ABSTRACT

BURNETT, IAIN CHARLES. Traffic Collisions in North Carolina: Weather, Human Factors, and Economic Analysis, 2013 to 2019. (Under the direction of Drs. Jane Harrison and Eric Edwards).

Traffic collisions are a significant worldwide issue and are currently one of the leading causes of accident-based mortality and disability for young people. Beyond the immediate consequences of loss of life or injury, traffic collisions can cause severe economic costs to society; previous work has found that when welfare and quality of life losses are factored in, the total social cost burden can equal 1% to 2% of a nation's GNP. These total social costs are comprised of direct losses due to death, injury, and property damage, as well as congestion, lost productivity, and other factors affecting families, firms, and communities. Member states of the United Nations and World Health Organization have committed to reducing global traffic fatalities by half this decade, and many communities have embraced goals to eliminate all traffic fatalities by 2050. To reach that goal, a full understanding of why collisions happen and what factors lead to injuries and fatalities is needed. During the years 2013 through 2019, North Carolina had an average of 258,203 traffic collisions responsible for 1,389 fatalities and 121,905 injuries. Even when adjusting for population growth in the state there is a net increase in collision, injury, and fatality rates over the course of this study, with total collision costs rising from $27.1 billion in 2013 to $35.2 billion in 2019. In that light, this study uses regression analysis with daily, county-level data to examine fixed effects and environmental factors that contribute to traffic collisions, injuries, and fatalities in the state of North Carolina. This study identifies the effects of known weather factors related to collision outcomes such as temperature, precipitation, and major adverse weather events. This study also introduces new explanatory variables including lag effects from adverse weather events to capture adaptive capacity, and

tropical cyclone forecast inclusion to capture the impact of stress. In addition, this study evaluates the heterogenous baseline collision and casualty rates found in North Carolina’s counties and across months and days of the week. This study finds that from 2013 to 2019, precipitation and adverse weather on average lead to an additional 7,800 collisions and 2,000 injuries with a social cost of $970 million per year, after controlling for other factors. This study also finds that when controlling for the presence of storm conditions, other environmental factors, and fixed effects, there is a statistically significant increase in collisions and injuries for counties anticipating the arrival of a tropical cyclone. Winter weather is a major contributor to traffic collisions, increasing the daily collision and injury incidence rates by 78% and 43%, respectively, and the six highest single-day collision totals in the state over the study period occurred during winter storms. Lastly, adverse weather creates a lag effect reducing collision and injury rates, an effect that is strongest in the first three days after the event. These findings likely represent a lower bound for social impacts of weather factors on traffic outcomes, as minor collisions are often not reported, especially under adverse weather conditions such as those studied here. This study also presents findings on county-level heterogeneity in traffic responses to adverse weather and other factors, which could inform local transportation and infrastructure choices. This study adds to public understanding of why collisions, injuries, and fatalities occur so that road user education, awareness building, and public campaigns can be more effective in shifting individual behavior and choices to result in fewer harmful and costly outcomes, especially due to adverse weather, and so that local leaders can implement beneficial traffic control, enforcement, and emergency response policies.

Traffic Collisions in North Carolina: Weather, Human Factors, and Economic Analysis, 2013 to 2019

by
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DEDICATION

This thesis is dedicated to my partner, Nicole, and our daughters, Rose and Iris. Thank you, Nicole, for your love, your support, and your enthusiasm for my pursuit of a graduate education.

BIOGRAPHY

Iain Burnett received his Bachelor of Science degree in Mechanical Engineering from the University of California, Santa Barbara in 2009. Prior to entering the master's program in economics at North Carolina State University, he worked as a process and project engineer in various manufacturing fields. His primary interest is the overlap between engineered systems and infrastructure, our environment, and society.

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CHAPTER 1: BACKGROUND AND MOTIVATION

1.1 Introduction

Traffic collisions are the second leading cause of all-age accidental injury deaths in North Carolina, increasing from 1,284 fatalities in 2013 up to 1,482 in 2019 (NCDOT, 2022). Traffic fatalities, while alarmingly high, are only a small portion of the casualties of traffic collisions. Over this study period of January 2013 through December 2019 in North Carolina, a daily average of 707 collisions resulted in 333 injuries and 3.8 fatalities (NCDOT, 2022). The issue is complex and heterogenous, with daily traffic collisions ranging from an average of 0.25 per day in Hyde County to 96 per day in Mecklenburg County, with similar magnitudes of disparity for injuries (0.63 to 52 per day) and fatalities (0.0015 to 0.25 per day). The total social cost of these collisions amounts to over $84 million per day given the valuation of a statistical life, plus direct and indirect costs of collisions that include medical costs, vehicle damage, emergency response, and congestion, as well as lost quality of life and other welfare considerations (NCDOT, 2020). Importantly, North Carolina is a growing state and on average, the total number of collisions, injuries, and fatalities is increasing at a faster rate than the state's population.

Using extensive data sets from a variety of sources, this study seeks to identify the relative importance of explanatory factors that influence traffic collision, injury, and fatality rates. This information is then used to estimate the relative cost of these factors. Given North Carolina's proximity to the Atlantic Ocean and frequent occurrence of tropical storms, this study also seeks to understand if tropical storms and their forecasts are a significant factor.

Much work has been done on the factors associated with traffic collisions (hereafter "collisions" or "crashes") and the factors that can increase collision outcomes such as death or injury. This study will repeat these analyses using North Carolina data to determine if outcomes in this state are in line with previously studied effects. North Carolina provides an interesting and heterogenous environment for conducting such a study – the state is effectively split into three topographic regions with Blue Ridge Mountains in the western third, the Piedmont region in the center, and the Coastal Plain in the east. Among these regions are an effective mix of urban (n=30) and rural counties (n=70), with varying levels of economic well-being. These initial regressions will serve as a baseline for understanding and providing confidence in later analyses.

Moving forward, this paper will introduce a new set of explanatory variables regarding weather event lags. This concept is based on an anchoring effect seen in many areas of research, and tests the idea that in regards to severe weather and traffic collisions, people drive differently after the weather has passed (a short term behavioral modification). Finally, this study introduces a novel explanatory variable regarding tropical cyclone forecasts. Tropical cyclone forecast cones can cover hundreds of thousands of square miles across multiple states and even a minor bump in collision, injury, or fatality rates can lead to large absolute increases in negative outcomes due to the population affected. Given that people covered by a tropical cyclone forecast may never experience the storm (a Type 1 error), these effects may be overlooked when it comes to assessing the actual cost of tropical cyclones.

This study first reviews the magnitude of traffic collisions globally, domestically, and specific to North Carolina. Then, the study reviews ways that society is trying to address and mitigate this issue. Next, the study examines relevant previous literature to identify factors that affect collision frequency and outcomes of death or injury, as well as relevant studies relating to tropical cyclones and the general public’s ability to interpret weather forecasts, as these may both factor into traffic collisions. Next is a discussion on the theoretical approach and model used for analysis and a primer on how to interpret results. The following section covers data and methods, including sources and how explanatory variables link to outcome variables. Next is the study's analysis and results, with discussion of explanatory variables and fixed effects. The last sections provide economic implications of results, followed by caveats, limitations, suggested areas for future research, and concluding thoughts.

1.2 Magnitude of Traffic Collisions Globally and Domestically

Nearly all countries face significant issues with traffic collisions and their resulting injuries and fatalities. Low-income countries face total injury costs amounting to roughly 1% of their gross national product, while middle- and high-income countries have injury costs roughly equal to 1.5% and 2% of their GNPs, respectively (Alemany, 2013). In their 2004 report, the World Health Organization identified traffic collisions as the 2nd leading cause of death worldwide among 5-29 year olds, the 3rd leading cause among 30-44 year olds, and the 11th leading cause of death for all ages (Dalvi, 2004). Updates in 2010 moved traffic collisions to the 9th leading cause of death for all ages, with projections that the trend would continue and by 2030 traffic collisions would be the 5th leading cause of death (Saunier, 2011). Traffic casualties are unique among the other leading causes of death such as cardiopulmonary diseases, cancers, diabetes, and transmissible illnesses such as malaria and tuberculosis, in that a large portion of injuries and deaths are among otherwise young and healthy people, especially males. Factoring in lost human capital and the household impacts of losing a young wage earner pushes the total social cost of traffic collisions and their resulting casualties much higher.

Compared to other high-income nations, the United States has roughly double the traffic fatality rate and has not made substantial improvements over the last two decades (Ecola, 2018).

Domestically, a 2015 study from the National Highway Traffic Safety Administration found that in 2010, traffic collisions were responsible for 32,999 fatalities, 3.9 million injuries, and 24 million damaged vehicles over 13.6 million crashes (NHTSA, 2015). These had direct economic costs of $242 billion, or 1.6% of GDP; factoring in quality of life reductions from short term, long term, and permanent disability, as well as the loss of loved ones, brings the total social cost to $836 billion. The study estimates that 60% of property damage only (PDO) crashes and 24% of injury crashes are not reported to the police, meaning that the previously mentioned direct and total social costs can be considered low bounded estimates. A more recent report indicated that in 2019 some 36,355 people were killed and 2.7 million people were injured in traffic collisions; both of these categories displayed similar trends of large annual increases between 2013 and 2016, followed by smaller annual reductions between 2017 and 2019 (NCSA, 2022).

1.3 Summary of Issue in North Carolina

Following a pattern seen around the world, in 2019 traffic collisions were the second leading cause of injury deaths for all ages in North Carolina after poisoning (a category that includes medicine and drug overdoses). Broken down by age group, collisions were the leading cause of injury death for ages 1-24 and the second leading cause of death for ages 25 and over (NCHHS, 2021). The circumstances and causes of traffic fatalities and injuries are myriad. For a sample of how heterogeneous the problem is, of the 1,482 people killed in traffic collisions in North Carolina in 2019: 18 were bicyclists, 183 were motorcyclists, 32 were moped or motor scooter riders, and 231 were pedestrians (NCDOT, 2020). Broken down by driver and passenger characteristics, the state report found in the same year that 25.6% of fatalities involved speeding, 23.7% involved alcohol use, 43% of vehicle occupants killed were unbelted, 10.5% involved distracted drivers, and 55.4% involved lane departures. Figure 1.1 gives a year-by-year overview of the collisions, injuries, and fatalities in the state.

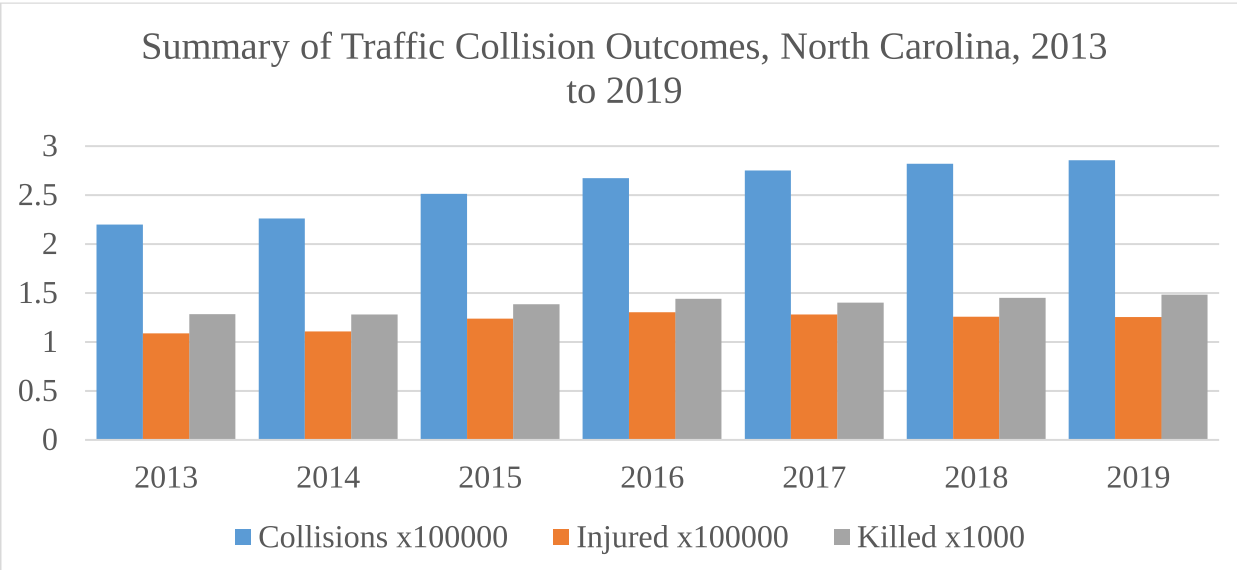

Figure 1.1: Summary of collisions, injuries, and fatalities by year. Collisions and injuries are measured in hundred thousands; fatalities in thousands.

In North Carolina during 2019, traffic collisions were responsible for 17.7% more fatalities than firearms, with 1,567 motor vehicle trauma fatalities compared to 1,331 firearm based self-inflicted or assault fatalities (NCHHS, 2021). However, violent crime and gun policy were both majority issues during the 2022 midterm elections while vehicle fatalities did not make the top eighteen list of concerns for the US electorate (Schaeffer, 2022). The World Health Organization report made note of the dilemma that in many cultures and communities, traffic collisions and their resulting deaths and injuries are seen as an inevitable cost of using roadways, and therefore are not looked at as a problem to be solved (WHO, 2021).

Collisions and their resulting injuries, fatalities, and associated costs are a significant financial burden for the state. In economic terms, the North Carolina Department of Transportation estimated the cost of traffic collisions in 2019 was $30.8 billion, based on an average cost per crash of $82,396. Looked at a different way, collisions cost the state $3.5 million per hour (NCDOT, 2020). Relative to North Carolina's all industry total GDP of $594 billion in 2019, the direct costs of traffic collisions are an annual burden valued at more than 5% of the state's economy (USBEA, 2023).

Collision outcomes are also heterogeneous across North Carolina's 100 counties, likely prohibiting any attempts to address this issue with a one-size-fits-all solution (NCDOT, 2022). During 2019, collision rates varied between 11.69 and 39.85 collisions per thousand people, with the two highest rates coming in Jones County (population 9,311) and Mecklenburg County (population 1,107,514). Injury rates varied between 3.67 and 19.0 injuries per thousand people, with high rates showing up in low-, mid- and high-population counties. Fatality rates ranged from 0 to 0.75 fatalities per thousand people, with many of the highest rates in low population counties. A full summary of population weighted collision rates can be found in Appendix B.

1.4 Social Efforts to Address Traffic Collisions

As it stands, road traffic crashes are the leading killer of children and young adults worldwide. Globally, both the United Nations and the World Health Organization have committed to the "Decade of Action for Road Safety 2021-2030." Their goal is to meet the United Nations Sustainable Development Goal to ensure healthy lives and promote well-being for all at all ages by reducing traffic injuries and deaths in half by the year 2030 through improvements to roads and vehicles, laws and law enforcement, and emergency care for the injured (UN, 2020; WHO, 2021).

As an example of how this may play out, in 2000 the government of the Spanish region of Catalonia responded to the EU's call for safer roads and implemented new policies intended to cut traffic collision fatalities in half by the year 2010. These policies included: lowering traffic speeds; reducing alcohol use and driving; improving infrastructure and adding road safety equipment such as speed cameras; public education campaigns; and an increased police focus on road safety combined with the criminalization of certain traffic offenses. Over a ten year period, it is estimated that the new road safety policies led to 26,063 fewer collisions and 2,902 fewer fatalities (a 57% reduction). Total social cost savings amounted to 18 billion euros (in 2011 values). While some aspects of the policy backfired (such as an increase in motorcycle collisions and injuries), and others were repealed due to popular demand, the program as a whole brought many benefits (Garcia-Altes, 2013).

Locally and globally, many governments are embracing a longer term, ambitious "Road to Zero" program with aims to eliminate all traffic fatalities by 2050. Sweden has achieved 50% traffic fatality reductions through its adoption of Vision Zero, and more than 45 communities in the United States (including the cities of Durham and Charlotte in North Carolina) have publicly adopted Vision Zero policies that implement known solutions, involve diverse stakeholders, and prioritize behavioral shifts among the public and government agencies involved (Ecola, 2018). While that work proceeds, there is still a recognized need to research and study road traffic safety interventions to identify what works under what conditions, as four decades of road safety advances have left substantial knowledge gaps in the field with occasionally conflicting results (Mohan, 2020).

1.5 What This Study Adds

Traffic is a complex, multivariate system due to heterogenous types and qualities of roadways, vehicle traffic overlap with non-vehicle road users, variable weather conditions, and variable driver performance. This study makes use of county-level, daily data for all hundred counties in North Carolina, allowing for examination of state level outcomes and differences among counties. In total, the study answers four questions in the affirmative:

1. Can traffic collision outcomes be modeled?
2. Are there leading and lagging effects related to weather factors?
3. Are there identifiable factors that make traffic collisions predictable?
4. Can costs be assigned to these weather and human factors?

These results can be used as the cost of the status quo, while also creating a benchmark for the benefits of addressing traffic collisions. Given the identifiable and often predictable nature of weather, these results may also inform policy considerations and outreach strategies for government leaders, transportation and public safety departments, emergency managers, and healthcare providers to help prevent or mitigate the negative outcomes of collisions.

1.5.1 Comprehensive Analysis of North Carolina Traffic Collisions, Injuries, and Fatalities

In line with the goals of Road to Zero and Vision Zero programs, this study provides a comprehensive analysis of variable and fixed effects associated with traffic collisions, injuries, and fatalities in North Carolina. While similar studies have been performed before, North Carolina provides a useful stage for analysis due to its four distinct seasons and wide range of extreme weather events (including tropical cyclones), terrain that stretches from mountains to barrier islands, and county population densities ranging from less than 10 people per square mile to more than 2,000 people per square mile.

1.5.2 Incorporation of New Explanatory Variables for Traffic Outcomes

Beyond providing actionable data for North Carolina communities, this study adds hypotheses testing two explanatory variables that are potentially novel to traffic studies. The first is a weather event lag variable, which looks at the presence of major weather events over the past seven days as an explanatory variable for traffic collision outcomes today. The hypothesis is that adaptation leads to fewer collisions and related negative outcomes after any adverse weather event, a beneficial 'lag effect.' The second new explanatory variable set is around tropical cyclone forecasts. The hypothesis is that tropical cyclone forecast stress leads to more collisions and related negative outcomes ahead of cyclone arrival, independent of the ex post cyclone arrival. This will be determined by a county's presence inside or adjacent to a National Hurricane Center forecast cone. A suggested effect is shown in Figure 1.2 for both hypotheses, though it should be cautioned that the y-axis is unitless and is intended only to show direction and magnitude of effect.

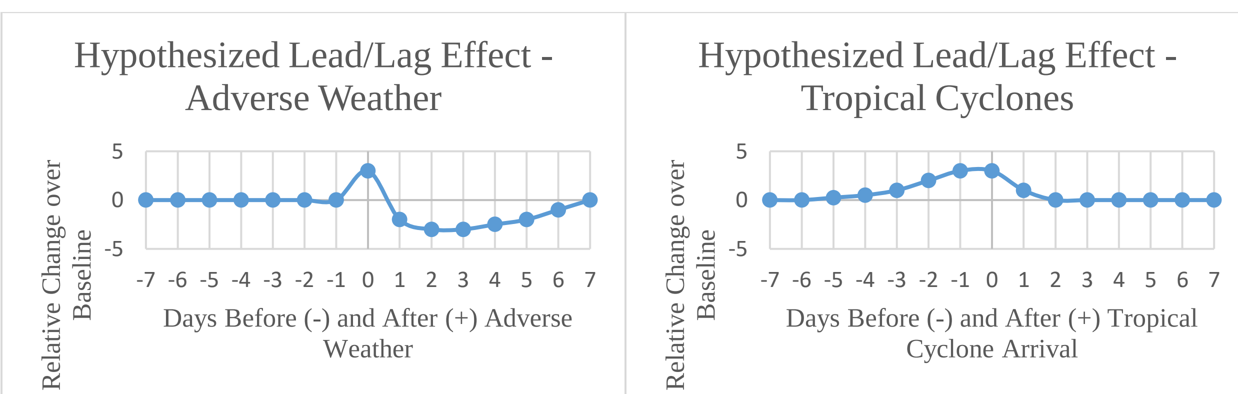

Figure 1.2: Hypothesized Lead/Lag Effects: Adverse Weather, and Tropical Cyclones

CHAPTER 2: LITERATURE REVIEW

2.1 Studies Identifying Traffic Collision Factors

Traffic studies are a well-established area of research, with research done from units of analysis as large as countries to as small as a single intersection or crosswalk. These are typically done to explain why a traffic event happens or does not happen, or why an event of interest happens more or less on one day or time than another. This section includes a review of relevant studies that help to directly identify explanatory variables or provide plausible pathways for explanatory variables that are used in the study's analyses.

