0.1640
Day of Week		
Monday	0.3859***	0.0695
Tuesday	0.5549***	0.0828
Wednesday	0.4447***	0.0733
Thursday	0.4418***	0.0584
Friday	0.5044***	0.0702
Saturday	0.4203***	0.0841
Weather Controls		
Precipitation (mm)	0.0040	0.0038
Precipitation^2	-9.29x10^-5	7.36x10^-5
Precipitation^3	7.12x10^-7**	3.58x10^-7
Post-WEA x Precipitation	0.0068	0.0069
Post-WEA x Precipitation^2	-9.73x10^-5	16.9x10^-5
Post-WEA x Precipiation^3	4.42x10^-8	9.93x10^-7
Wind Speed (m/s)	-0.0272	0.0174
Fixed Effects		
County	Yes	
Month-by-Year	Yes	
Observations	1850	
Number of Days	133	

***Significant at the 1 % level
**Significance at the 5 % level
*Significance at the 10 % level

[a]Baseline time category of 12am-4am

Table A16. WEA treatment effect on number of daily car accidents conditional on flash flood warning in post-WEA period with post-WEA interaction on precipitation variables

Warning	With WEA	Without WEA	DD Treatment Effect	Per 100,000 Licensed Drivers	Percent Change
Flash Flood	3.381***	4.050***	-0.669**	-1.296**	-16.523***
	(0.125)	(0.275)	(0.299)	(0.572)	(6.384)

Note: Standard errors in parentheses.
***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Table A17. Poisson model of daily car accidents with post-WEA interaction with control variables

Variables	Coefficient	Standard Error
WEA Period x Warning County		
Warning County	0.3126***	0.0816
WEA Period x Warning County	-0.1746**	0.0888
Alert Time of Day[a]		
4am - 8am	0.1593**	0.0643
8am - 12pm	0.0738	0.0605
12pm - 4pm	0.0459	0.0848
4pm - 8pm	0.0804	0.0754
8pm - 12am	0.0710	0.1306
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-0.5004***	0.1526
Warning County x 8am - 12pm	-0.5726***	0.1530
Warning County x 12pm - 4pm	0.0308	0.1313
Warning County x 4pm - 8pm	0.0149	0.0995
Warning County x 8pm - 12am	-0.2123	0.1422
Day of Week		
Monday	0.3262***	0.0678
Tuesday	0.6431***	0.1467
Wednesday	0.4672***	0.1174
Thursday	0.4224***	0.0678
Friday	0.4827***	0.1073
Saturday	0.3334***	0.1291
Post-WEA x Day of Week		
Monday	0.1047	0.1233
Tuesday	-0.1110	0.1811
Wednesday	-0.0303	0.1476
Thursday	0.0397	0.1007
Friday	0.0697	0.1727
Saturday	0.1518	0.1809
Weather Controls		
Precipitation (mm)	0.0042	0.0036
Precipitation^2	-10.8x10^-5	6.61x10^-5
Precipitation^3	8.02x10^-7***	3.11x10^-7
Post-WEA x Precipitation	0.0066	0.0069
Post-WEA x Precipitation^2	-7.97x10^-5	16.8x10^-5
Post-WEA x Precipiation^3	-7.4x10^-8	9.75x10^-7
Wind Speed (m/s)	-0.0061	0.0219

Post-WEA x Wind Speed	-0.0354	0.0224
Fixed Effects		
County	Yes	
Month-by-Year	Yes	
Observations	1850	
Number of Days	133	

***Significant at the 1 % level
**Significance at the 5 % level
*Significance at the 10 % level
[a]Baseline time category of 12am-4am

Table A18. WEA treatment effect on number of daily car accidents conditional on flash flood warning in post-WEA period with post-WEA interaction on control variables

Warning	With WEA	Without WEA	DD Treatment Effect	Per 100,000 Licensed Drivers	Percent Change
Flash Flood	3.381***	4.025***	-0.645*	-1.258*	-16.022**
	(0.12)	(0.339)	(0.351)	(0.685)	(7.456)