2.1.1 Weather

Weather events are an obvious source of variation in driving ability and vehicle performance. Rain or snow can reduce road friction and visibility, and can be a source of road ice if it precedes subfreezing temperatures. In significant enough volumes, or in certain topographies, rain can also lead to puddling or flooding of roads, which can have dramatic effects on vehicle performance. Wind can destabilize or blow vehicles off the road or into other traffic. Tropical cyclones and thunderstorms typically combine many of these factors into one event – thunderstorms tend to arrive quickly as fronts or individual cells, while cyclones are vast but arrive relatively slowly. Despite the seemingly obvious negative effects of weather on driving ability, weather-related crashes are relatively common. A report found that 24% of US highway crashes were weather-related, with respondents identifying visibility, traction, stopping ability, and vehicle control as primary collision factors. Of concern, approximately one third of drivers surveyed do not reduce their speeds during rainfall (Pisano, 2008).

Rain and snow are particularly common hazards with traffic collisions. At a macro level, a study of traffic collisions in the contiguous United States between 1975-2000 found significant relationships between precipitation and collision outcomes. The first is that rain has a monotonically increasing effect on the number of traffic collisions, property damage only (PDO) collisions, injury collisions, and fatality collisions, though interestingly, very light rain (less than 0.02 inches) actually decreases fatal crashes. Snowfall exhibits an inverted-U relationship, with a low positive effect for all categories under light snow, the highest collision, injury, and fatality counts at moderate snowfall (up to 0.78”), and a negative relationship for high snowfall and PDO, injury, and fatal collisions. Unsurprisingly, total collision counts increases monotonically for snowfall.

Rainfall also exhibited two interesting lagging effects on collision outcomes. The first is that rain yesterday (but not today) decreases collision fatalities today, arguably because it cleaned the roads. The second is a lag effect that outcomes on rainy days are affected by days since last rainfall, with increasing collision, PDO, injury, and fatality counts based on the number of days since last rain – the proposed mechanism is that oil, dust, and other debris accumulates on the road over time and creates traction hazards when wet (Eisenberg, 2004). A study from Canada found that traffic collisions increased by 50 to 100 percent on days with precipitation, with stronger effects from winter weather such as snow, sleet, or freezing rain. Of note, precipitation events can be short lived and so a doubling of daily counts might correlate to a much larger collision rate increase during the precipitation event (Luo, 2017). A similar conclusion was made in a study that found snowy days in the United Kingdom led to 25% more collision injuries and fatalities, but when correlated to traffic volumes, collision rates were actually increasing by 100%. In Iowa, more crashes and more severe crashes happened on the first snow day of the year, more multivehicle crashes happened in rain and especially on highways, and on rural highways, moderate snowfall increased the collision rate by 13x.

Precipitation combined with wind can exacerbate negative outcomes. Combined snowfall and high winds (up to 40mph) led to collision rates 25x higher than Iowa's baseline (Maze, 2006). A study in central Canada evaluated the interaction of strong winds with rain and snow, and found that wind and precipitation together produced higher rates of negative traffic outcomes than either factor alone. Snowfall leads to more negative outcomes than rain, while both types of precipitation showed similar patterns of a relatively constant outcome rate until some threshold was passed (i.e. inches per hour of precipitation), at which point negative outcome rates increased rapidly. Although rare in the study area, very low visibility from mist or fog was associated with the highest outcome rates (Pennelly, 2018).

Wind can present hazards on its own. A study from southern California found that strong wind without rain increased collision rates and doubled traffic collision fatalities. The proposed mechanism was two-fold: first, that wind itself makes vehicles more difficult to control, and second, that wind picks up dust from nearby agricultural and desert regions and reduces visibility (Bhattachan, 2019). Beyond visibility issues, the visual distraction of dust, plant material, or other debris blowing onto the road can potentially cause drivers to swerve, stop, or take other potentially unnecessary corrective action. In addition, high wind may cause tree and tree limb falls, especially in cold or wet weather, presenting hazards to vehicles. According to the Beaufort Scale, small light objects such as leaves, paper, or plastic bags can be blown by winds as slow as 13mph, winds of 39mph can break branches off trees and cause cars to veer in motion, and winds greater than 55mph can uproot trees (NWS, 2023).

Beyond the direct effects of rainfall on roadways, rain also creates a lag effect through flooding. A study from an urban area in China found that the strongest traffic outcome effects occurred in the first “dry” hour after two hours or more of rainfall, that the effect increases for the heaviest rainfall, and that the effect is strongest if the “dry” hour occurs during morning or afternoon commutes (Zhu, 2018). This makes intuitive sense if people judge driving conditions based on current weather, without considering that past weather (rainfall) caused puddling and flooding on roadways. An indirect pathway for floods to impact traffic collisions is through road closures, as drivers, pedestrians, and bicyclists may be routed onto roads they are unfamiliar with, and where they face increased congestion.

2.1.2 Wildlife and Animals

A sometimes overlooked cause of collisions is wildlife and other animals on roadways. There are typically more than two million deer-vehicle collisions in the United States each year with a price tag in the billions of dollars, responsible for hundreds of fatalities and tens of thousands of injuries (Cunningham, 2022). Deer tend to make up the majority of animal-vehicle collisions, with one study in Texas pegging deer and other wildlife as involved in 64% of such collisions, and domestic animals such as cattle and dogs making up 31% (Wilkins, 2019). Interestingly, this study suggests that daylight savings time is partly responsible for collisions due to shifting more commute times to dawn and dusk when deer are most active.

As loose cattle and other livestock are relatively rare in the United States, at least in densely populated and highly traveled areas, and dog impacts seem less likely to result in major injuries or fatalities, most studies have attempted to identify relevant factors for deer-vehicle collisions. One study evaluating these such deer-vehicle collisions across the United States between 1995 and 2004 found that the most likely factors leading to a fatal collision (for a person) are for the collision to occur in a rural county, in the fall, on straight roads with speed limits of 55mph or higher, and with clear weather. Up to 90% of the collisions happen between dusk and dawn. Of interest to this study, North Carolina averaged four fatal deer-vehicle collisions each year between 1995 and 2004 (Langley, 2006).

Of concern, the nationwide animal crash rate is increasing, which could be indicative of more deer, suburban buildup, or other traffic changes. A study from Canada found that deer-vehicle collisions are more frequent near suburban areas where people provide reliable food sources to deer, both intentionally or unintentionally by landscaping. This study also found that 50% of these collisions occur during the mating season, between September and December (McCance, 2015). A similar study identified suburban regions interspersed with forest, grassland, or agriculture as prime locations for deer-vehicle collisions (McKee, 2012).

2.1.3 Urban/Rural Factors and Population Density

Population density has many direct and indirect effects on road safety, and previous research has identified the differences in frequency and severity of traffic collisions in urban, suburban, and rural areas (Clark, 2004). In the simplest terms, suburban and rural roads tend to be more dangerous because of higher speed limits and higher per capita distance traveled, while urban travel is typically done for less miles at lower speeds (Ewing, 2009). A similar study in Indiana examined the difference between urban, exurban, and rural collision rates; there was no clear pattern between density and rates, but some indication that counties with large draws (e.g. a casino) or exclusively rural road types may have more collisions, including more fatal collisions, while being in or next to an urban center might mediate driver behavior (Nunn, 2015).

2.1.4 Congestion and Traffic Volume

Traffic volume variations within counties or regions can lead to changes in collision outcomes. A study of highway traffic in France found that the lowest traffic collision rates occurred during flows of 1000-1500 vehicles per hour, then increased steadily up to 3000 vehicles per hour (Martin, 2002). A recent study from New York City found that traffic volume and collisions trend together with an elasticity of 1.2 to 1.7 (Cappellari, 2022). A similar study performed after London introduced congestion charges found that reducing travel also reduced collision rates, and this had a positive spillover effect to nearby regions that also saw decreased traffic volume and decreased collisions (Green, 2016). Globally, COVID-19 caused major changes in traffic volumes and this natural experiment allowed researchers to confirm this elasticity across urban and suburban regions (Yasin, 2021).

Weather can indirectly impact traffic volumes through evacuation orders, emergency declarations, or business and school closures. A study using data and simulations of a hypothetical full evacuation of a coastal Virginia region found that collisions would likely increase but at a slower rate than the increase in traffic volume (Robinson, 2018). Winter storms can reduce traffic demand by 7% to 56%, with the larger reductions for discretionary travel outside of commute hours and heavier precipitation rates. In Iowa, snow and low winds can reduce travel volume by 20%, while snow plus high winds reduce volumes by 80%. Of note, commercial vehicles are much less likely than passenger vehicles to defer their travel during inclement weather. Weather can also affect traffic volume due to behavioral adjustments. Drivers tend to increase the distance between them and the next car in response to inclement weather, which can decrease a road’s carrying capacity (Maze, 2006). Rain, ice, and snow all increase congestion, and when collisions do occur they can involve more vehicles at once (Lu, 2020).

Congestion can also cause drivers to seek other routes where they may be less familiar of conditions, pedestrian crossings, or typical entry and exit areas for vehicles.

2.1.5 Terrain Type and Road Design

Civil engineers are now responsible for designing roads, though in the United States many roads evolved over hundreds of years of use by wagons, horses, and slower vehicles of the early 20th century. Some older cities were nearly entirely built for pedestrians, horses, and bicycles, and only recently adapted for vehicles. Rural roads can be excessively twisty or steep with limited sightlines, or entirely straight and flat with few visual reference points for judging distance and speed. While this study does not incorporate any data on road design, there are some overall patterns worth mentioning.

In recent years communities have embraced traffic-calming measures, an effort strongly boosted by the pandemic and renewed interested in reclaiming roads for pedestrians and cyclists. These re-engineered roadways tend to have narrow lanes, intentional obstructions, and roadside trees that are intentionally “unforgiving” for drivers. Forcing drivers to go slower and be more aware tends to result in lower collision rates than standard “wide-open” streets (Ewing, 2009). Of note, the beneficial effect of roadside trees on collision rates is speed dependent – at higher speeds, roadside trees actually lead to higher collision rates with worse outcomes (Wolf, 2006).

Road topography also has a large impact on collision rates. A pair of studies from Malaysia, where there are a large amount of heavily used mountain and non-mountain roads, found that single car crashes were more prevalent in the mountains. Horizontally sloped roads, that is where the road slopes to the side, were consistently associated with higher collision rates and these sloped roads are more commonly found in mountain areas (Musa, 2020; Rusli, 2017).

2.1.6 Holidays and Calendar Factors

Not all days are created equally for traffic collision rates. With equivalent high traffic volumes, weekdays have higher collision rates than weekends (Martin, 2002). A study in Canada found that holidays lead to higher rates of rural collisions, multivehicle collisions, and out-of-towner collisions, but fewer speeding-related or alcohol-related collisions (Anowar, 2013). The week after daylight savings has likewise been found to be statistically significant when it comes to impacting traffic collisions, with 19% more collisions than expected found in the United Kingdom (Raynham, 2020).

2.1.7 Stress

Stress is another factor connected with negative consequences in traffic outcomes. For the purposes of this study, fear is interchangeable with stress – both are psychological and physical responses to external stimuli (APA, 2020). In decision making contexts, stress tends to induce risk-taking (Hengen, 2021). With driving, stress levels from occupational or personal concerns increase collisions and are significantly correlated with fatal accidents, while increasing levels of job satisfaction, personal relationship satisfaction, mental health, and physical health have negative correlations with traffic collision rates (Cartwright, 1996).

Stress also plays a significant role in increasing at-fault crashes, an effect more prominent in high risk drivers who do not accurately assess driving conditions and their emotional state. For drivers with low emotional awareness, stress may worsen driving performance and reduce the likelihood of taking beneficial advice about driving conditions or dangers. This is true for generalized stress levels, but has a very large effect for heightened emotional states from current life events at home or work (Legree, 2003). In a similar vein, emotional states correlate with risky driving and low perception of risk, while emotional regulation, which is similar to emotional awareness but adds in skill at self-regulation, is linked with safer driving behaviors and fewer negative traffic outcomes such as risk taking or traffic violations (Baltruschat, 2021). Interestingly, stress about daily economic conditions unrelated to an individual's personal finances can also create short term increases in collision rates (Vandoros, 2018). In a similar vein, acute stress has negative effects on task performance for medical professionals (LeBlanc, 2009). Stress of any form can reduce performance, including with driving.

2.1.8 Distraction

In a technologically connected world, distraction is a major issue. Correlations have been found between texting rates and traffic collisions, often for single car/single occupant collisions (Wilson, 2010). The United States experienced a 52% increase in fatal pedestrian-vehicle collisions between 2009 and 2019, an effect attributed to increased distraction by driver and pedestrian (Schwebel, 2021). Over the same time period, smartphone penetration in the United States grew from 20% to over 70% of the population (O'Dea, 2020). Of note, device distraction can be cognitive, visual, and/or auditory, with impacts to driver awareness, gap acceptance, and cognitive abilities. Visual distractions have the largest impact on lateral control measures (i.e. steering ability), while cognitive distractions most strongly affect visual scanning behavior, with corresponding reductions in reaction time (Papantoniou, 2017). Technology-based cognitive distractions such as checking a phone screen or changing the radio also tend to lead to higher speeds among drivers, which compounds the effects of lower awareness and higher tolerance for a close gap to the next vehicle (Garcia-Herrero, 2021).

However, not all distractions are technology based. A survey of forty-four drivers hospitalized by traffic collisions found that nineteen were distracted by phones, twelve were deep in thought, six were talking with other passengers, four were picking things up, and three were adjusting their radio. This is evidence that even when distractions do not take a driver's eyes off the road, thinking increases cognitive load, leading to more traffic collisions (Engstrom, 2018; Razi-Ardakani, 2018). Outside of the context of driving, increased cognitive load is also associated with higher rates of occupational injuries (Bonsang, 2021). If multiple drivers, or driver and pedestrian or cyclist are distracted, it could follow that collision rates increase.

2.2 Studies Identifying Factors for Traffic Collision Injuries and Fatalities

Collisions on their own have a broad impact, but unfortunately many collisions also involve injuries or fatalities. Despite absolute declines between 1999 and 2019, largely driven by the period between 1999 and 2006, vehicle collision fatality rates have increased since 2010 (Spencer, 2021). This section reviews studies that have previously identified factors leading to higher rates of injury or fatality.

Across America, population density is negatively correlated with fatal collision rates and urban areas consistently have the lowest per capita fatality rate (Clark, 2004). Urban areas also tend to have a unitary elastic response between traffic volume and collision fatalities, while rural areas have an elasticity of 1.5, meaning that every unit increase in traffic volume leads to a 1.5 unit increase in fatal collision rates (Ewing, 2009). Mountain roads tend to be in rural regions, and these also have fatality rates 16% higher than non-mountain roads (Rusli, 2017).

The COVID-19 pandemic created a natural experiment in terms of dramatically reducing the number of vehicles on the road. In general, fewer vehicles led to higher speeds and higher injury and fatality rates across the globe (Yasin, 2021). When calculated out, the effect was so striking that the social cost of congestion in NYC was lower than the social cost of increased traffic injuries and fatalities during pandemic lockdown periods; however, this effect was nonlinear and heavy congestion is required to reduce the fatal collision rate (Cappellari, 2022).

In a study of European traffic collision fatalities, low and middle-income countries have higher fatality rates (21.5 and 19.5 per 100k, respectively) than high-income countries (10.9 per 100k), and within countries, rural areas have higher fatality rates while urban areas have higher collision and injury rates (Cabrera-Arnau, 2020). Across the US results are similar, with no difference in collision fatality rates when commercial vehicles are involved compared to any other vehicle type (Pisano, 2008). In a study from Ecuador, weekends were found to have the highest fatality rate and pedestrians made up 22% of those killed (Algora-Buenafe, 2017). In terms of driver age, increasing fatality rates for young male drivers has been the primary factor in overall fatality rates increasing, while fatality rates for adults older than 70 has been dropping primarily due to safer cars (Spencer, 2021; Cox, 2021).

In the United Kingdom, more pedestrian injuries and fatalities occur on minor urban roads where sidewalks may be less common (Aldred, 2019). In the United States, pedestrian fatalities increased by 40% between 2009 and 2016 after decades of improvement, with the worst-case factor being a male walking in the dark on a fast (>35mph) multilane roadside away from intersections (Schneider, 2020). The pedestrian injury rate increases even more in the week following daylight savings (Raynham, 2020). In a study of twenty states, warmer weather decreases non-fatal accidents and increases fatal accidents, presumably because of an increase in pedestrians, cyclists, and motorcycles on roadways (Leard, 2015).

Most relevant to this study, weather plays a major role in the outcomes of traffic collisions in terms of injuries and fatalities. Between the years 1994 and 2011, annual weather-related traffic fatalities were an order of magnitude higher (6911 vs 571) compared to all other weather-related fatalities, including direct exposure to tornadoes, floods, tropical storms, lightning, heat, cold, riptides, and high winds (Ashley, 2015). Highways and poor lighting conditions increase the odds of an adverse weather collision resulting in a fatality, and more than half (65%) of weather-related fatalities occur between November and April. Surprisingly, traffic fatalities during adverse weather are negatively correlated with alcohol/drug use, not wearing a seatbelt, or speeding (Saha, 2016). These factors indicates that road conditions plus vehicle and driver performance are likely culprits, and therefore can be correlated with weather variables.

2.3 Studies Evaluating Tropical Cyclones' Effect on Stress and Health

Hurricanes and tropical storms get people's attention in a way few other weather systems or natural disasters can. Often long before landfall, these spiraling tempests get daily and often continuous "wall-to-wall" coverage on local news (Daniels, 2007). The standard graphic with any news update is the five day forecast cone, showing the cyclone's current location, its projected path and growth over the next 120 hours, and a cone showing all probable paths. Updates are often accompanied by satellite or radar imagery of the storm, and after landfall, with live videos of waves crashing against seawalls and trees bending in the wind. These displays of nature are 'awesome' in the literal sense as "causing feelings of great fear". As communities spring into action, news coverage adds vignettes of people filling sandbags, boarding up windows, and panic shopping at home improvement stores or supermarkets.

Fear holds attention in a primal way, and framing a news story in the context of fear is no recent innovation (Altheide, 1997). Tropical cyclones seem ready made for this presentation, as severe storms rank among the most strongly feared phenomenon for Americans (Bacon, 2012). On top of this, tropical cyclones are unique among natural disasters in that they are given common first names, an anthromorphism that render a sense of familiarity and agency that adds to their emotional punch; this effect is further heightened by journalistic sensationalism in coverage of tropical storms (Parc, 2019). Ex post, many areas covered by a forecast cone are either spared from the worst weather or missed entirely. Ex ante, no rational agent knows where the cyclone will actually go and thus reacts as if the threat were certain – this “cry wolf” phenomenon carries deep costs by bringing the psychological burden of a discrete future event to the present (Breznitz, 2013). This concept holds in weather forecasts, and when a person is only provided with an upper bound worst-case scenario for future conditions, they hold a biased understanding and anchor in their belief that the worst-case will happen (Joslyn, 2011).

Studies on the effects of tropical cyclone forecasts are rare, but one found a negative effect on pregnancy outcomes due to time spent in a forecast cone, independent of the actual arrival of a cyclone (Hochard, 2022). More commonly, research looks for connections between actual incidence of tropical storms with health and economic impacts. These impacts include direct and indirect damages, plus increases in injury-induced fatalities, nonfatal injuries, non-injury mortality from cardiorespiratory disease and infections, and mental health episodes during and after the event (Kousky, 2014; Yan, 2021; Merdjanoff, 2022). Tropical cyclone exposure is also associated with increased hospitalization in older adults (Parks, 2021). Increased mortality has been found to extend after a tropical cyclone (Parks, 2022). Injuries and fatalities from flooding associated with tropical cyclones are well documented (Czajkowski, 2011). Hurricane and tropical storm arrival can also reduce housing stock, leading to fewer transactions at higher prices (Graff Zivin, 2023). Most of these studies only evaluated direct or lagging effects and have not looked at leading effects, though some or all of these factors may be on the general public's minds when a cyclone is on the horizon, potentially increasing cognitive load and stress.

For the 2-3% of Americans affected by a clinical phobia of storms (including thunderstorms, hurricanes, snowstorms, wind, and rain), symptoms can present themselves five to seven days before the weather system's predicted arrival (Coleman, 2014). For the general population, media coverage of a tropical cyclone's approach can lead to non-trivial amounts of stress, which can linger after the cyclone passes (Thompson, 2019). Acute stress from a tropical cyclone can both instigate and worsen mental health conditions (Espinel, 2019). Even for individuals that are not stressed, cyclones are disruptive to everyday life and preparations may require non-standard planning. Work and personal trips might need to be cancelled or shifted. Arrangements made need to be made for friends and relatives, especially for the elderly and those in a coastal or flood plain zone. Normal activities may require more thought given the situation. All of these factors may contribute to increased traffic collisions through the pathways of cognitive load, stress, and distraction combined with traffic congestion.

2.4 Studies Evaluating Public's Ability to Interpret Weather Forecasts

It is safe to assume that most adults have experienced driving in inclement weather, and given the high quality of modern weather forecasting, how is it that weather-related traffic collisions are still an issue? There is some evidence that people are biased towards believing that the worst-case weather forecast will come true, though being provided with uncertainty estimates and ranges helps improve prediction accuracy (Nadav-Greenberg, 2008). Bias and inflexibility potentially explain why people are still “caught unaware” by weather that they fully knew was coming. Anchoring effects are a bias that the future will mirror the present, and even when people know of a forecasted adverse weather event, they behave and plan based on the weather at the moment (which may not be adverse); on top of this, the anchoring effect creates a sort of psychological buffer that makes it a challenge to adapt quickly when the forecasted weather arrives (Givi, 2019). A study performed in the context of weather forecasts and driving exemplifies the issue, finding that even when drivers are given an accurate forecast for weather conditions over their planned route, they make few (if any) adaptations and do not adjust their driving style or route until the adverse weather is upon them (Kilpelainen, 2007). This may explain why improvements in weather forecast quality and availability, including emergency alerts via smartphone, have so far not led to a dramatic decrease in weather related traffic collisions, injuries, or fatalities.

As discussed previously, tropical cyclones create a unique psychological effect that is likely amplified by media coverage. The five day forecast cone is the standard information source to the public during tropical cyclone coverage and has been for the past decades, and yet the public frequently misinterprets it (Broad, 2007). This may partly be due to challenges with uncertainty, or issues with the graphic and accompanying reporting. In reality, tropical storms are dynamic systems dependent on oceanic and atmospheric conditions which themselves are dynamic. After each year’s hurricane season which runs from June to November, the NWS calculates and reports the track error for each storm by comparing forecast positions to actual positions – these values are averaged with the previous four years information to generate the uncertainty radius for the next season’s forecast cones (Cangialosi, 2022). On all time horizons (24hr, 48hr, 72hr, 96hr, and 120hr), as shown in Figure 2.1 this forecast accuracy has improved more than two-fold between 2003 and 2022 with current forecast cone radii measuring approximately 230 nautical miles at five days out and 45 nautical miles one day out. Despite these improvements, tropical cyclone forecast cone areas are typically hundreds of thousands of square miles (for reference, all of North Carolina is around fifty thousand square miles). Interestingly, cyclones often have radii many times larger than the one day forecast cone – hurricanes tend to be more compact and powerful (though still hundreds of miles wide), while tropical storms tend to be even larger with winds and heavy rain felt for hundreds of miles in any direction from the eye. These sometimes conflicting factors mean that many of the people initially warned by inclusion in a forecast cone will not experience the cyclone, some will experience the cyclone as predicted, and still others will experience the cyclone without ever being included in a forecast cone.

Arguably the largest decision a household needs to make in light of a tropical cyclone is whether to evacuate or not, especially for coastal and flood-prone areas. Evacuations are costly for individuals and communities, potentially biasing evacuation orders (Whitehead, 2003). Underlying this cost of evacuation is the benefit of lives saved, and a finding that individual risk of fatality in coastal counties rises sharply with cyclone strength and disregard for an evacuation order (Czajkowski, 2010). Regardless of an evacuation recommendation or order, households must perceive risk to decide to go (Dash, 2007). Of note, when evaluating a tropical cyclone forecast the public may put more weight on the track line than the error cone, and may reduce preparations even when their county is still within the possible field of impact (Sherman-Morris, 2017). Tourists use a similar decision making scheme as households, but those with less experience with tropical cyclones tend towards a higher belief in risks (Cahyanto, 2014).

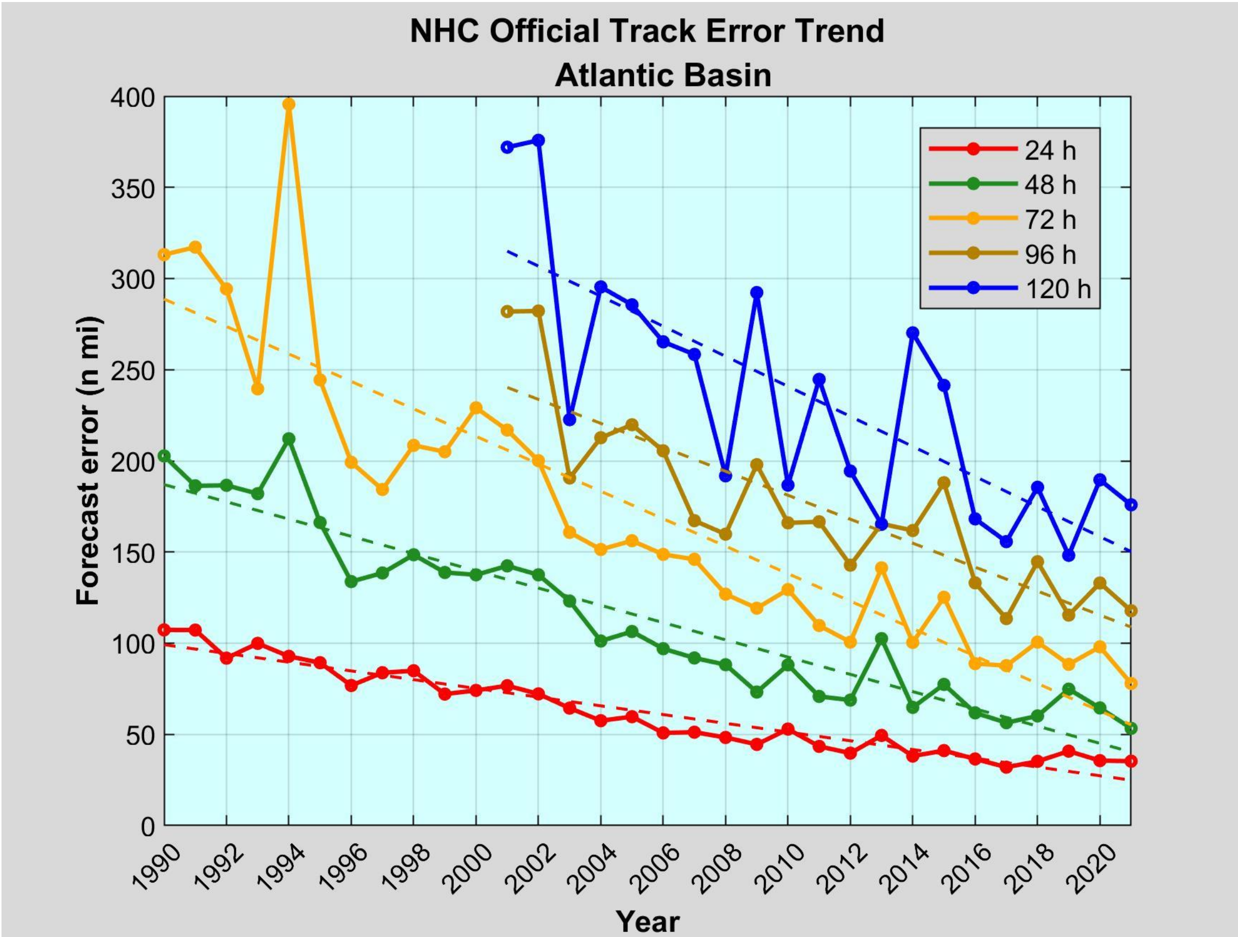

Figure 2.1: Improvements and limits of tropical cyclone forecast error, by days until arrival.

All of this indicates that the public does pay attention to approaching tropical cyclones, that they do consider the risks, and that they may adjust their behavior based on a personal decision-making framework – these are all strong indications that tropical cyclone forecasts are on people's minds, and either are a source of stress, or at a minimum, a source of cognitive load and distraction.

CHAPTER 3: THEORETICAL APPROACH AND MODEL

3.1 A Regression Model for Traffic Collision Data

Traffic studies are an established branch of research, and much work has been done to progress the accuracy and explanatory power of models used for predicting. As traffic collisions, injuries, and deaths are (integer) count data that cannot take negative values, Poisson regressions were used for many years with good results (Coxe, 2009). As units of analysis got smaller, Poisson regressions fell out of favor with researchers due to less time-smoothing and resulting data more likely to be overdispersed with a variance larger than the mean, while under a Poisson distribution mean and variance are assumed equal. As seen in Table 3.1, variances in this study are larger than means for collisions, injuries, and fatalities, providing evidence of overdispersion among the three outcome types.

Table 3.1: Summary statistics for collision, injury, and fatality data in North Carolina, 2013 to 2019 (n = 255,600 county-days).

Collisions		Injuries		Fatalities	
Percentiles		Percentiles		Percentiles	
1%	0	1%	0	1%	0
25%	1	25%	0	25%	0
50%	3	50%	1	50%	0
75%	7	75%	4	75%	0
99%	87	99%	41	99%	1
Min	0	Min	0	Min	0
Max	410	Max	128	Max	6
Mean	7.074	Mean	3.339	Mean	0.038
Std. dev.	14.47	Std. dev.	7.36	Std. dev.	0.216
Variance	209.4	Variance	54.1	Variance	0.047
Skewness	5.624	Skewness	5.512	Skewness	6.875
Kurtosis	45.4	Kurtosis	43.6	Kurtosis	65.2

A natural progression from Poisson was to use negative binomial regressions in traffic studies, which can have unequal means and variances, and is based upon an underlying relationship between explanatory variables and outcomes that follows a gamma distribution (Chang, 2005; Eisenberg, 2004). A benefit of the negative binomial regression was that if data did in fact follow a Poisson distribution, the negative binomial regression would arrive at the same results.

Over the past decades, a few models other than Poisson and negative binomial have often been used to explain traffic collision data. When spatial effects are being evaluated such as collisions at particular locations, or tests of a hypothesis that collisions are not independent occurrences, then a random effect negative binomial can be used with a better goodness of fit than Poisson or negative binomial alone (Diaz-Corro, 2021). Negative multinomial models and conditional Poisson models both struggle with overdispersed data, while unconditional negative binomial regressions using dummy variables for fixed effects tends to provide good, if generally low, estimators without "incidental parameter" bias (Allison, 2002). In some realms, machine learning algorithms and artificial neural networks are proving valuable as no knowledge of the underlying relationship is needed ahead of time; however, these have large computational requirements and may be unsuitable for some datasets.

An expansion of the negative binomial regression finding favor in some traffic studies is the zero inflated negative binomial (ZINB) regression. This regression sandwiches together two explanatory models; the first is a logit or probit model to explain zero-count or "degenerate zero" data, that is whether a count will be zero or not, and the second is a negative binomial model to explain positive count data (Yan, 2012). A caveat for using a ZINB regression is that there must be a compelling underlying reason why there are two states, and that zeros are not just a possible outcome of a single state system or an artifact of model misspecification (Washington, 2020).

In our study, there does not seem to be underlying factors that would predispose a county for zero-counts. The study data suggests a strong negative correlation between county population and likelihood of a zero count for daily traffic outcomes, suggesting that population weighting is the appropriate way to handle the zeros. With no compelling reason to believe that daily traffic collision outcomes are bimodal, or at least without data that suggests so, this study will proceed with a negative binomial regression model.

3.2 Confirming Applicability of Study Data for Negative Binomial Regression

To confirm the negative binomial regression's applicability for this study, it is necessary to analyze the dataset's county-day observations. The first test is to check if the data follows a normal distribution using a quantile plot, plus a Shapiro-Francia test and a skewness and kurtosis test. If data did follow a normal distribution, the negative binomial regression would be an inappropriate choice.

First, quantile-quantile plots are used to compare collisions against injuries, and collisions against fatalities, to see if both data sets share a common distribution. This would be the case if the same factors that explained collisions also explained injuries and fatalities. Based on Figure 3.1, it seems that the factors leading to collisions are not the same as the factors leading to injuries or fatalities. Next, normal quantile plots for collisions, injuries, and fatalities in Figure 3.2 are reviewed to see if they follow a 45-degree line, which would be indicative of normality. These are far from the 45-degree line and are not likely to be normal.

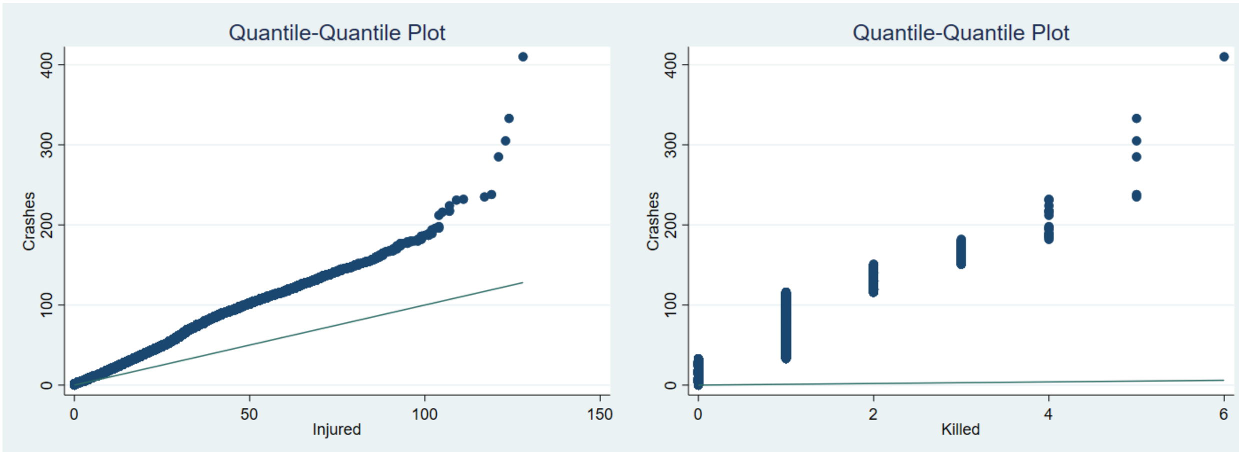

Figure 3.1: Q-Q plots for collision, injury, and fatality data.

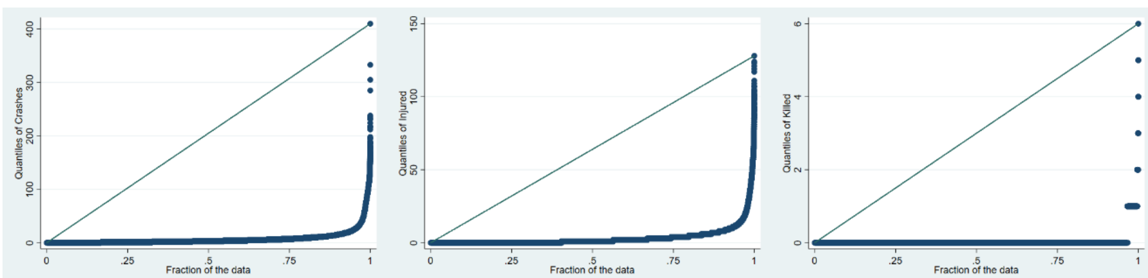

Figure 3.2: Normal Quantile plots for collisions (left), injuries (center), and fatalities (right) data. County-day units of observation.

Under normality, W’ and V’ for the Shapiro-Francia test are 1. W’ decreasing or V’ growing are indicative of departure or deviation from normality. In this study’s case, collisions (W’ = 0.47691, V’ = 6.4e+04), injuries (W’ = 0.54424, V’ = 5.6e+04), and fatalities (W’ = 0.95241, V’ = 5850) all display statistically significant departures from normality.

A complement to the Shapiro-Francia test is an evaluation of data skewness and kurtosis. Skewness near zero is symmetric and indicative of normality (positive is skewed right). Kurtosis near 3 is indicative of normality (larger than 3 indicates a growing peak and shallowing tail). Recall from Table 3.1 that skewness is above 5.5 for all variables and kurtosis is above 43 for all variables, both indications that the probability of normality is 0.0000 when weighted against county population.

Based on these tests, it is safe to conclude that this data does not follow a normal distribution and also the three categories of outcomes do not follow the same distributions. In review, the data in Table 3.1 compares count means with count variance; all three are unequal, and by more than a magnitude for collisions and injuries. Of 255,600 observations in the data set, 42,726 had zero collisions (16.7%), 103,452 had zero injuries (40.4%), and 246,942 had zero fatalities (96.6%). Checking conditional data with zero-count entries removed, there are still unequal means and variances (collisions mean = 8.49, variance = 239; injuries mean = 5.61, variance = 78.2; fatalities mean = 1.12, variance = 0.159). This disparity eliminates a Poisson regression and allows the study to confidently proceed with a negative binomial model. As a final check, a visual evaluation of histograms for each data set in Figure 3.3 shows that all have fairly equivalent high peaks clustered around zero with long tails.

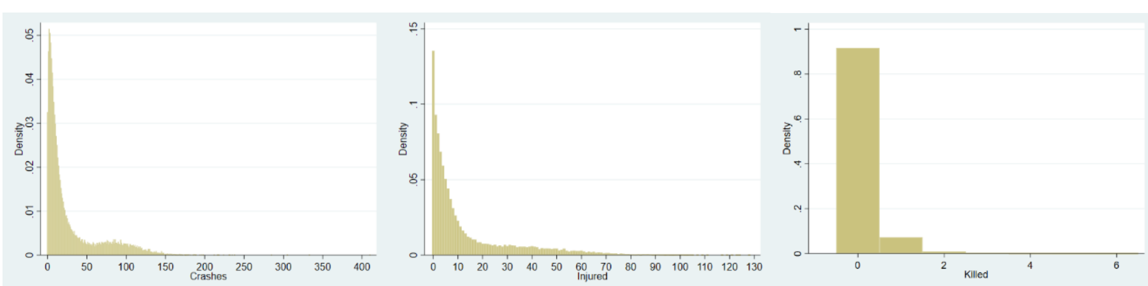

Figure 3.3: Histograms for county-day outcomes for collisions (left), injuries (center), and fatalities (right).

As an aside, this study also checks the data aggregated at a state level. While this will not impact regression choice given the county-day units of observation, it may be informative for explaining the model choices that other studies have made given data aggregation at a county-month, state-day, or state-month level.