Note: Standard errors in parentheses.
***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Table A19. Difference-in-differences (DD) Poisson model for daily number of car accidents with county-level fixed effects (Incident Rate Ratios Reported)

Variables	Incident Rate Ratio	Standard Error
WEA Period x Warning County		
Warning County	1.3543***	0.4688
WEA Period x Warning County	0.8410***	0.2835
Alert Time of Day[a]		
4am - 8am	1.1438	0.7993
8am - 12pm	1.0206	5.3070
12pm - 4pm	1.0388	2.4952
4pm - 8pm	1.0386	2.5516
8pm - 12am	1.0672	2.3342
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	0.6044***	0.1726
Warning County x 8am - 12pm	0.6273	0.5406
Warning County x 12pm - 4pm	1.0305	4.4292
Warning County x 4pm - 8pm	1.0465	2.8853
Warning County x 8pm - 12am	0.7956	0.5435
Day of Week		
Monday	1.4863***	0.3339
Tuesday	1.7538***	0.2163
Wednesday	1.5548***	0.2374
Thursday	1.5579***	0.2299
Friday	1.6636***	0.2488
Saturday	1.5364***	0.4316
Weather Controls		
Precipitation (mm)	1.0088***	0.3630
Precipitation^2	0.9998***	0.3599
Precipitation^3	1.0000**	0.3932
Wind Speed (m/s)	0.9755	0.7633
Fixed Effects		
County	Yes	
Month-by-Year	Yes	
Observations	1820	
Number of Counties	130	

***Significant at the 1 % level

**Significance at the 5 % level

*Significance at the 10 % level

[a]Baseline time category of 12am-4am

Table A20. Linear model of daily number of car accidents using two-way clustered at date and county level

Variables	Coefficient	Standard Error
WEA Period x Warning County		
Warning County	0.4155	0.6497
WEA Period x Warning County	-0.8189***	0.3124
Alert Time of Day[a]		
4am - 8am	-0.3237	0.6485
8am - 12pm	-0.8369	0.9252
12pm - 4pm	-0.6690	0.7305
4pm - 8pm	-0.5357	0.6731
8pm - 12am	-0.5664	0.8365
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-0.9701	0.7874
Warning County x 8am - 12pm	0.4330	1.0476
Warning County x 12pm - 4pm	1.3225	0.9419
Warning County x 4pm - 8pm	0.9793	0.9478
Warning County x 8pm - 12am	-0.0292	0.8452
Day of Week		
Monday	1.1780***	0.3457
Tuesday	1.4119***	0.3810
Wednesday	1.4089***	0.4507
Thursday	1.2449***	0.3066
Friday	1.5035***	0.4846
Saturday	1.2590***	0.2472
Weather Controls		
Precipitation (mm)	0.0229**	0.0100
Precipitation^2	-3.67x10^-4*	1.90x10^-4
Precipitation^3	1.44x10^-6	9.96x10^-7
Wind Speed (m/s)	0.0021	0.0963
Fixed Effects		
County	Yes	
Month-by-Year	Yes	
Observations	1850	
Number of Counties	134	
Number of Days	133	

***Significant at the 1 % level
**Significance at the 5 % level
*Significance at the 10 % level
[a]Baseline time category of 12am-4am