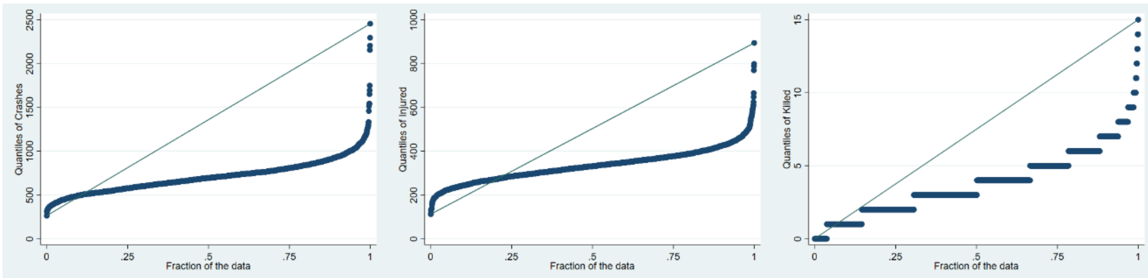

Figure 3.4: Normal Quantile plots for collisions (left), injuries (center), and fatalities (right). State-day unit of observation.

State-wide collisions, injuries, and fatalities still deviate from a normal distribution (though less so). One separating factor is that this state-level data lacks an overdispersion problem or an excess of zero-counts that county-day data had, and other models (not explored here) may be suitable for analyzing less granular outcomes.

3.3 How to Interpret Results

The results emerging from a negative binomial regression are intuitive and meaningful. Negative (positive) coefficients means that increasing continuous data or presence of an indicator variable predicts lower (higher) counts of the dependent variable.

In general, negative binomial regressions are represented by the following equation:

$$\ln(Dependent) = Constant + \sum_{i=1}^{n} \beta_i * X_i$$

Due to the properties of natural logs, this equation can be rearranged to this:

$$\widehat{Dependent} = e^{Constant + \sum_{i=1}^{n} \beta_i * X_i}$$

Which can be rearranged to:

$$\widehat{Dependent} = e^{Constant} * e^{\beta_1 * X_1} * e^{\beta_2 * X_2} * \dots * e^{\beta_n * X_n}$$

This fact lets us interpret each coefficient directly. A one unit change in the explanatory variable (x) will change the log of the dependent variable by the given coefficient (β), or change the dependent variable by $e^{\beta * x}$, all other explanatory variables held constant. As an example, if β_1= 0.5 and X_1 is an indicator variable that can only take 0 or 1, then the presence of that indicator variable (equal to 1) would change the dependent variable by $e^{0.5*1} = e^{0.5} = 1.648$, which represents a 64.8% increase over the null state (because $e^0 = 1$).

This study uses an exposure modifier which is based on the county population. This exposure coefficient is set to 1 to form a weight, which allows output to be evaluated as a "rate of outcome per person". To calculate an absolute number of outcomes would need to incorporate the exposure weight, ω_i, or population, of county i:

$$\widehat{Dependent_\iota} = \omega_i * e^{Constant} * e^{\beta_1 * X_1} * e^{\beta_2 * X_2} * \dots * e^{\beta_n * X_n}$$

For example, if upon finishing the collision regression analysis, it is found that for some set of available conditions: $Constant + \sum_{i=1}^{n} \beta_i * X_i = -9$

Given that the county in question has a population, or weight, of 100,000, this could predict the number of outcomes given those conditions as: $\widehat{Dependent_\iota} = 100000 * e^{-9} =$ 12.3 collisions (for example).

As a final note, all study regressions will incorporate fixed effects to some degree. The data shows notable trends based on Year, Month of Year, and Day of Week, and these will be controlled for with "Date Fixed Effects". The first basic regression will capture why this matters. North Carolina's counties have a great deal of heterogeneity relating to their traffic outcomes, which at a broad level can be described by their topography, road quality and quantity, presence of an interstate or other major throughway, and numerous other factors that are likely unobservable or unmeasurable – for example, maybe one county has prioritized pedestrian safety projects, while another has a relatively large police force focused on traffic safety, and yet another continuously neglects road damage such as potholes and slumps. Most regressions will also incorporate "County Fixed Effects." As such, the county level coefficient will be a catchall for these factors.

CHAPTER 4: DATA AND METHODS

This study involves a diverse set of data from many federal agencies, state agencies, and public universities. All data used in this study is publicly available by request from the agency or by direct download. The primary unit of analysis for this study is the county-day. With 2,556 days between January 1, 2013 and December 31, 2019, and 100 counties, this gives a total of 255,600 county-day observations.

4.1 North Carolina Department of Transportation (NC DOT)

The DOT is a large agency responsible for the state's airports, highways, ports, railways, and more.[1] This agency was responsible for providing the dependent variables of this study.

4.1.1 Traffic Collision Data

Anonymized data for traffic collisions by county and day was obtained through a public records request to NC DOT. Each collision included a unique incident identifier, the date of incident, county where incident occurred, the number and types of injuries, the number of fatalities, and how many occupants were in the vehicle or vehicles. This data is collected by emergency responders using a DMV-349 form (NC DMV, 2023).

To qualify for reporting, a crash must result in one or more of the following: 1) a fatality, 2) a personal injury (described below), 3) property damage of $1000 or more, 4) property damage of any amount if leads to vehicle seizure, 5) vehicle seizure that leads to forfeiture.

[1] https://www.ncdot.gov/

Traffic fatalities are amended up to 12 months after the incident if the collision was responsible for a death. At least one car must be in motion to qualify for reporting, but there is no limit to the number of vehicles, pedestrians, pedal cyclists, or motorcycles reported in one crash incident.

Injuries are designated by the responding emergency personnel as “A” for Suspected Serious Injury, “B” for Suspected Minor Injury, and “C” for Possibly Injury. A-injuries include severe lacerations, broken bones, crushes, significant skull or torso injuries, significant burns, loss of consciousness, or paralysis. B-injuries are any evident injury that is not considered serious or life-threatening, such lumps, abrasions, bruises, or minor lacerations. C-injuries are reported or claimed by the victim but are not readily evident to the emergency responder, including pain, nausea, muscle or ligament damage, or momentary loss of consciousness.

A decision was made to combine all injuries per county-day into a single statistic (“Injured”). In this data set, there were 853,338 reported injuries across the study period, and of those 23,834 (2.79%) were A-injuries, 180,135 (21.11%) were B-injuries, and 649,369 (76.10%) were C-injuries. Broken down further, of the 556,131 collisions that resulted in injuries or fatalities, how those injuries and fatalities were distributed appears somewhat scattered: “A only” incidents accounts for 2.33% of injury or fatality causing collisions, “B only” for 18.30%, “C only” for 70.28%, “A&B only” for 0.62%, “B&C only” for 6.63%, “A&B&C only” for 0.69%, “injuries plus fatalities” for 0.69%, and “fatalities only” for 0.92% of collisions. That is to say, once road conditions, driver behavior, other factors, and random chance result in an injury causing collision, the severity of injuries is distributed like a random variable. Therefore, this study is interested in all collisions that cause injuries.

4.2 National Oceanic and Atmospheric Administration (NOAA)

NOAA is a large federal agency responsible for weather analysis and communication, fisheries management, coastal restoration, and support for marine commerce, among others.[2] NOAA oversees many of the departments that provided explanatory variable data in this study.

4.2.1 National Centers for Environmental Information (NCEI)

NCEI has a publicly available database that stores daily records for all notable weather events in the United States dating to 1950.[3] Records are delivered by the National Weather Service, and sourced by: county, state and federal emergency management officials; local law enforcement officials; skywarn spotters; NWS damage surveys; newspaper clipping services; the insurance industry; and the general public. Reports are based on actual observed or measured conditions. Records are searchable by: state, territory, or area; date; county or "zone" county subsets; begin and end date; and event type.

There are 49 event types to choose from, and here are the ones deemed relevant for this traffic study. To simplify analysis, events were aggregated into five categories. Flood events are relevant for their ability to create direct hazards via standing or moving water on roadways, and indirect hazards via traffic congestion. Wind events involve the direct hazard of sustained winds of 30 mph (strong wind) or 40 mph (high wind) for at least an hour, with higher gusts possible; funnel clouds and tornados can be acute hazards and indirect hazards via stress or distraction. Thunderstorm wind events are strong downburst and straight-line winds associated with

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[2] https://www.noaa.gov/
[3] https://www.ncdc.noaa.gov/stormevents

lightning-producing storm clouds, and are direct hazards due to their rapid arrival and dynamic winds. Storm events (cyclones) are direct hazards via rainfall, flooding, and/or strong winds that tropical storms and hurricanes bring, and may also serve as indirect hazards due to stress, distraction, and traffic congestion. Winter events include any wintry precipitation, with or without wind, that are direct hazards via impacts to vehicle performance and driver visibility, and indirect hazards due to stress, distraction, and traffic congestion.

These events were logged for each county-day using an indicator variable to note if one or more events occurred that day. The number of event positive county-days, and the types of event per category, are as follows:

- Flood event (n = 1287 county-days): Coastal Flood, Flash Flood, Flood, Storm Surge/Tide
- Wind event (n = 650 county-days): Funnel Cloud, High Wind, Strong Wind, Tornado
- Thunderstorm Wind event (n = 2670 county-days): Thunderstorm Wind
- Storm event (n = 398 county-days): Hurricane, Tropical Storm
- Winter event (n = 3175 county-days): Blizzard, Heavy Snow, Ice Storm, Sleet, Winter Storm, Winter Weather

This study also tests if these events have lagged impacts on traffic collision outcomes for up to a week. The assumption is that any effect, whether environmental or psychological, would be short lived and soon return to baseline levels. For each event type, there is an "event lag" indicator variable that turns on if an event occurred in the prior three days, and another indicator variable that turns on if an event occurred between four and seven days prior. For example, if a county has a flood event logged for a given day, "FlEvLag123" would be 1 for the next three days, and then "FlEvLag4567" would be 1 for the following four days. This lag effect is not impacted by the occurrence of a new distinct event, or the continuation of an existing event – it is meant to indicate community adaptation and dynamic conditions following adverse weather. For broader regressions, all events are combined into an "AnyEv" indicator variable that turns on if at least one of the five above events is true, with corresponding "AnyEvLag123" and "AnyEvLag4567".

4.2.2 National Operational Hydrologic Remote Sensing Center (NOHRSC)

NOHRSC operates under NOAA and the National Weather Service and provided the North Carolina county border map KMZ file.[4] This file is used to overlay county perimeters onto Google Earth Pro (Version 7.3.6.9345 (64-bit)). This formed the basis for the study's tropical cyclone forecast data coding, as detailed below.

4.2.3 National Hurricane Center (NHC)

The National Hurricane Center is a component of the National Centers for Environmental Prediction.[5] This specialized meteorology group is focused on tropical cyclones, generating cyclone tracks and predictions using advanced satellite, radar, buoy, ship, and aircraft weather data analyzed through complex algorithms and forecasting models. Forecasts are typically made at least twice per day for newly formed potential cyclones, with precise estimates of the cyclone's center and strength given for 12 hours, 24 hours, 36 hours, 48 hours, 72 hours, 96

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[4] https://www.nohrsc.noaa.gov/
[5] https://www.nhc.noaa.gov/gis/

hours, and 120 hours after the advisory issue. If the cyclone is expected to dissipate, the forecast duration may be shorter. As cyclones strengthen to tropical depression, tropical storm, or hurricane status, or as the storm approaches land, the agency will issue at least four advisories per day, with additional interim advisories provided for critical events such as landfall or storm strength changes. The following definitions from the NHC glossary are relevant for this study:

- Tropical Cyclone: A warm-core non-frontal synoptic-scale cyclone, originating over tropical or subtropical waters, with organized deep convection and a closed surface wind circulation about a well-defined center. Once formed, a tropical cyclone is maintained by the extraction of heat energy from the ocean at high temperature and heat export at the low temperatures of the upper troposphere. In this they differ from extratropical cyclones, which derive their energy from horizontal temperature contrasts in the atmosphere (baroclinic effects).
- Tropical Depression: A tropical cyclone in which the maximum sustained surface wind speed (using the U.S. 1-minute average) is 33 kt (38 mph or 62 km/hr) or less.
- Tropical Storm: A tropical cyclone in which the maximum sustained surface wind speed (using the U.S. 1-minute average) ranges from 34 kt (39 mph or 63 km/hr) to 63 kt (73 mph or 118 km/hr).
- Hurricane / Typhoon: A tropical cyclone in which the maximum sustained surface wind (using the U.S. 1-minute average) is 64 kt (74 mph or 119 km/hr) or more. The term hurricane is used for Northern Hemisphere tropical cyclones east of the International Dateline to the Greenwich Meridian. The term typhoon is used for Pacific tropical cyclones north of the Equator west of the International Dateline.

The agency maintains GIS files of all tropical cyclone advisories issued, including the forecast track, cone of uncertainty, and watches/warnings. These files were downloaded as separate KMZ files. The primary interest is if the inclusion of a county underneath a tropical cyclone forecast cone of uncertainty or forecast track is an explanatory variable for traffic collision outcomes.

Cyclones have the potential to strengthen or weaken rapidly, and the NHC does not visually differentiate the forecast tracks and cone of uncertainty for tropical depressions, tropical storms, or hurricanes; therefore the study considers all of these equivalent for their potential impact on the public. That is to say, whether the cyclone is currently a tropical depression, tropical storm, or hurricane, if it is forecast via the cone of uncertainty (hereafter, "cone" or "forecast cone") to reach a county, the county will be assigned an indicator variable for forecast cone. To further differentiate the effect of a forecast cone, counties are assigned a "day until" indicator variable: Cone0 (arriving today, or < 24 hours), Cone1 (arriving tomorrow, or in 24 – 48 hours), Cone2 (arriving in two days, or 48 – 72 hours), Cone3 (arriving in three days, or 72 – 96 hours), and Cone4 (arriving four or more days from now, or 96+ hours). For the purposes of this study, the eye or center of the cyclone denotes arrival, though in reality, rain and tropical storm-force winds can precede the cyclone eye's arrival by a day or more.

For broader regressions, there are also indicator variables "Cone" which indicates a county is in a cone at any day, "Cone01" which indicates a county is either in "Cone0" or "Cone1", and "Cone234" which indicates a county is either in "Cone2", "Cone3", or "Cone4". Note that for some counties, it was possible to have a 1 on the same date for "Cone01" and "Cone234" – those limited cases (n = 11) were the result of Tropical Depression Eight forming off the Atlantic Coast while the remnants of Hurricane Hermine approached from overland in August 2016.

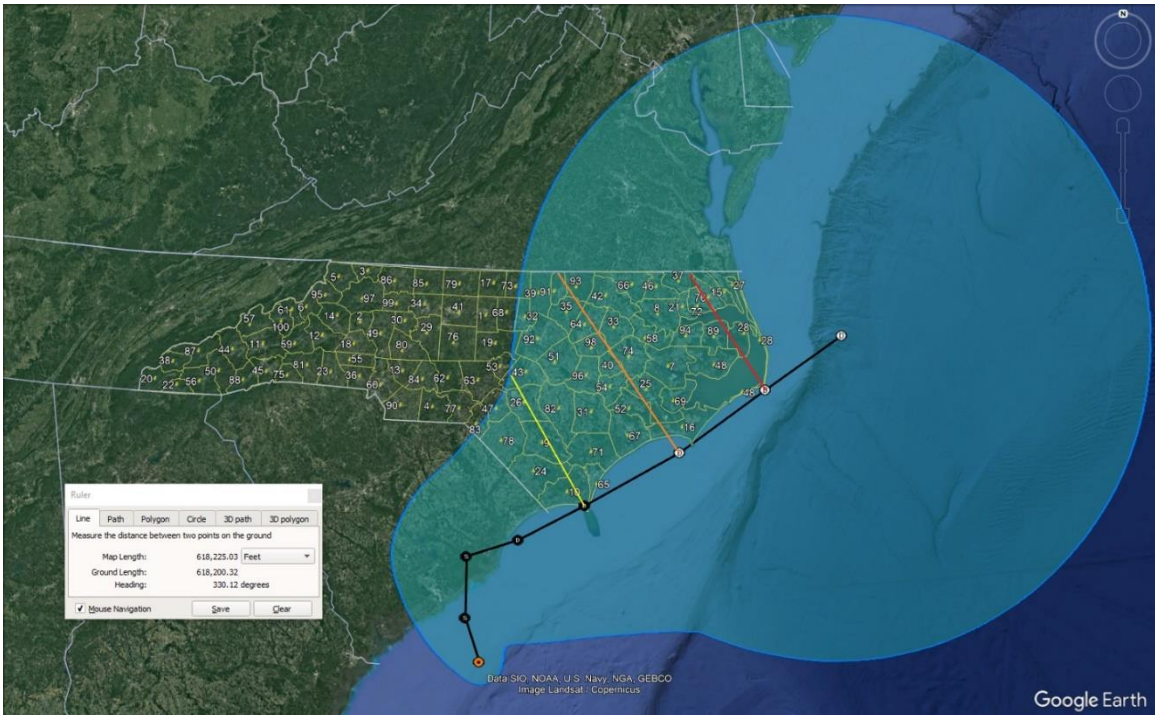

Figure 4.1: Tropical Storm Bonnie, Advisory #7, Valid at: 5:00 AM EDT Sun May 29, 2016.

To explain this study's coding method, below is an actual example from Tropical Storm Bonnie, using advisory #7 issued at 5am EDT on May 29, 2016. In Figure 4.1, the pink dot near the bottom of the image shows the cyclone's current eye location and serves as the origin of the track line. No counties in North Carolina are expected to be reached by 2am of the next day (2^{nd} black dot on track line); therefore no counties are coded as "Cone0". All counties under the cone and between the South Carolina border (closer to the origin) and the yellow line (including those under the yellow line) are coded as "Cone1". All covered counties between the yellow line (exclusive) and the orange line (inclusive) are coded as "Cone2". All counties between the orange line (exclusive) and the red line (inclusive) are coded as “Cone3”. Finally, all counties between the red line (exclusive) and the remainder of the forecast cone are coded as “Cone4”.

To align tropical cyclone forecasts with traffic collision outcomes, the study uses the tropical cyclone advisory issued at or closest to 6am EDT on each day (here after the “6am advisory”). A comparison of tropical cyclone related news stories with NHC forecast cone archives showed that the 6am advisory is the graphic typically referenced for the day’s news cycle, which indicated to us that it would have the greatest impact on the public. The 6am advisory graphic also provided forecasted eye locations for 2am on each of the following days (the origins for the yellow, orange, and red lines in Figure 4.1) and those 2am markers would serve as daily cutoffs. A perpendicular line created from each of the 2am markers on the forecast track identified the cutoff for each Cone# identifier; if the cutoff line touched a county, that county would be counted in the preceding zone.

In addition to identifying counties under a forecast cone, this study also sought to understand if there were any spillover effects on counties just outside of the cone. To do this, a relationship matrix evaluated each county’s neighbors to determine if at least one was in a forecast cone – if at least one neighbor was in a forecast cone (that is, “Cone” = 1), and the county of interest was not, it was assigned an indicator variable value of 1 for spillover “SpOver”. Of note, spillovers from outside of the state are not considered – if a county in Virginia, Tennessee, Georgia, or South Carolina was in a forecast cone and its neighboring county across the border in North Carolina was not, it was excluded. For narrower regressions, there is also an indicator variable “SpOver01” that checked the relationship matrix against “Cone01” and another indicator variable “SpOver234” that checked the relationship matrix against “Cone234”. Note that for some counties, it was possible to have the relationship map return a 1 on the same date for “SpOver01” and “SpOver234” – those limited cases (n = 21) were also the result of Tropical Depression Eight forming off the Atlantic Coast while the remnants of Hurricane Hermine approached from overland in late August 2016.

Finally, if a county lies directly underneath the forecast track line, which indicates the expected path of the eye of the cyclone, that county is assigned a separate indicator variable “Line”. This is to test if the forecast track line modifies the impact of being in a forecast cone.

This process was repeated for the 27 tropical cyclones between 2013 and 2019 that had at least one forecast cone touching North Carolina at the 6am advisory. In total, this comprised 74 days of forecasts, with 2,807 county-days of “cone” across all North Carolina counties. The most frequently affected county had 48 county-days of “cone”, while the least frequently affected county had 15 county-days. On average, counties have 4.99 neighbors, with a minimum of 2 and a maximum of 9. During the same period, there were 651 county-days of spillover in the state. The most frequently affected county had 21 county-days of spillover, and the least frequently affected county had 1 county-day of spillover. Overall, each of the 74 forecast days affected an average of 37.9 counties under the cone, with another 8.79 counties considered spillover.

4.2.4 Office for Coastal Management

The Office of Coastal Management is a division within NOAA responsible for coastal management and conservation.[6] Similar to the NHC archival forecast tracks, this group has a hurricane track tool that allows for a rapid overview of historic tropical cyclones’ actual paths.

[6] https://coast.noaa.gov/hurricanes/

This tool was used to identify hurricanes that made landfall on the continental United States between 2013 and 2019. In total, ten hurricanes made landfall over this period: Arthur in 2013; Hermine and Matthew in 2016; Harvey, Irma, and Nate in 2017; Florence and Michael in 2018; and Barry and Dorian in 2019. This data was used to create a recent hurricane landfall indicator variable “RecHurLan” that applied to all counties for the rest of the month and the entirety of the next month. This is an exploratory variable to test if the public reacts more strongly to a tropical cyclone forecast cone if they have a fresh memory (whether experienced or through media) of a hurricane coming ashore in the United States. This concept also led to two new dummy variables, “PostMatt” and “PostFlor” that stand for post-Hurricane Matthew and post-Hurricane Florence, respectively, as these hurricanes were significant events in North Carolina in terms of lives lost, damage, and disruption.

4.3 Parameter-Elevation Regressions on Independent Slopes Model (PRISM)

PRISM is a repository of time-series weather data hosted by Oregon State University and available for public download.[7] The explorer tool allows users to search and download historic weather data either at a state and county level, or by specific coordinates. This tool provided daily precipitation (“Precip” in inches) and mean temperature (“MeanTemp” in degF) data for each county from the years 2012 through 2019. The data was considered stable and unlikely to be corrected, and the interpolate option was not used.

[7] https://prism.oregonstate.edu/explorer/

Once downloaded, each file was modified to produce additional explanatory variables. A "SnowIce" indicator variable checked if the MeanTemp that day was less than or equal to 35 degrees Fahrenheit and if precipitation was greater than 0" on that day, the preceding day, or the following day. This study evaluates the preceding day as rain followed by a freeze can be a source of ice and other driving hazards. This study also evaluates the following day as weather stations report precipitation with automatic rain gauges, and spot checks of documented snow events typically showed up as precipitation the next day, likely due to a time lag for snow to melt.

At the county level, the 5th percentile and 95th percentile temperatures were calculated using the daily mean temperatures between 12/1/2012 and 12/31/2019. A very hot "Vhot" day was indicated if the mean temperature on any given day was greater than or equal to the 95th percentile temperature. A very cold "Vcold" day was indicated if the mean temperature on any given day was less than or equal to the 5th percentile temperature. These days are then summed according to the following strategy – a continuous variable "VhotSum" sums the number of "Vhot" days between three days ago and today (maximum of 4; any day with "Vhot" also has "VhotSum" >= 1), and a separate continuous variable "VcoldSum" sums the number of "Vcold" days between thirty days ago and three days ago (maximum of 29). Negative health outcomes have been documented for both types of days; very hot days can lead to increased negative health outcomes immediately and over the following three days, while very cold days have a lagging effect where the accumulation of very cold days between thirty and three days prior correlates to negative health outcomes (Xu, 2014; Lippmann, 2013; Zhao, 2017; Guo, 2014). These explanatory variables seek to understand if the same mechanisms that cause health effects may increase stress, distraction, or cognitive load (or some combination of), leading to changed traffic outcomes.

Finally, a three day precipitation lag (“Ppt3day”) indicator variable was created. This evaluates the preceding three county-days, and if the sum over those three days is 0” and there is any measurable rain today, the indicator variable “Ppt3day” is assigned a 1 for that county-day.

4.4 Other Data Sources

The remaining explanatory data comes from a group of state and federal agencies.

4.4.1 US Office of Personnel Management (OPM)

Holidays typically result in unusual traffic volumes or routes, all other things held equal. This study creates an indicator variable “Holiday” and use the concepts of “major” and “minor” holidays (Levine, 1995). Minor holidays are day-of events and major holidays are multi-day events:

- Minor Holidays: New Year's Day, Cinco de Mayo, Mother’s Day, Father’s Day, Columbus Day or Indigenous Peoples’ Day, Halloween
- Major Holidays: Memorial Day, Fourth of July, Labor Day, Thanksgiving, Christmas

This data is combined with federally observed holidays provided by the Office of Personnel Management from 2013 to 2019 to identify which day of the week the federal holiday fell on and adapt accordingly. Memorial Day is the last Monday in May, and the preceding Friday, Saturday, and Sunday are also counted as holidays. The Fourth of July is variable – if it falls on or next to a weekend, then the entire weekend is considered a holiday; if it falls on a

Wednesday, just the observed day and Tuesday are considered a holiday. Thanksgiving is consistently a Thursday, and the preceding Wednesday is also included. For Christmas, the 24th, 25th, and 26th are counted as holidays. In total, there are 159 holiday days captured between 2013 and 2019, and these were applied equally to every county.[8]

4.4.2 North Carolina Department of Health and Human Services (NC HHS)

NC HHS is a state agency that focuses on health, families, and workforces.[9] They provided data on county classifications for rural versus urban: NC HHS defines rural as a "non-metropolitan or outlying metropolitan county" and urban as "a central metropolitan county."

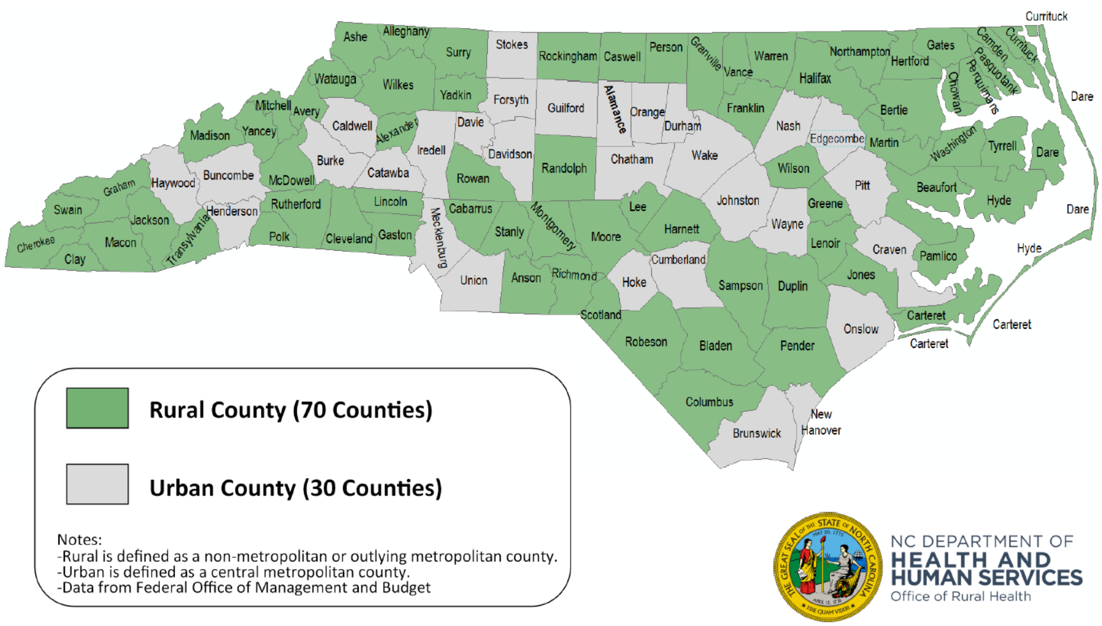

Figure 4.2: North Carolina Rural-Urban county classifications.

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[8] https://www.opm.gov/policy-data-oversight/pay-leave/federal-holidays/#url=Historical-Data
[9] https://www.ncdhhs.gov/

4.4.3 North Carolina Office of State Budget and Management (NC OSBM)

NC OSBM provides budget services and policy analysis for the state government.[10] North Carolina has experienced rapid growth and sizable demographic shifts over the past decade, with the state as a whole growing from 9,535,751 people in 2010 to 10,456,593 people in 2020, a 9.7% increase. Within the state, low population counties tended to get smaller and high population counties tended to get larger. Between 2010 and 2020, 51 "shrinking" counties comprising 20% of the state's population saw losses on average, while 49 "growing" counties comprising 80% of the state's population saw gains on average. To improve regression accuracy, annual county populations from NC OSBM are used as analytical or exposure weights.

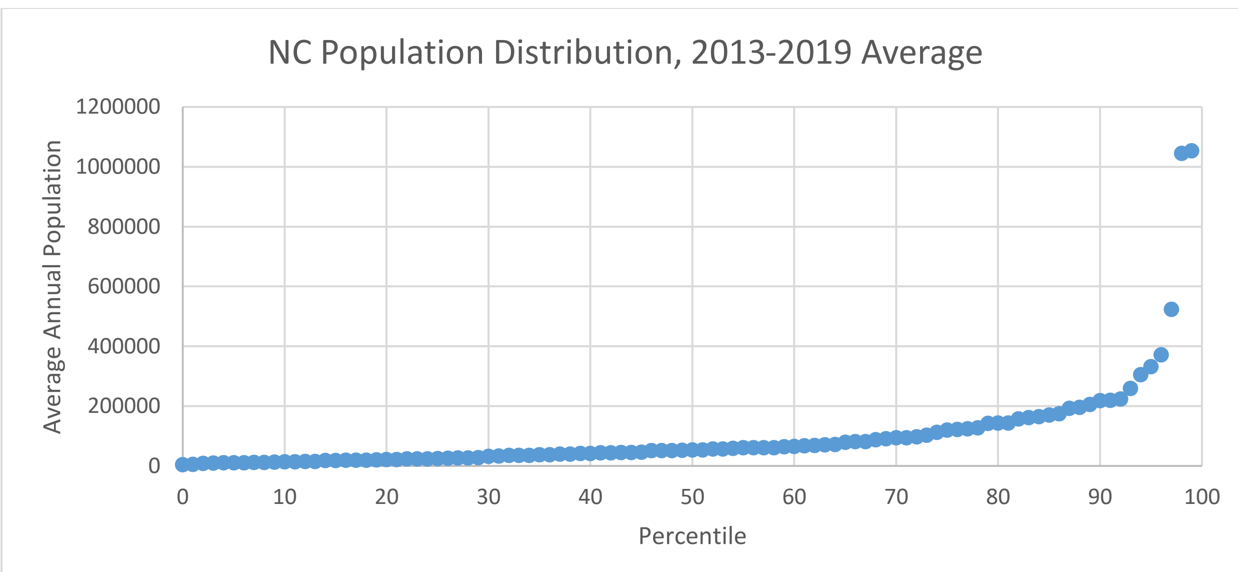

Figure 4.3: Distribution of North Carolina's county population averages, 2013-2019.

[10] https://www.osbm.nc.gov/

Over the course of this study's data period, the average annual county population was 100,833 (std. dev 160,549). This average county population varied from 3,922 (Tyrrell) up to 1,052,989 (Mecklenburg), distributed as seen in Figure 4.3.

4.4.4 North Carolina Department of Commerce (NC Commerce)

NC Commerce is a state agency that focuses on economic, community, and workforce development.[11] The State of North Carolina mandates an annual three-tier ranking of its one hundred counties in terms of economic distress. These tiers are based on: average unemployment rate (past year), median household income (past year), percentage growth in population (past three years), and adjusted property tax base per capita (past year). The resulting score identifies each county as tier one or most distressed (n=40), tier two or distressed (n=40), and tier three or least distressed (n=40).

Annual distress rankings from 2013 through 2019 are used to create indicator variables Most Distressed ("DistMost"), Distressed ("Distress"), and Least Distressed ("DistLeast") that represent each county-year's ranking. These are included as dummy variables as previous studies found differences in collision outcomes based on economic wellbeing. Although this is a lagging rank, there are 59 counties whose rank does not change over the study period (comprising all three tiers), 32 counties whose rank fluctuates between Tier 1 and Tier 2, and 9 counties whose rank fluctuates between Tier 2 and Tier 3.

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[11] https://www.commerce.nc.gov/

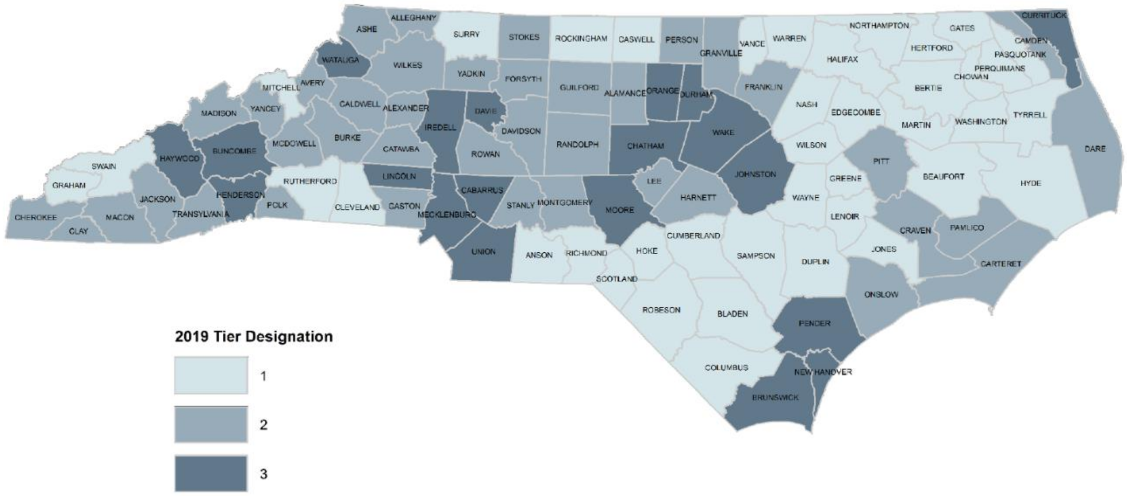


Figure 4.4: North Carolina county economic distress levels, 2019.

4.4.5 North Carolina Forest Service (NCFS)

NCFS is a state agency that helps manage, develop, and protect the state's forest resources.[12] The North Carolina Forest Service categorizes each county into one of three regions: Mountains, Piedmont, and Coastal Plain. The topography of each region may have unique road, traffic, and wildlife characteristics.

The Coastal Plains (n=41) is dominated by flat terrain interspersed with wetlands, rivers, and swamps; this region also incorporates the Outer Banks, a series of barrier islands separated from mainland by narrow sounds and inlets. The Piedmont (n=36) is dominated by gentle hills, lakes, and rivers, plus a great deal of agricultural land. The Blue Ridge Mountains (n=23) make

[12] https://www.ncforestservice.gov/index.htm

up the western portion of the state, with mountains, valleys, and heterogeneous roads. Indicator variables "Mountains", "Piedmont", and "Coastal" identify each county.

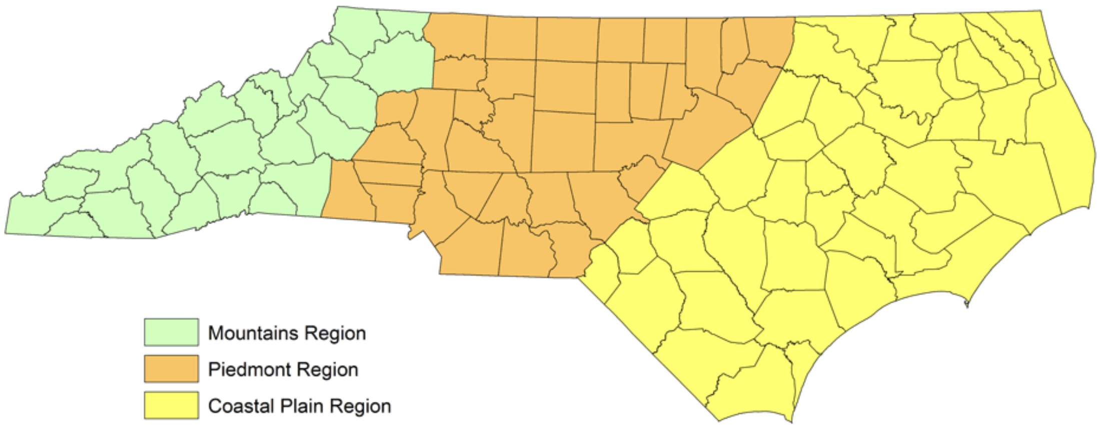


Figure 4.5: North Carolina regions map.

CHAPTER 5: ANALYSIS AND RESULTS

This section includes the results of the study's regression analyses. All regressions were run on Stata BE-Basic Edition, Version 17.0.[13] Data sheets were compiled on Microsoft Excel (2019). Each section includes comments on interpretation of the results and any impacts to the remaining analyses. As a reminder, negative binomial regressions are used for all models. Stata prompts and full results for all regressions can be found in Appendix C.

5.1 Baseline Regressions

This section includes high level analyses used to understand the fixed effects that will come into effect for the remaining regressions. First, only date fixed effects are applied for year, month, and day of week to capture large scale time-series trends (Baseline #1). Then, county fixed effects are added to differentiate between North Carolina's 100 counties (Baseline #2), then run again using annual population to weight the date and county-level fixed effects (Baseline #3). The progression of coefficients seems reasonable, and the fixed effects coefficients from Baseline #3 are displayed in Figures 5.1, 5.2, 5.3, and 5.4. From this point on, all regressions are run with population weighting for county-day observations.