Table A21. Poisson model for dropping observations on or near major US holidays

Variables	Coefficient	Standard Error
WEA Period x Warning County		
Warning County	0.3063***	0.0888
WEA Period x Warning County	-0.1661**	0.0666
Alert Time of Day[a]		
4am - 8am	0.1265***	0.0461
8am - 12pm	0.0287	0.063
12pm - 4pm	0.0466	0.0845
4pm - 8pm	0.0554	0.071
8pm - 12am	0.0695	0.1399
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-0.499***	0.1568
Warning County x 8am - 12pm	-0.4744***	0.1504
Warning County x 12pm - 4pm	0.0182	0.1256
Warning County x 4pm - 8pm	0.0213	0.1057
Warning County x 8pm - 12am	-0.2336	0.1701
Day of Week		
Monday	0.4092***	0.0722
Tuesday	0.5651***	0.0845
Wednesday	0.4372***	0.074
Thursday	0.4393***	0.0617
Friday	0.5134***	0.0684
Saturday	0.43***	0.0865
Weather Controls		
Precipitation (mm)	0.0092***	0.0031
Precipitation^2	-17.9x10^-5***	6.76x10^-5
Precipitation^3	9.19x10^-7**	3.85x10^-5
Wind Speed (m/s)	-0.0244	0.0181
Fixed Effects		
County	Yes	
Month-by-Year	Yes	
Observations	1808	
Number of Days	130	

***Significant at the 1 % level
**Significance at the 5 % level
*Significance at the 10 % level
[a]Baseline time category of 12am-4am

Table A22. WEA treatment effect on number of daily car accidents dropping observations from major US holidays

Warning	With WEA	Without WEA	DD Treatment Effect	Per 100,000 Licensed Drivers	Percent Change
Flash Flood	3.402***	4.016***	-0.615**	-1.190**	-15.301***
	(0.125)	(0.252)	(0.260)	(0.497)	(5.645)

Note: Standard errors in parentheses.
***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Table A23: Average hourly traffic volume (number of cars per hour) for flash flood warnings in pre-WEA period

Hour	Average Hourly Traffic Volume	Deviation From Hourly Average
12am - 1am	292	-59
1am - 2am	204	-36
2am - 3am	172	-31
3am - 4am	185	-26
4am - 5am	318	-27
5am - 6am	704	-38
6am - 7am	1211	-51
7am - 8am	1694	-52
8am - 9am	1726	-61
9am - 10am	1567	-92
10am - 11am	1568	-105
11am - 12pm	1629	-113
12pm - 1pm	1715	-112
1pm - 2pm	1725	-130
2pm - 3pm	1823	-151
3pm - 4pm	1958	-160
4pm - 5pm	2041	-188
5pm - 6pm	2059	-201
6pm - 7pm	1706	-194
7pm - 8pm	1329	-162
8pm - 9pm	1026	-164
9pm - 10pm	803	-120
10pm - 11pm	665	-109
11pm - 12am	442	-85

Note: Deviation refers to the average difference in hourly traffic volume from quarterly traffic monitoring station trends

Table A24: Regression discontinuity models of the impact of non-wireless flash flood warnings on hourly traffic volume in pre-WEA period

	Flash Flood Warning		**Falsification Tests**	
	(1)	**(2)**	**(3)**	**(4)**
Pre-WEA	8.83	8.86	-4.10	3.12
	(7.93)	(7.70)	(7.28)	(4.69)
Station-Day Fixed Effects	Yes	No	Yes	Yes
Number of Stations	305	305	305	389
Observations	18877	18877	18783	53051

***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Bootstrapped standard errors in parentheses calculated based upon 1,000 bootstrapped replications.

Model 1 uses a sample of alerts from all hours of the day and includes station-by-day fixed effects. Model 2 excludes station by day fixed effects but is otherwise identical to Model 1. Models 3 and 4 present falsification tests using data from the day immediately prior to flash flood warnings and from counties neighboring flash flood warning counties, respectively.