[13] StataCorp, 4905 Lakeway Drive, College Station ,TX

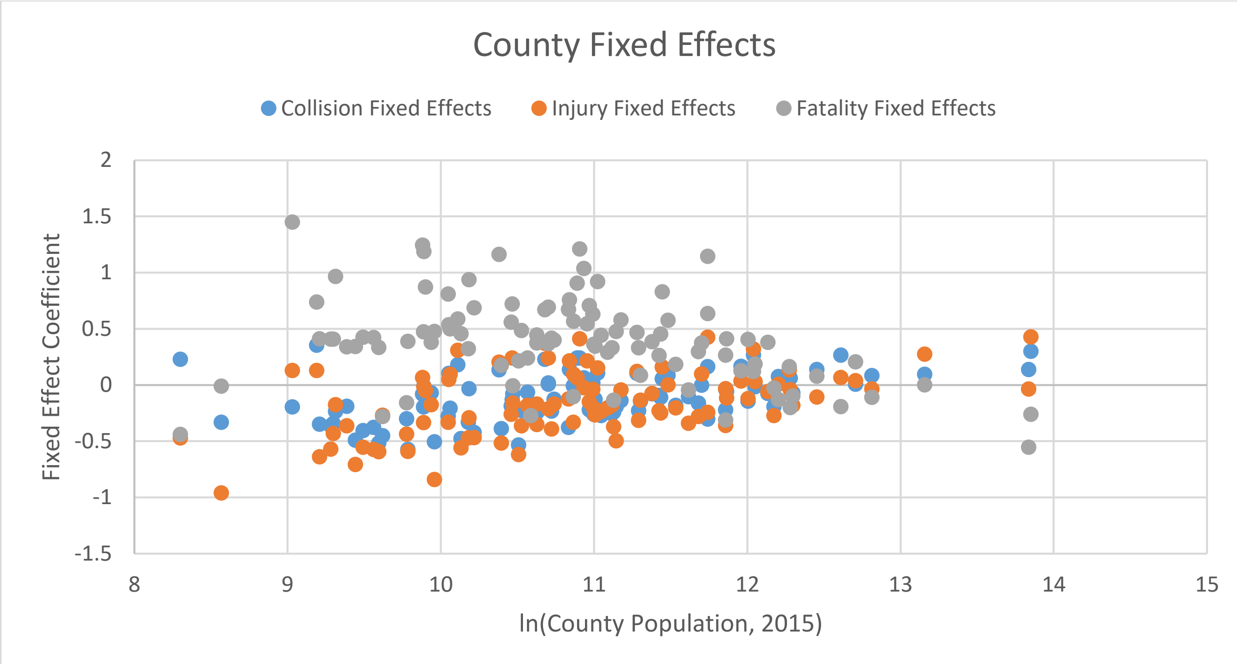
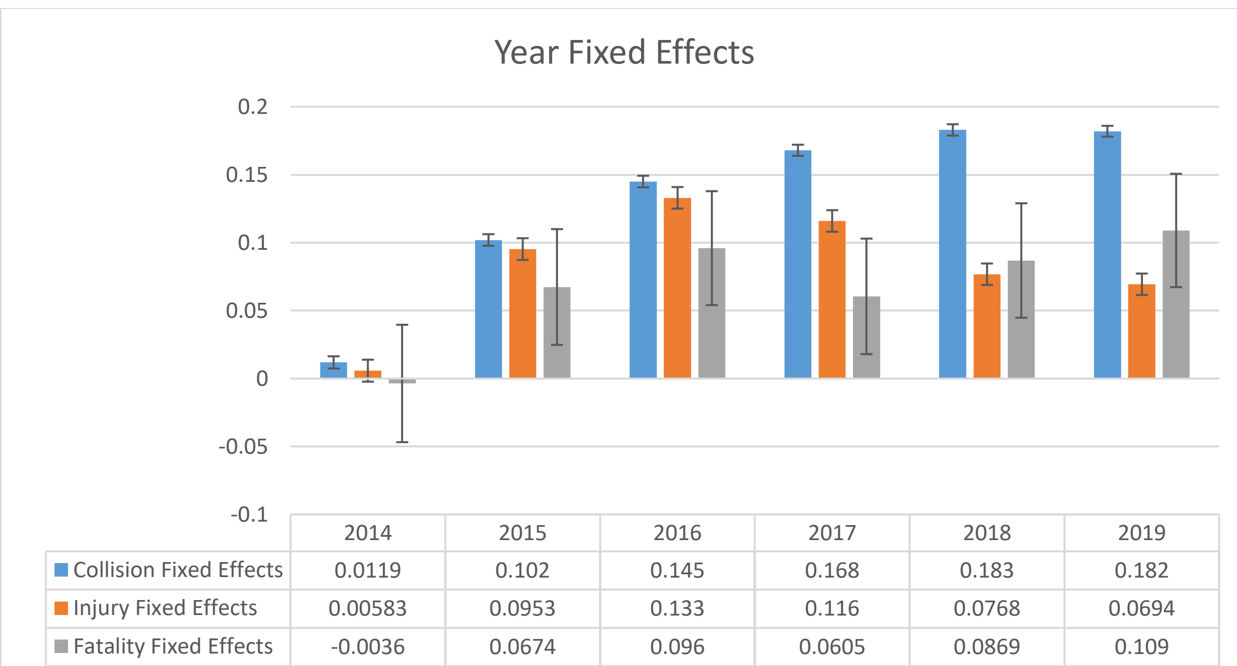


Figure 5.1: Baseline county fixed effect coefficients (Alamance = 0).



	2014	2015	2016	2017	2018	2019
Collision Fixed Effects	0.0119	0.102	0.145	0.168	0.183	0.182
Injury Fixed Effects	0.00583	0.0953	0.133	0.116	0.0768	0.0694
Fatality Fixed Effects	-0.0036	0.0674	0.096	0.0605	0.0869	0.109

Figure 5.2: Baseline year fixed effect coefficients (2013 = 0).

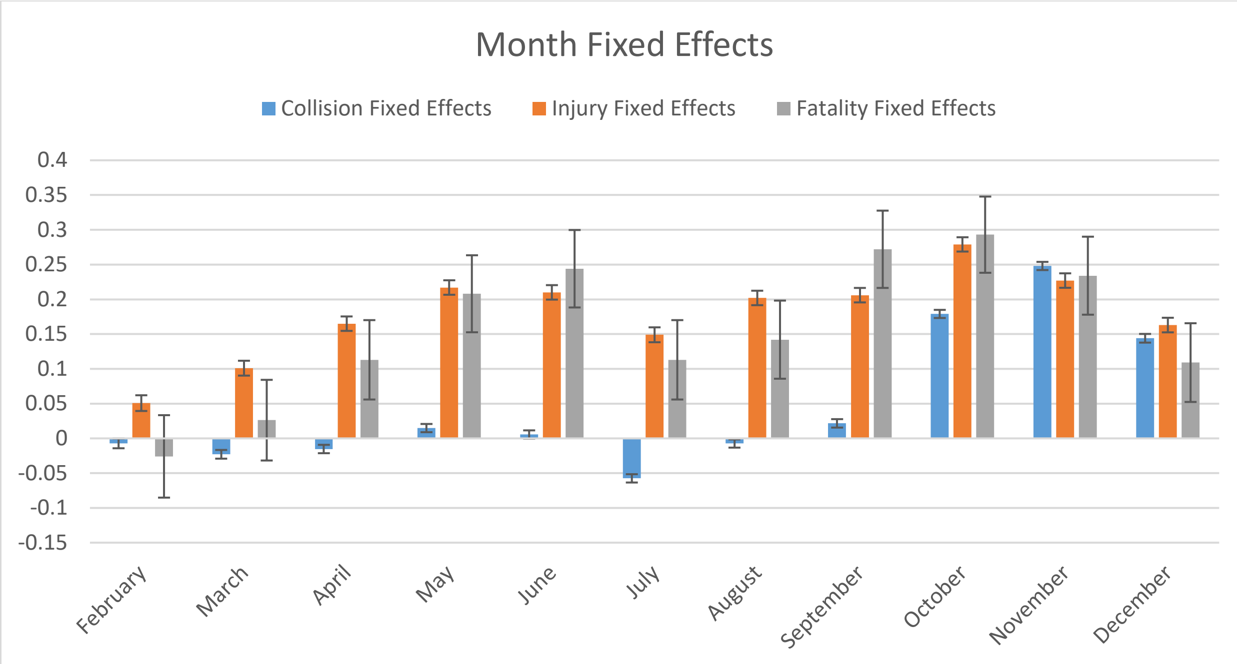
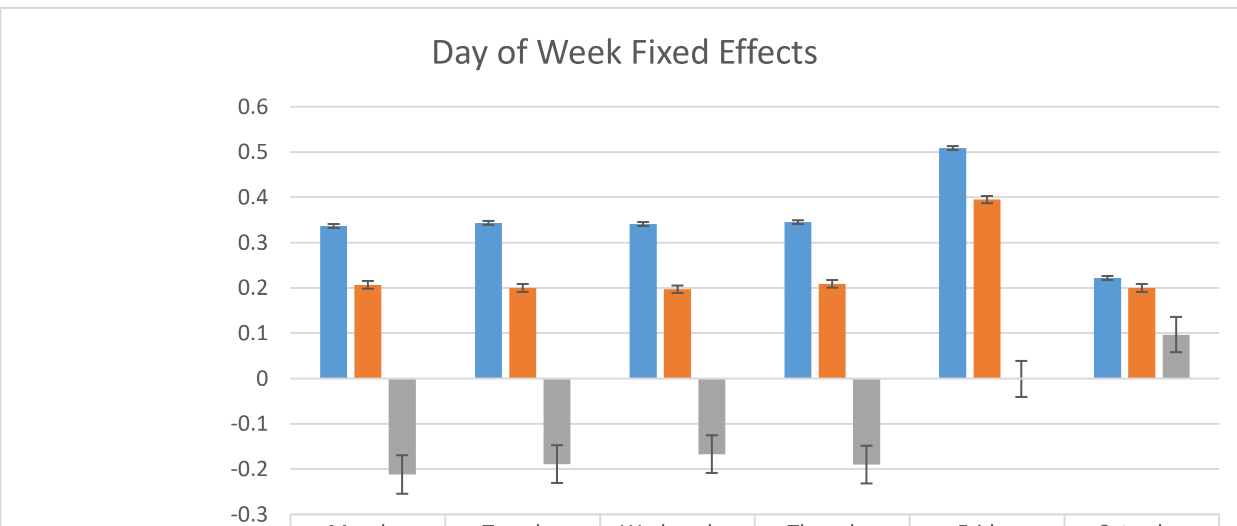


Figure 5.3: Baseline month of year fixed effect coefficients (January = 0).



	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Collision Fixed Effects	0.337	0.344	0.341	0.345	0.509	0.222
Injury Fixed Effects	0.207	0.2	0.197	0.209	0.395	0.2
Fatality Fixed Effects	-0.212	-0.189	-0.167	-0.19	-0.00109	0.097

Figure 5.4: Baseline day of week fixed effect coefficients (Sunday = 0).

Using population weighted county- and time-fixed effects seems an appropriate choice. The county fixed effect coefficients reflect conditions of the county, rather than capturing the influence of population. However, a trend appears when county fixed effects are plotted against population (Figure 5.1) – collisions and injury rates increase with increasing population, while fatality rates decrease with increasing population. At a county level, these results may be indicative of a number of factors including traffic density, road quality, road mileage and speed limits, presence of exits on an interstate or highway, traffic calming measures, public sentiment, law enforcement presence, and many other factors. They may also reflect differences in collision reporting, rather than collision occurrence. All other things equal, a county with a lower coefficient (closer to negative infinity) has a documented lower per capita outcome rate.

Interesting trends stand out in the time fixed effects. The first is that collision rates increased year to year, but appeared to taper off in 2018 and 2019, injury rates went up until 2016 and then started to return to baseline, and fatality rates may go up or down in any given year. By month, October through December have high collision rates, while injuries and fatality rates are highest in spring and fall. By day of week, Fridays have the highest collision and injury rate, while Saturdays and Sundays have the highest fatality rates.

Most of the county fixed effects coefficients are significant at $p<0.01$ for collisions and injuries, with some fatality coefficients also significant. Year fixed effect coefficients follow a similar trend, while month and day of week coefficients are mostly significant at $p<0.01$ for all categories, with some exceptions for coefficients with nearly null effects. From here out, this study will not display these full fixed effect coefficients anymore – if something stands out, it will be commented on. Otherwise, “County Fixed Effects” stands for county-level fixed effects, and “Date Fixed Effects” stands for year, month, and day of week fixed effects.

5.2 Independent Factor Regressions

In this section are the results of high-level regression analyses looking at small sets of explanatory variables. The purpose of this is to look for congruity or contrast with trends and correlations identified in previous studies, as well as to explore trends with novel variables. This will be useful for gaining confidence in the results of more complicated regressions later in this study, and to provide easy to understand standalone results relevant to North Carolina.

Table 5.1: Independent factors, regression #1 coefficients (basic weather).

Regression #1 VARIABLES	Collisions NB	Injuries NB	Fatalities NB
Precipitation (inches)	0.0673***	0.0338***	0.0173
	(0.00315)	(0.00542)	(0.0291)
Rain After 3 or more Dry Days	0.0674***	0.0548***	-0.0496
	(0.00398)	(0.00716)	(0.0403)
Snow or Ice Conditions	0.163***	0.0279*	-0.257***
	(0.0103)	(0.0156)	(0.0867)
Very Hot Day (≥ 95th percentile)	0.0276***	0.0294**	-0.151**
	(0.00668)	(0.0144)	(0.0749)
Very Cold Day (≤ 5th percentile)	0.00460	-0.0262**	0.00270
	(0.00804)	(0.0132)	(0.0724)
Sum of Very Hot Days (3 days ago to today)	-0.0124***	-0.00914*	0.0442*
	(0.00231)	(0.00492)	(0.0242)
Sum of Very Cold Days (30 to 3 days ago)	-0.000188	-0.00247**	-0.00729
	(0.000649)	(0.00125)	(0.00606)
County Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	255,600	255,600	255,600

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The first Independent Factor regressions evaluate established or previously identified effects on traffic collisions, injuries, and fatalities. The first three are: 1) Basic Precipitation and Temperature Factors, 2) Adverse Weather Events, and 3) Special Calendar Days (holidays and daylight savings weeks).

Results in Table 5.1 match expectations from previous studies, with strong effects for precipitation, and additive effects during wintery conditions or if it has not rained in the past three days. The effects of very hot days are also interesting, as a single hot day would tend to increase collisions and injuries, and decrease fatalities, while a series of hot days would see these effects neutralized.

Table 5.2: Independent factors, regression #2 coefficients (adverse weather events).

Regression #2 VARIABLES	Collisions NB	Injuries NB	Fatalities NB
Flood Event	0.167***	0.0829***	0.120
	(0.0146)	(0.0258)	(0.128)
Wind Event	0.101***	0.0320	0.198
	(0.0203)	(0.0418)	(0.202)
Thunderstorm Wind Event	0.107***	0.0908***	-0.0882
	(0.00791)	(0.0170)	(0.0976)
Storm Event (Tropical Cyclone)	-0.0662	-0.184***	0.0631
	(0.0420)	(0.0578)	(0.237)
Winter Event	0.610***	0.325***	-0.189
	(0.0179)	(0.0224)	(0.123)
County Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	255,600	255,600	255,600

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The effects from adverse weather also match expectations. Two of the results in Table 5.2 jump out – the first is a large reduction in injuries during tropical cyclones, and the second is a large increase in collisions and injuries during winter events. Results from the third independent factors regression in Table 5.3 also match previous studies. Collisions and injuries go down for holidays, while increasing for daylight savings. The large but statistically insignificant effect on holiday and daylight savings fatalities are worth noting to see if the effect becomes significant with a fully specified model. These can be considered as modifiers for month fixed effects, as they occur on roughly the same days each year for every county.

Table 5.3: Independent factors, regression #3 coefficients (special calendar days).

Regression #3 VARIABLES	Collisions NB	Injuries NB	Fatalities NB
Holiday	-0.0860***	-0.0308***	0.0677
	(0.00529)	(0.00964)	(0.0454)
Daylight Savings Time week	0.0294***	0.0464***	-0.0629
	(0.00605)	(0.0126)	(0.0655)
County Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	255,600	255,600	255,600

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The next three regressions also evaluate established or previously identified effects on collisions, and are run without county fixed effects in order to evaluate county characteristics that would otherwise be colinear. These include: 4) Urban-Rural, 5) Region (Mountains, Piedmont, or Coastal Plain), and 6) Economic Distress level. The results in Table 5.4 provide insight into North Carolina's county fixed effect coefficients. Urban counties show higher collision and injury rates but much lower fatality rates; urban counties tend to be larger with a mean population over the study period of 224,352 versus 47,896 for rural counties. Relative to the Coastal Plain counties, the Mountain counties have lower outcomes in all categories and the Piedmont counties have higher collision rates but lower injuries and fatalities; this is somewhat surprising as previous studies had identified mountain roads as more dangerous. Economic conditions match with previous study findings that poorer counties have higher fatality rates, while richer counties have higher collision rates.

Table 5.4: Independent factors, coefficients for regressions #4, #5, and #6 (county-level effects).

VARIABLES	Collisions NB	Injuries NB	Fatalities NB
Regression #4			
Urban (relative to Rural)	0.0922***	0.0661***	-0.478***
	(0.00232)	(0.00420)	(0.0228)
Regression #5			
Mountains County	-0.131***	-0.275***	-0.241***
	(0.00367)	(0.00676)	(0.0373)
Piedmont County	0.0320***	-0.0412***	-0.395***
	(0.00254)	(0.00471)	(0.0252)
Coastal Plains County = o,	-	-	-
Regression #6			
Most Distressed County	-0.0657***	0.0878***	0.714***
	(0.00314)	(0.00574)	(0.0304)
Distressed County	-0.0872***	-0.00727	0.358***
	(0.00262)	(0.00450)	(0.0262)
Least Distressed County = o,	-	-	-
County Fixed Effects	No	No	No
Date Fixed Effects	Yes	Yes	Yes
Observations	255,600	255,600	255,600

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The final Independent Factor regressions evaluate novel explanatory variables. These are: 7) cyclone factors with macro forecast effects to catch gross effects, 8) cyclone factors with micro forecast effects to catch granular effects, and 9) Adverse Weather Events with weather event lag effects. The results in Table 5.5 do not demonstrate consistent significance, signaling that the model is not completely specified or the factors are not granular enough to identify a dynamic effect. However, some interesting results stand out for injuries - the equal and opposite signed coefficients for forecast line and storm event indicate that for counties in the cyclone's path there are more injuries before the cyclone arrives, a net zero effect upon cyclone arrival, and a reduction in injuries as the cyclone leaves.

Table 5.5: Independent factors, regression #7 coefficients (cyclone factors with macro forecast effects).

Regression #7 VARIABLES	Collisions NB	Injuries NB	Fatalities NB
Cone, Any Arrival Timing	0.0174	0.00794	-0.0531
	(0.0110)	(0.0204)	(0.111)
Spillover, Any Arrival Time	0.0438*	0.0190	-0.210
	(0.0224)	(0.0394)	(0.198)
Forecast Line over County	0.0561	0.175***	0.0977
	(0.0408)	(0.0664)	(0.379)
Storm Event (Tropical Cyclone)	-0.0248	-0.175***	0.142
	(0.0411)	(0.0575)	(0.241)
Recent Storm Event False Positive	0.0161***	-0.00926	0.0430
	(0.00323)	(0.00641)	(0.0333)
Recent Hurricane Landfall, USA	-0.0215***	-0.00437	-0.0261
	(0.00395)	(0.00804)	(0.0420)
Post Hurricane Matthew (1 or 0)	-0.0143*	-0.00297	-0.0590
	(0.00757)	(0.0143)	(0.0758)
Post Hurricane Florence (1 or 0)	0.0138**	-0.0103	-0.152**
	(0.00695)	(0.0138)	(0.0725)
County Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	255,600	255,600	255,600

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In evaluating the coefficients and statistical significance of each in Table 5.6, the study finds that using a granular level for forecast timescale better matches the theory that tropical cyclones are an exogenous shock to traffic collisions, with differing directions of effects based on the time factor. The Cone and Spillover terms with arrival greater than 48 hours are unlikely to be coincident with a tropical cyclone, and given that this area can cover most of the state, the total exposure of the effect is large. The Cone and Spillover terms with arrival in less than 48 hours are likely to be coincident with a Storm Event, but not guaranteed; therefore the positive and significant impact on collisions and injuries needs further understanding. In addition, the

Forecast Line term has a significant correlation to injuries – whether this is for counties about to be hit by the eye of a storm, or counties 5 days out, is unknown without further evaluation.

Table 5.6: Independent factors, regression #8 coefficients (cyclone factors with micro forecast effects).

Regression #8 VARIABLES	Collisions NB	Injuries NB	Fatalities NB
Cone, Arrival <48 hours	0.170***	0.130***	-0.203
	(0.0279)	(0.0449)	(0.221)
Cone, Arrival >48 hours	-0.0197*	-0.0205	-0.0158
	(0.0112)	(0.0221)	(0.123)
Spillover, Arrival <48 hours	0.148***	0.0183	0.0912
	(0.0388)	(0.0606)	(0.262)
Spillover, Arrival >48 hours	-0.0556**	-0.0316	-0.159
	(0.0222)	(0.0458)	(0.213)
Forecast Line over County	0.0186	0.140**	0.150
	(0.0406)	(0.0652)	(0.370)
Storm Event (Tropical Cyclone)	-0.0950**	-0.219***	0.139
	(0.0412)	(0.0591)	(0.247)
Recent Storm Event False Positive	0.0158***	-0.00915	0.0426
	(0.00323)	(0.00641)	(0.0333)
Recent Hurricane Landfall, USA	-0.0212***	-0.00409	-0.0271
	(0.00395)	(0.00803)	(0.0420)
Post Hurricane Matthew (1 or 0)	-0.0149**	-0.00369	-0.0570
	(0.00757)	(0.0143)	(0.0758)
Post Hurricane Florence (1 or 0)	0.0118*	-0.0119	-0.151**
	(0.00694)	(0.0138)	(0.0725)
County Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	255,600	255,600	255,600

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In all cases, these effects are not independently meaningful because of interactions between the terms – there is a lot going on when a tropical cyclone approaches, and a full model may better tease out the effects of forecast cones, storms, and other factors. Of note, the post Hurricane Matthew and post Hurricane Florence indicator variables are not worth using as they are nearly colinear with years and are simply shifting some of the year fixed effect coefficients from 2017 through 2019 to those factors. The other two potential psychological factors of "Recent Storm Event False Positive" and "Recent Hurricane Landfall, USA" are likewise shifting some of the month of year fixed effect coefficients from June through September, bringing them closer to zero and making them less likely to be statistically significant – these will also be removed.

Finally, this study evaluates adverse weather events and their lag effects, with results seen in Table 5.7. These factors are interesting and significant for collisions, and in limited cases also significant for injuries and fatalities. Importantly, these represent effects that last for a week after each adverse weather event (n = 42,301 county-days), potentially reversing some of the negative traffic outcomes of adverse weather or mitigating ongoing multi-day events. All of the lag effects show a temporary decrease in collisions during days 1-3 that returns towards baseline during days 4-7, and injuries largely follow the same trend. This may be an indication of protective adaptation or deferred travel due to communication about the hazards of the storm.

As a final note, besides for the recent hurricane indicators previously mentioned, there were no other unreasonable or large shifts in the fixed effects coefficients based on inclusion of one or more of these independent factors. This provides confidence that the fixed effects are relatively stable.

Table 5.7: Independent factors, regression #9 coefficients (adverse weather events and weather event lags).

Regression #9 VARIABLES	Collisions NB	Injuries NB	Fatalities NB
Flood Event	0.189***	0.107***	0.123
	(0.0147)	(0.0263)	(0.133)
Wind Event	0.0997***	0.0297	0.172
	(0.0201)	(0.0418)	(0.203)
Thunderstorm Wind Event	0.107***	0.0901***	-0.0869
	(0.00791)	(0.0170)	(0.0975)
Storm Event (Tropical Cyclone)	-0.0116	-0.146**	0.0711
	(0.0422)	(0.0602)	(0.242)
Winter Event	0.626***	0.368***	-0.0714
	(0.0187)	(0.0230)	(0.128)
Flood Event, 1-3 Day Lag	-0.0348***	-0.0521***	0.0821
	(0.00925)	(0.0182)	(0.0888)
Flood Event, 4-7 Day Lag	-0.0222***	-0.000996	-0.349***
	(0.00718)	(0.0155)	(0.0902)
Wind Event, 1-3 Day Lag	-0.0228*	-0.0152	0.124
	(0.0131)	(0.0263)	(0.130)
Wind Event, 4-7 Day Lag	-0.0226**	-0.0111	-0.000769
	(0.0108)	(0.0222)	(0.121)
Thunderstorm Wind Event, 1-3 Day Lag	-0.0180***	-0.0105	-0.0306
	(0.00503)	(0.0108)	(0.0561)
Thunderstorm Wind Event, 4-7 Day Lag	-0.00872*	-0.0286***	0.00912
	(0.00451)	(0.00966)	(0.0508)
Storm Event (Tropical Cyclone), 1-3 Day Lag	-0.144***	-0.0845**	-0.0333
	(0.0226)	(0.0418)	(0.173)
Storm Event (Tropical Cyclone), 4-7 Day Lag	-0.0345**	-0.0549*	-0.275
	(0.0143)	(0.0312)	(0.189)
Winter Event, 1-3 Day Lag	-0.0509***	-0.139***	-0.359***
	(0.0100)	(0.0159)	(0.103)
Winter Event, 4-7 Day Lag	0.00659	-0.0267**	0.0665
	(0.00726)	(0.0134)	(0.0693)
County Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	255,600	255,600	255,600

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.3 Explanatory Regressions

This section begins the study's main contributions. The first goal is to understand typical environmental factors related to traffic collision outcomes, using all of the relevant factors identified independently in the previous section. As previously discussed some environmental factors have interactive effects on traffic collision outcomes, and these factors are tested as interactive variables. These interactive effects look at combinations of precipitation with Thunderstorm Wind Events, Wind Events, and Storm Events. While they may initially seem inappropriate to combine, the three have the common factor of forceful wind.

The three regressions include: 1) full factors without interactive effects or weather lag effects, 2) full factors without interactive effects and with weather lag effects, and 3) full factors with interactive effects and weather lag effects. Combining multiple independent factors in the 1st and 2nd regressions did not dramatically shift any of the previously identified coefficients, which is a good indication that they are not correlated. Likewise, adding interactive terms in the 3rd regression did not dramatically alter the independent factors.

Select results from Explanatory Regression #3 are presented in Table 5.8, highlighting the sometimes dramatic changes in collisions, injuries, and fatalities that can occur when multiple weather types interact. These effects are additive in the exponent. For example, assume there is a thunderstorm wind event plus two inches of precipitation. To calculate the relative change in collisions, take the baseline factor coefficients for Precipitation (2 x 0.0696) and Thunderstorm Wind Event (0.100), plus two times the interactive factor for Thunderstorm Wind Event with Precipitation (2 x 0.0196). Using the previously discussed relationship between coefficients and outcome rates, calculate $e^{(2*0.0696+0.100+2*0.0196)} = e^{(0.2784)} = 1.321$, which implies a 32.1% increase in collisions, all other things equal. If it has also been three days or more since the last rain, one can expect $e^{(0.2784+\ 0.0499)} =\ e^{(0.3283)} = 1.389$, or a 38.9% increase in collisions.

Table 5.8: Explanatory regression #3 coefficients, interaction of precipitation with adverse weather events.

Regression #3 VARIABLES	Collisions NB	Injuries NB	Fatalities NB
Rain After 3 or more Dry Days	0.0499***	0.0438***	-0.0454
	(0.00382)	(0.00716)	(0.0406)
Snow or Ice Conditions	0.0787***	-0.0141	-0.188**
	(0.00967)	(0.0141)	(0.0775)
Baseline			
Precipitation (inches)	0.0696***	0.0446***	-0.0118
	(0.00311)	(0.00585)	(0.0338)
Wind Event	0.140***	0.0723	0.292
	(0.0221)	(0.0472)	(0.217)
Thunderstorm Wind Event	0.100***	0.0949***	-0.153
	(0.00868)	(0.0187)	(0.106)
Storm Event (Cyclone)	0.0765	-0.0213	-0.294
	(0.0503)	(0.0705)	(0.324)
Modifier over baseline, per inch of precipitation			
+ Precipitation with Wind Event	-0.0931***	-0.0905**	-0.194
	(0.0220)	(0.0457)	(0.158)
+ Precipitation with Thunderstorm Wind Event	0.0196	-0.0395	0.280*
	(0.0185)	(0.0315)	(0.163)
+ Precipitation with Storm Event (Cyclone)	-0.0941***	-0.112***	0.177**
	(0.0204)	(0.0328)	(0.0773)
County Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	255,600	255,600	255,600

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A result from Table 5.8 that stands out is the negative relationship between increasing rainfall and decreasing collisions during wind events and storm events. These events tend to be larger and last longer than thunderstorms, and this potentially is evidence that drivers and other road users adapt to current conditions, given enough time.

5.4 Forecast Baseline Regressions

This section continues the main contributions of the study in understanding how environmental factors and weather forecasts relate to traffic collision outcomes. This includes the explanatory variables that significantly impact traffic collisions, injuries, and fatalities in the state, including weather event lags and the additional novel variables related to tropical cyclone forecasts. Two forecast baseline regressions are run using a highly simplified set of variables. This section makes use of a new indicator variable “CSP” that is set to 1 if either Cone = 1 or SpOver = 1. The primary objective is to see if separating Storm Events (Cyclones) from precipitation changes the previously identified effects, and to see if there are significant differences in outcomes depending on the interaction of a forecast cone and Storm Event (Cyclone).

Table 5.9: Forecast baseline regression #2 coefficients, simple interaction effects.

VARIABLES	Collisions NB	Injuries NB	Fatalities NB
No Storm, Cone or Spillover, No Line	0.0180*	-0.00379	-0.108
	(0.00963)	(0.0186)	(0.101)
No Storm, Cone or Spillover, Line	0.0378	0.139**	0.0529
	(0.0400)	(0.0613)	(0.382)
Storm, No Cone or Spillover	-0.285***	-0.401***	-0.0645
	(0.0599)	(0.0858)	(0.350)
Storm, Cone or Spillover, No Line	0.00804	-0.0751	0.223
	(0.0651)	(0.0777)	(0.331)
Storm, Cone or Spillover, Line	0.158	0.185	-0.0681
County Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	255,600	255,600	255,600

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The other coefficients are excluded from Table 5.9, though they are stable with similar magnitudes and same directions of effect as in previous regressions. Likewise, the “Any Event Lag” coefficients show the same trend as before, with a stronger effect on days 1-3 and a weaker but still reducing effect on days 4-7. In both forecast baseline regressions, the presence of a storm event (cyclone) without any forecast effect has significant negative correlation with collisions and injuries, and the presence of a forecast effect without a storm event (cyclone) has significant positive correlations with collisions and injuries. When both are present, results are inconclusive which may indicate a transition in direction of effect.

Next is an aside to discuss tropical cyclones and attempt to explain this effect through a description of Hurricane Florence on September 14, 2018. In Figure 5.5 there are side by side advisory images just before the hurricane made landfall on the North Carolina coast. The image on the left shows the progression of forecast cones: yellow is the cone’s upper bound from two days prior, pink is from one day prior, and blue shows the latest eye location, cone, and track line. The image on the right shows the historic and current bounds of Florence’s tropical storm-force (orange) and hurricane-force (red) winds as of September 14th. Recall that the Storm Event is classified only by steady wind speeds greater than 39mph, and on this day thirty-four counties are under a Storm Event (Cyclone).

Another thirty-four counties in the western half of the state are experiencing “No Storm, Cone or Spillover;” the weather is not there yet, but it is coming and this is likely a source of anticipatory stress and distraction. This is the effect looked for with the forecast terms, and in this baseline regression there is a small percentage increase in collisions and injuries.

Twenty-five counties in the eastern half of the Piedmont and north half of the Coastal Plain are experiencing “Storm, No Cone or Spillover” – they have tropical storm-force winds and are averaging 2” of rain. Many of these counties were under Cone01 and Cone234 over the preceding days, and anticipatory stress may have primed residents for adaptive measures.

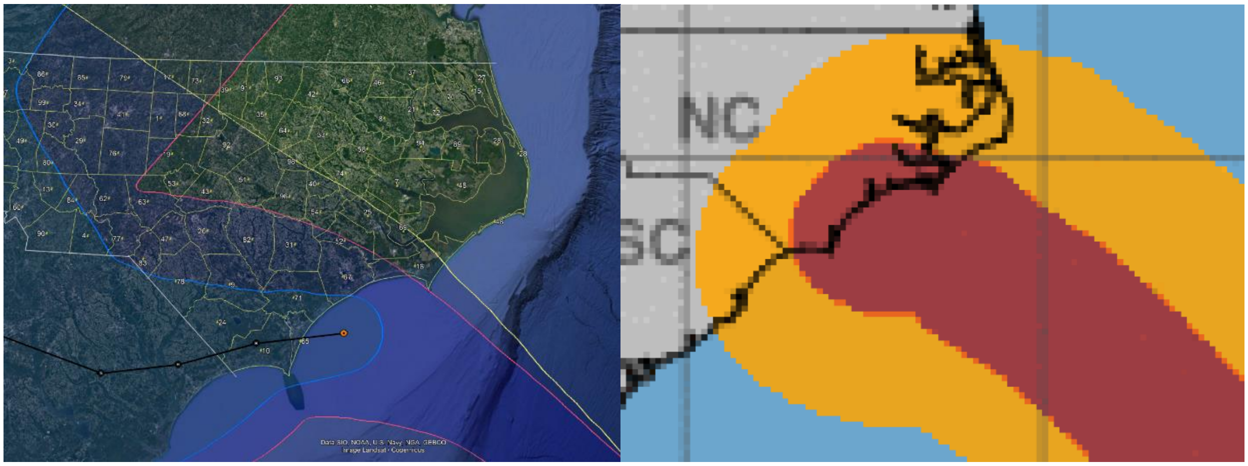


Figure 5.5: Comparison of forecast cone with storm event graphics, Hurricane Florence, September 14, 2018.

Six counties in the southeast of the Coastal Plain are experiencing “Storm, Cone or Spillover” – they have tropical-storm or hurricane-force winds, and are also averaging 3.5” of rain. As there is still a precipitation effect (collision coefficient = 0.0648*** for both regressions), the full effect of the cyclone is a predicted net increase in collisions for the first group, a net decrease in collisions for the second group, and a net increase in collisions for the third group.

In reality all three groups experienced less collisions than predicted, but that is a risk of regressions – individual observations may be wrong, especially on outlier days and in this particular case, when significant uncontrolled factors such as mandatory evacuations come into play.

5.5 All Factor Forecast Regressions

Finally this study moves into the fully specified regressions using forecast terms, individual lag effects, and other key variables. This section will provide completely specified results controlling for all significant fixed and variable effects, which will then be used for subsequent economic analysis.

The first (Forecast #1) will use the macro forecast timescale (Cone and SpOver variables) without interactive effects. Forecast #2 will repeat this analysis but with a micro forecast timescale (Cone01, Cone234, SpOver01, and SpOver234 variables). Forecast #3 will interact macro forecast variables with Storm Events, and Forecast #4 will do the same with micro forecast variables. With interaction, the primary interest is in teasing apart the effects of a cyclone (Storm Event) with and without the presence of a forecast cone, and the effect of a forecast line based on time until storm arrival. As a reminder, the spillover effect is meant to capture changes in outcomes to the counties immediately adjacent to the forecast cone.

In Forecast Regression #1, forecast variables are evaluated independently alongside other explanatory variables of value. This confirms previous regression results that the presence of a forecast cone leads to a small positive overall increase in collisions, with coefficients of 0.0180 (cone) and 0.0367 (spillover), with $p<0.1$. When made more granular in Forecast #2, results confirm the effect is still split by forecasted arrival, with reductions in collisions for projected arrival greater than 48 hours, and increases in collisions for projected arrival in less than 48 hours. The forecast line continues to have a significant impact on injuries, with a coefficient of 0.165 at $p<0.05$ (macro timescale) and coefficient of 0.134 at $p<0.05$ (micro timescale). Importantly for the next steps, none of the independent explanatory factors or fixed effects have changed dramatically due to inclusion of the forecast variables.

For interpreting the last regressions, an assumption is made that there are three potential outcomes. The first outcome is a “No Storm Event / County Not Experiencing Storm” where conditions have not reached tropical cyclone level and any weather impact on traffic collision outcomes will be captured by other weather effect variables. The second is “Storm Event / County Experiencing Incoming Storm” which means a cyclone must be active in the county and the county must be in or adjacent to the forecast cone. The last potential outcome is “Storm Event / County Experiencing Outgoing Storm or Graze” – this could occur if the cyclone center has passed over the county and the county is experiencing backside effects, or if the county was far off the cyclone’s path and is experiencing the outer portion of the cyclone. A county underneath the forecast line is documented as “Line Effect.”

There are few significant results from Forecast #3 using macro forecast timescales in Table 5.10, but the increased injuries in condition c) due to inclusion under the forecast line is consistent with previous results. The large and significant decrease in collisions and injuries in condition g) is likely a sign of drivers taking precaution by deferring travel, or at least properly adjusting their driving routes and behavior due to the cyclone.

Next, the results of Forecast Regression #4 using a micro forecast timescale are in Table 5.11. There are a few statistically significant effects and these are worth noting. The first two are in regards to the increase in collisions for condition d) and the increase in injuries for condition e); this may be capturing some of the stress, preparations (such as buying food or gasoline), and evacuations related to the imminent arrival of a storm. Three other interesting results stand out regarding counties actually experiencing a storm. The large declines in injuries for condition g) and collisions, injuries, and fatalities for condition h) are interesting, though this study may be missing a net change if precipitation captures the effect.

Table 5.10: Forecast regression #3 coefficients, variable interactions and macro forecast effects.

Regression #3 VARIABLES	Collisions NB	Injuries NB	Fatalities NB
No Storm Event / County Not Experiencing Storm			
a) Next to Forecast Cone (Spillover)	0.0333	0.0198	-0.374*
	(0.0208)	(0.0406)	(0.222)
b) In Cone	0.0122	-0.00918	-0.0426
	(0.0108)	(0.0207)	(0.112)
c) In Cone, Line Effect	0.0353	0.140**	0.0490
	(0.0400)	(0.0613)	(0.382)
Storm Event / County Experiencing Incoming Storm			
d) Next to Forecast Cone (Spillover)	-0.0225	-0.308**	0.702
	(0.119)	(0.142)	(0.451)
e) In Cone	0.0395	0.0296	-0.221
	(0.0767)	(0.0915)	(0.488)
f) In Cone, Line Effect	0.169	0.185	-0.0646
	(0.153)	(0.271)	(1.142)
Storm Event / County Experiencing Outgoing Storm or Graze			
g) Not In Cone, Not Next to Cone	-0.204***	-0.371***	-0.0681
	(0.0606)	(0.0901)	(0.353)
County Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	255,600	255,600	255,600

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To confirm, precipitation statistics for conditions d), e), g), and h) are checked to see the full impact of the Precipitation coefficient. Mean (and maximum) daily precipitation under conditions are: d) is 0.302” (5.79”); e) is 0.407” (2.85”); g) is 1.51” (8.02”); and h) is 0.236” (0.66”). These means represent non-trivial increases to collision and injury rates before the Storm Event, but are not enough to flip the sign of the negative (reducing) effect during the Storm Event. These results provide some confirmation that a tropical cyclone’s approach may lead to non-weather related increases in traffic collisions and injuries, and while cyclone winds do bring negative consequences, the dominant effect on collisions and injuries still appears to come from precipitation.

Table 5.11: Forecast regression #4 coefficients, variable interactions and micro forecast effects.

Regression #4 VARIABLES	Collisions NB	Injuries NB	Fatalities NB
No Storm Event / County Not Experiencing Storm			
a) Next to Forecast Cone (Spillover)	0.0332	0.0198	-0.374*
	(0.0208)	(0.0406)	(0.222)
b) In Cone, Projected Arrival > 48 hours	-0.00935	-0.0178	0.0209
	(0.0112)	(0.0223)	(0.121)
c) In Cone, Projected Arrival > 48 hours, Line Effect	-0.00765	0.0782	-0.399
	(0.0450)	(0.0695)	(0.529)
d) In Cone, Projected Arrival < 48 hours	0.134***	0.0431	-0.442
	(0.0306)	(0.0530)	(0.292)
e) In Cone, Projected Arrival < 48 hours, Line Effect	0.117	0.240**	0.505
	(0.0770)	(0.111)	(0.490)
f) In Cone, Projected Arrival of Two Storms (2016)	-0.318	-0.411	-15.42***
	(0.256)	(0.421)	(0.421)
Storm Event / County Experiencing Incoming Storm			
g) Next to Forecast Cone (Spillover)	-0.0219	-0.308**	0.702
	(0.120)	(0.142)	(0.451)
h) In Cone, Projected Arrival > 48 hours	-0.437***	-0.365*	-16.82***
	(0.158)	(0.221)	(0.455)
i) In Cone, Projected Arrival < 48 hours	0.0590	0.0489	-0.178
	(0.0786)	(0.0946)	(0.489)
j) In Cone, Projected Arrival < 48 hours, Line Effect	0.170	0.186	-0.0650
	(0.153)	(0.271)	(1.142)
Storm Event / County Experiencing Outgoing Storm or Graze			
k) Not In Cone, Not Next to Cone	-0.203***	-0.370***	-0.0681
	(0.0605)	(0.0900)	(0.353)
County Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	255,600	255,600	255,600

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.6 Testing Validity

A likelihood-ratio test in Stata is used to compare models and determine if added variables substantially improve the model fit. Three comparisons are made using Stata's "lrtest" function to compare the nested (constrained) model against the unconstrained model with additional variables. This is a chi-squared test which compares the log-likelihoods of the two models, and assuming the constrained model is true, uses the difference in degrees of freedom of the two models for the test statistic value (Greene, 2018).