Figure A1. Frequency of WEA messages by county in Virginia

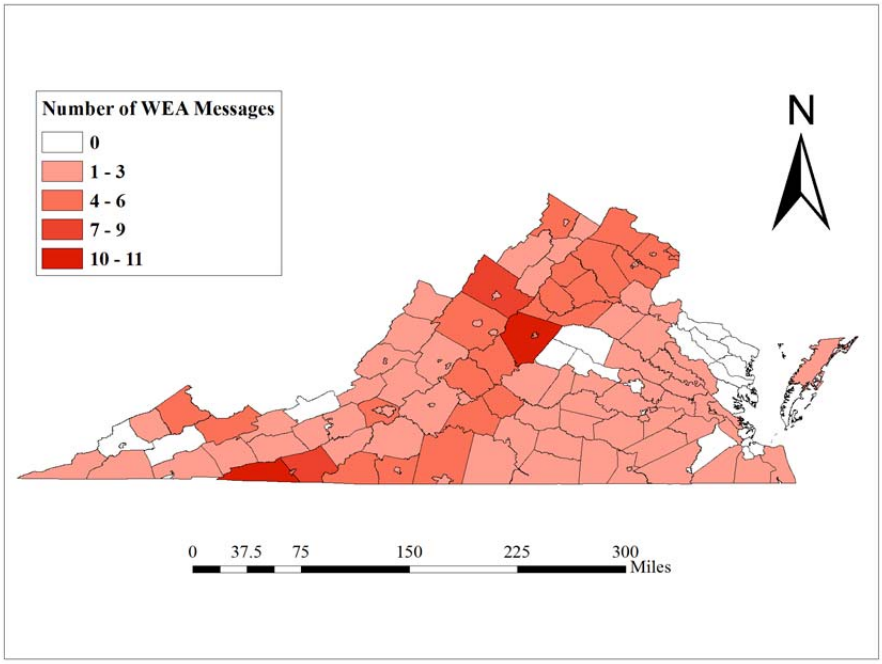


Figure A2. Traffic monitoring station locations in Virginia

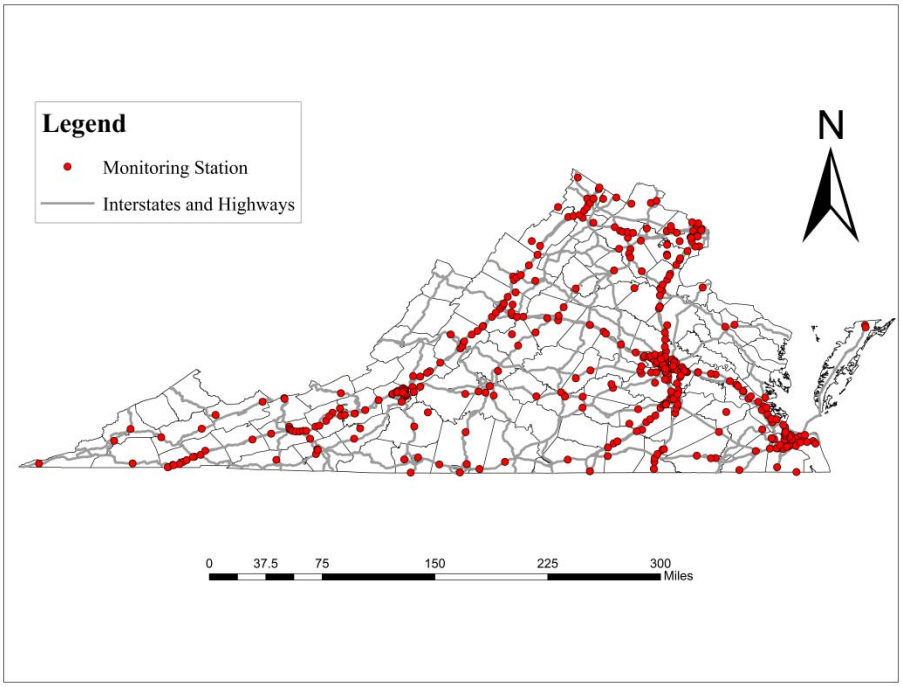
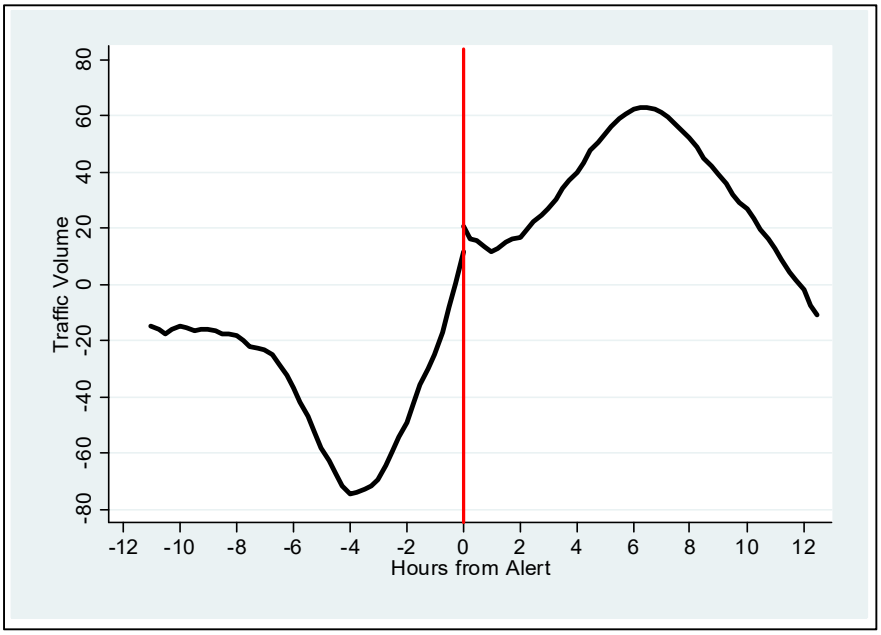
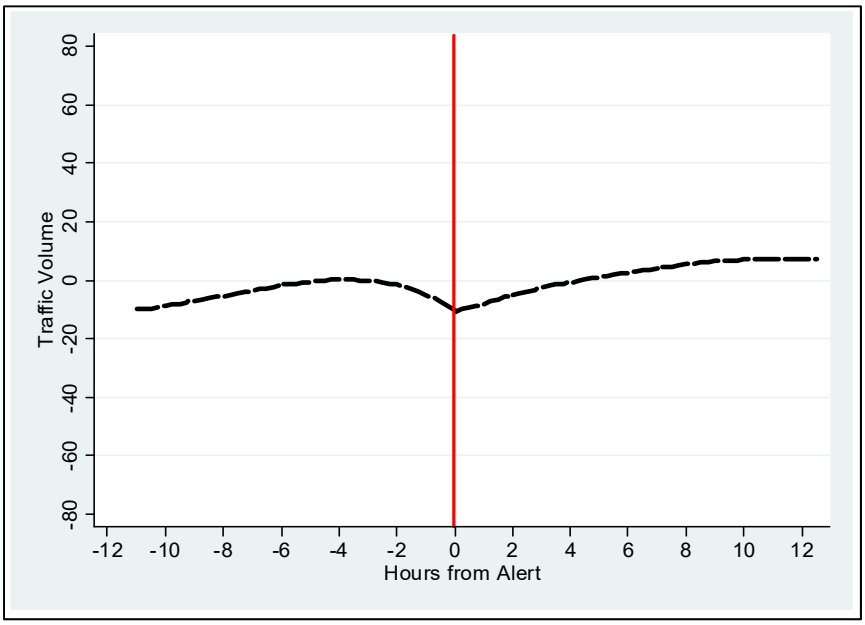


Figure A3. Local linear regression on traffic volume for hours from alert for non-wireless flash flood warning days in pre-WEA period



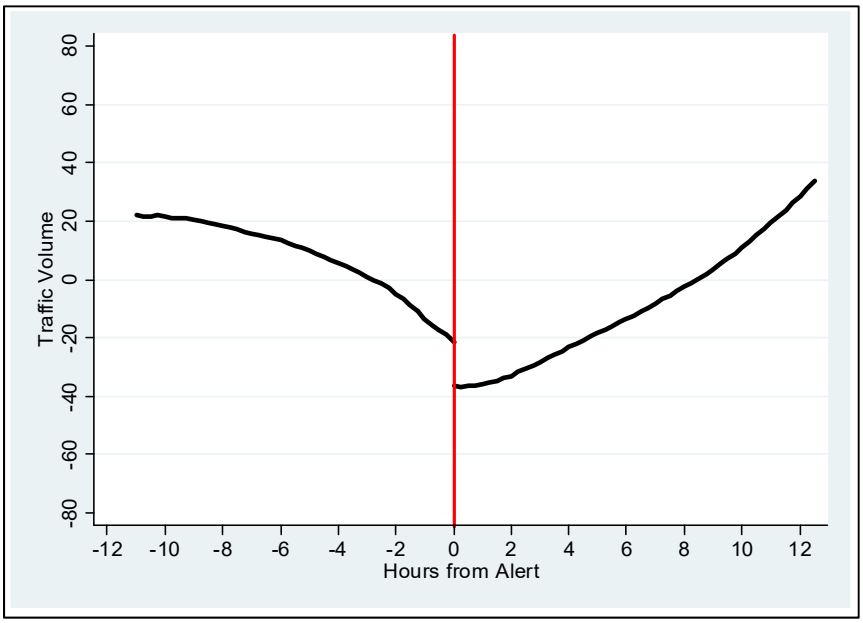
Note: Deviation in traffic volume after controlling for average hourly trends using quarter-station and station-by-day fixed effects based on Model 1 specification.

Figure A4. Local linear regression on traffic volume for hours from alert based on temporal falsification test using data from day prior to alert in the post-WEA period



Note: Deviation in traffic volume after controlling for average hourly trends using quarter-station and station-by-day fixed effects based on Model 3 specification for temporal falsification test.

Figure A5. Local linear regression on traffic volume for hours from alert based on falsification test using data from counties neighboring flash flood warnings in the post-WEA period



Note: Deviation in traffic volume after controlling for average hourly trends using quarter-station and station-by-day fixed effects based on Model 4 specification for falsification test using counties neighboring flash flood warnings.

End Notes

[1] For a full list of NWS flash flood watch and flash flood warning criteria, see sections 4.2.2 and 5.2.2, respectively: http://www.nws.noaa.gov/directives/sym/pd01009022curr.pdf

[2] WEA messages may only be issued to areas with cell phone coverage, gaps in service most often overlap with locations of protected lands (e.g. national parks).

[3] For more information on other national systems for wireless emergency messages, see http://www.gsma.com/mobilefordevelopment/wp-content/uploads/2013/01/One2Many-Cell-Broadcast-Emergency-Alerts.pdf

[4] For more information on how flash floods develop and the hazards associated with these events see http://www.srh.noaa.gov/images/fwd/pdf/floodsandfloods.pdf

[5] A negative binomial model of daily car accident counts yielded virtually identical results.

[6] WEA message logs are located here: http://weather.noaa.gov/pub/logs/heapstats/2013/

[7] For reference, less than 5% of flash flood warnings were issued between 10pm - 12am.

[8] NCDC queryable database of weather station data is located here http://www.ncdc.noaa.gov/

[9] We also calculate total daily snowfall for each county in the analysis but because most flash flood events occur in the spring and summer, no snowfall occurred on any of the dates in the analysis.

[10] NHTSA estimates that there were approximately 13.6 million car accidents in 2010 that caused economic damages of approximately $277 billion.

[11] In unreported results, we also try estimating models with false treatment beginning variously in November 2011, December 2011, February 2012 and March 2012 with no change in significance of false treatment results.

[12] We thank an anonymous reviewer for pointing out this issue.

[13] In unreported results, we also experiment with alternative restrictions from the hour of the discontinuity such as dropping observations after the 10th minute and before the 50th of the hour, or after the 20th minute and before the 40th minute, as well as dropping no observations and dropping all observations from the hour of the discontinuity.

[14] The slightly differing sample populations in Model 3 versus Model 1 is due to a handful of continuous monitoring stations that were active on the day of a flash flood warning that were inactive the day prior.