Within the progression of analyses above are two major leaps. The first was the addition of lagged weather effects. The second was the addition of tropical cyclone forecast variables. These will be tested to validate the model build. The "Prob > X^2" column in the right indicates the probability that the added variables did not improve the model fit, and so a lower number indicates that the added variables were beneficial.

As the results in Table 5.12 show, adding the weather lag and tropical cyclone forecast effects improved these models, that adding weather lags made the most improvement of any modification, and that adding micro forecast variables was more beneficial than macro forecast variables. It is worth pointing out that fatalities are hard to model, but injuries can serve as a placeholder for "severe enough" collisions. In that light, adding weather lags and micro forecast variables improved the model for explaining both traffic collisions and casualties. From the starting point that Forecast #2 is the best non-interactive model and micro forecast variables were superior to macro forecast variables, one can compare coefficients between Forecast #2 and Forecast #4. Many variable coefficients were within a few thousandths or hundredths of a point of each other, and only Wind Events coefficients were significantly different (0.0773 vs 0.145) due to the added interactive term between wind and precipitation.

Table 5.12: Likelihood-ratio tests for select regression models.

	Likelihood-ratio Tests	Prob > X^2
Explanatory Regression #1 (no weather lags) nested within Explanatory Regression #2 (with weather lags)	Collisions: X^2 (10) = 314.67 Injuries: X^2 (10) = 130.18 Fatalities: X^2 (12) = 30.64	P = 0.0000 P = 0.0000 P = 0.0007
Explanatory Regression #2 (no forecast) nested within Forecast Regression #1 (macro forecast)	Collisions: X^2 (3) = 9.73 Injuries: X^2 (3) = 7.38 Fatalities: X^2 (3) = 1.37	P = 0.0211 P = 0.0607 P = 0.7131
Explanatory Regression #2 (no forecast) nested within Forecast Regression #2 (micro forecast)	Collisions: X^2 (5) = 65.76 Injuries: X^2 (5) = 14.99 Fatalities: X^2 (5) = 1.49	P = 0.0000 P = 0.0104 P = 0.9140

As a final check, coefficients from Forecast Regression #4 were used to predict values for all 255,600 county-days, and then evaluated the residuals for collisions, injuries, and fatalities by subtracting predicted from actual values. Scatter plots for the three categories are shown in Figure 5.6. Collision and injury plots generally appear balanced around the x-axis with some heteroskedasticity. The fatality plot is lower bounded near zero, but this makes sense as the mean fatalities are close to zero. The higher peak indicates a clustering of multi-fatality collisions in small counties where the predicted number of fatalities is closer to zero than the larger counties with predicted fatalities closer to 0.5. Next the residuals are summarized.

For collisions, the median residual was -0.275, the mean was 0.0112, and the standard deviation was 4.332. The smallest residual was -118, meaning 118 fewer collisions occurred than were predicted (Mecklenburg County, February 13, 2014). The largest residual was 270, meaning 270 more collisions occurred than were predicted (Wake County, February 24, 2015).

For injuries, the median residual was -0.320, the mean was 0.00329, and the standard deviation was 3.105. The smallest residual was -50 (Mecklenburg County, January 22, 2016) and the largest was 85 (Wake County, December 17, 2016 – freezing rain). For fatalities, the median residual was -0.025, the mean was ~0, and the standard deviation was 0.212. The smallest residual was -0.43 and the largest was 5.96.

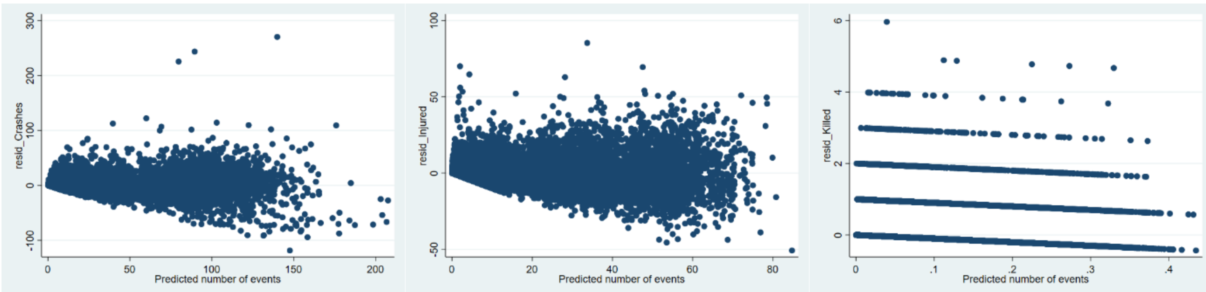


Figure 5.6: Predicted-Residuals scatter plots for collisions (left), injuries (center), and fatalities (right).

For all three categories, percentiles skewed towards large positive residuals (i.e. more actual than predicted) rather than negative residuals. This makes sense as all three categories are zero bounded, and this study revealed that environmental factors mostly make traffic collisions more likely and more dangerous – this is confirmed by the two largest residuals correlating with major winter storms in urban areas. Of interest, the smallest negative residuals also correlated with winter weather – both occurred in Mecklenburg County on the day following major ice and snowstorms, and may have coincided with dramatic reduction in traffic volume due to emergency declarations and work/school closures. Based on these checks of likelihood ratios and residuals, the results of Forecast Regression #4 will be used for the remainder of the study.

5.7 Interpreting Variables and Fixed Effects

In this section is an evaluation of each variable from Forecast Regression #4, summarized by transforming the coefficient into an incidence-rate ratio. This value reflects the expected percent change in outcomes (count of collisions, injuries, or fatalities) given the presence of the conditions listed for binary variables or a one unit increase for continuous or discrete variables. Note that the effect rates below should only be considered when holding all other units constant; for continuous and discrete variables the variable is set equal to 1.

Here a few of the notable results from Table 5.13 are presented. The first block is associated with precipitation, typically rain or small amounts of snow (sleet, freezing rain, or major snow events would be captured by Winter Event). Precipitation is a very common occurrence in the state – 38.7% of all county-days during the study period had precipitation, with an average amount of 0.4” on each of those days. The top 10% of county-days had more than an inch of precipitation each.

The second block of results evaluates the interaction of wind and precipitation. Wind events are fairly rare (accounting for 0.25% of county-days), but lead to large increases in collision and injury outcomes. Interestingly, this effect is mitigated by an average of 0.95” of precipitation that occurs on two thirds of these wind event days. Thunderstorm winds account for 1% of county-days, and also lead to large increases in collision and injury outcomes; this effect is amplified by precipitation in 53% of all thunderstorm wind events, with an average of 0.43” of precipitation on those days.

Table 5.13: Incidence rate ratios for forecast regression #4. Statistically significant effects are bolded.

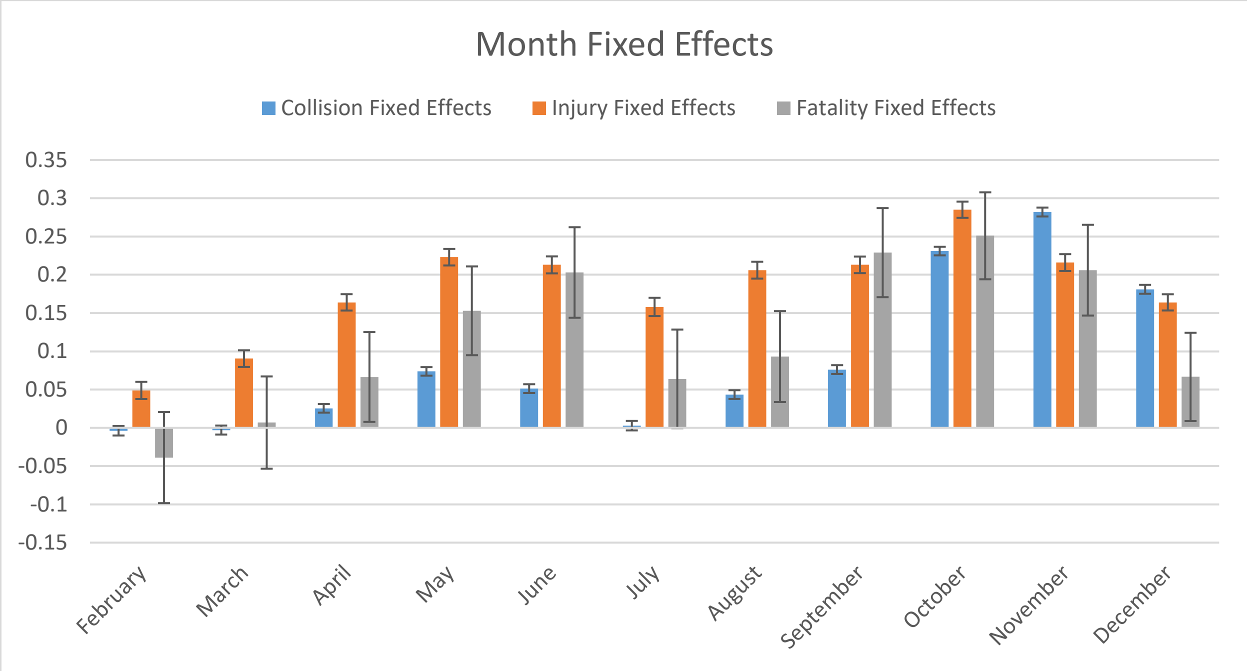
VARIABLES	Collisions	Injuries	Fatalities
Precipitation After 3 or more Dry Days	**5.2%**	**4.6%**	-4.7%
Snow or Ice Conditions	**8.2%**	-1.4%	**-17.1%**
Precipitation (per inch)	**6.8%**	**4.1%**	0.4%
Wind Event, Baseline	**15.6%**	8.0%	33.6%
+ Precipitation (per inch) with Wind Event	**-3.7%**	**-5.6%**	-15.2%
Thunderstorm Wind Event, Baseline	**10.5%**	**9.9%**	-14.0%
+ Precipitation (per inch) with Thunderstorm Wind Event	9.4%	0.5%	30.5%
No Storm, Next to Forecast Cone	3.4%	2.0%	**-31.2%**
No Storm, Forecasted Arrival > 48 hours	-0.9%	-1.8%	2.1%
No Storm, Forecasted Arrival > 48 hours, Line Effect	-0.8%	8.1%	-32.9%
No Storm, Forecasted Arrival < 48 hours	**14.3%**	4.4%	-35.7%
No Storm, Forecasted Arrival < 48 hours, Line Effect	12.4%	**27.1%**	65.7%
No Storm, Forecasted Arrival of Two Storms (rare)	-27.2%	-33.7%	**-100.0%**
Storm Event, No Forecast Factors	-18.4%	-30.9%	-6.6%
Storm Event, Next to Forecast Cone	-2.2%	-26.5%	101.8%
Storm Event, Forecasted Arrival > 48 hours	**-35.4%**	**-30.6%**	**-100.0%**
Storm Event, Forecasted Arrival < 48 hours	6.1%	5.0%	-16.3%
Storm Event, Forecasted Arrival < 48 hours, Line Effect	18.5%	20.4%	-6.3%
Flood Event	**13.2%**	**7.5%**	13.0%
Winter Event	**78.8%**	**43.5%**	-0.8%
Flood Event, 1-3 Day Lag	**-5.2%**	**-6.0%**	7.7%
Flood Event, 4-7 Day Lag	-1.7%	0.3%	**-29.2%**
Wind Event, 1-3 Day Lag	**-3.4%**	-2.0%	13.4%
Wind Event, 4-7 Day Lag	**-2.1%**	-0.9%	-0.2%
Thunderstorm Wind Event, 1-3 Day Lag	**-2.3%**	-1.3%	-4.5%
Thunderstorm Wind Event, 4-7 Day Lag	**-0.8%**	**-2.7%**	1.1%
Storm Event (Tropical Cyclone), 1-3 Day Lag	**-14.1%**	**-6.7%**	-1.8%
Storm Event (Tropical Cyclone), 4-7 Day Lag	**-2.6%**	-4.7%	-23.8%
Winter Event, 1-3 Day Lag	**-7.9%**	**-12.6%**	**-25.9%**
Winter Event, 4-7 Day Lag	1.1%	**-2.7%**	6.7%
Holiday	**-8.6%**	**-3.2%**	6.8%
Daylight Savings Time week	**3.7%**	**5.1%**	-6.3%
Very Hot Day (95^{th} percentile)	**2.2%**	**2.6%**	**-13.9%**
Sum of Very Hot Days (3 days ago to today)	**-1.3%**	**-1.0%**	**4.5%**

The third block of results are all associated with tropical cyclones. As previously noted, there is generally a decrease in traffic collisions and injuries when the storm is far off (more than 48 hours until projected arrival), and an increase in traffic collisions and injuries as the storm approaches (less than 48 hours until projected arrival). This is notable given that 77% of the time a county is forecast to be hit in less than 48 hours, conditions on the ground are not documented as tropical storm conditions. It is also notable as Storm Events only account for 398 county-days, versus 2,807 “Cone” count-days and 651 “Spillover” county-days, and some of the Storm Event county-days occurred in counties never forecast to be affected; this means the false positive or type I error rate is at least 88.5%.

The fourth block of results summarizes the effects of flood events (large increases) and winter events (very large increases) in traffic collisions and injuries, as well as the lag effects of all adverse weather events. This lag effect may be a sign of adaptation as drivers and pedestrians re-orient themselves to the dangers of adverse weather, or due to reduced traffic volumes.

The fifth block captures other notable effects. Holidays and daylight savings time are calendar effects, fixed in time and predictable – that these are still associated with large changes in fatalities (holidays), or collisions and injuries (daylight savings) is a cause for concern and potentially a low hanging fruit for addressing. Also of note is the increase in collisions and injuries (and decrease in fatalities) with hot days, and the reversal of this effect with many hot days in a row. Further study may illuminate if this relates to a change in distribution of pedestrians or cyclists, people changing their activity schedules to avoid excessive temperatures, or some other effect.

Figure 5.7: Final month fixed effect coefficients from forecast regression #4 (January = 0).



For the most part, county, year, and day of week fixed effects stayed consistent or changed insignificantly as the study incorporated explanatory variables relating to environmental conditions and special calendar days. On the other hand, month fixed effects shifted fairly dramatically. This makes sense – adverse weather is highly correlated with certain months, and holidays and daylight savings week are fixed on the calendar. Uncovering reasons for the remaining month to month variation could shed more insight into remediating traffic collisions and reducing its burden on society.

CHAPTER 6: ECONOMIC IMPLICATIONS

Given the results of these regressions, what can be said about the social costs of traffic collisions due to typical weather, adverse weather events, tropical cyclones, and their forecasts?

6.1 Costs of Traffic Collisions and Collision-based Deaths and Injuries

Fatalities and injuries due to traffic collisions are one of the world's leading contributors to disability-adjusted life years (DALY), a metric used by the World Health Organization to assess years of life lost due to early mortality and years of healthy life lost due to disability. Injuries can lead to early retirement, long term disability, job change, and reduced welfare. Overall quality of life can diminish from pain, mobility impairment, and challenges with life tasks like transportation, dressing, and housework. As discussed earlier, traffic collision injuries are overrepresented by the young – collisions were the leading driver for long term care for 18-24 year olds and the most likely cause of disability for 25-54 year olds (Alemany, 2013). A similar metric to DALY is the quality-adjusted life years (QALY), and this helps measure the financial cost of injury based on a standardized assessment; injuries can reduce the value of life by 3 – 11% (minor to moderate injuries) up to 25 – 60% (severe injuries) for the duration of the injury.

Due to their prevalence and impacts to society, the costs of traffic collisions, injuries, and fatalities are well studied. Costs are typically broken down to major categories of human costs, vehicle costs, and general or other costs. Human costs include emergency medical treatment, long term care, loss of work and lost productivity at home, quality of life reductions, and legal spending. Vehicle costs include repairs, replacement, towing, and lost use. General costs account for congestion and delays caused by collisions, insurance premiums, emergency responder services, and non-vehicle property damage. One study assessing collisions in Australia found the breakdown of costs to be approximately 56% human costs, 27% vehicle costs, and 17% general social costs (Connelly, 2006). A study in the USA evaluated the direct economic burdens of traffic collisions and found significant values due to lost productivity (32%), property damage (31%), congestion (12%), and medical expenses (10%), with the remaining burden attributed to loss of life – of note, these do not account for welfare and quality of life losses, which increase and redistributes the costs dramatically (Blincoe, 2015).

Importantly, these costs are not spread equally among regions or communities. A limited study from Europe found that 75% of the patients in hospital intensive care units for traffic collisions were low income, and that even with subsidies many faced healthcare costs of thousands of euros (Papadakaki, 2017). Emergency room visits in the United States can cost thousands or tens of thousands of dollars, potentially meaning traffic collisions can lead to bankruptcy for someone already in financial crisis (Morrison, 2013).

This section evaluates existing traffic collision studies to draw together an estimate for collisions, injuries, and fatalities that can be applied to the study’s regression results. There are a few methods for valuing collisions, including cost of restitution for vehicle or property damage, the human capital approach which values lost productivity and the value of time related to congestion, and the willingness to pay approach which values lost quality of life. In a summary study of twenty industrialized nations, the United States placed the highest valuation on quality of life and only came in slightly lower than Switzerland for total value of a traffic collision fatality (Elvik, 1995). All costs are adjusted to January 2023 values using the Bureau of Labor Statistics inflation calculator, and as needed, Google Finance exchange rate lookup.[14]

Table 6.1: Cost estimates for injuries, fatalities, and property damage only collisions.

Any Injury	Minor Injury	Major Injury	Fatality	Damage Only	Source
	$13,807	$386,480	$1,783,754	$7,135	(Connelly, 2006)
$111,672			$11,262,504	$14,124	(Wettlaufer, 2016)
			$5,043,000		(Elvik, 1994)
$194,712			$4,172,400		(Cabrera-Arnau, 2021)
$24,957					(Pisano, 2008)
			$12,549,600		(US DOT)[15]
$181,347				$13,610	(Leard, 2015)
$128,172	$13,807	$386,480	$6,962,252	$11,623	Average Cost

Of particular relevance, the Federal Highway Administration collects state-level information for collision outcome costs, including for injuries and fatalities (Harmon, 2018). This information comes via surveys administered to federal highway specialists in each state, and North Carolina provided estimates that include comprehensive costs that cover direct and indirect costs (restitution and human capital costs) plus monetized values for pain and suffering (QALY) to best capture the full impact to society from a collision.

The top row values in Table 6.2 are based on the collision severity, which judges the incident as a whole by the worst outcome (e.g. a collision with one fatality and two minor injuries would be classified as a K/Fatality collision). The state uses average fatalities and

[14] https://www.bls.gov/data/inflation_calculator.htm, https://www.google.com/finance/
[15] https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis

injuries per collision type to calculate the total cost per incident, using the average number of injury type per collision type, multiplied by the average cost per person-injury (second row).

Table 6.2: North Carolina's state level incident and casualty costs.

No Injury	C/Possible Injury	B/Minor Injury	A/Major Injury	K/Fatality	
$8,710	$124,800	$228,000	$733,200	$13,106,600	Average Cost – Incident
$4,030	$79,552	$155,790	$571,987	$11,960,000	Average Cost – Person

To explain with an example, when North Carolina calculated these numbers the average K-incident included 1.09 fatalities, 0.13 A-Injuries, 0.34 B-Injuries, 0.29 C-Injuries, and 0.4 Noninjuries. The state's person-injury costs are on the higher end of the referenced studies and higher than what many states assign to traffic collisions, but all costs are within reason. To stay relevant to North Carolina, these state costs will be used for the study's economic analysis.

Summary statistics regarding collisions, injuries, and fatalities in North Carolina are used to calculate the total costs, yearly costs, and daily costs by the collision method (Table 6.3) and the casualty method (Table 6.4). Similar numbers are reached for total costs using two different metrics of costs per incident versus cost per casualty. The difference between the two results could be a result of more people per incident, or a shift up in average incident severity, since the state's 2013 calculation. To estimate an average collision cost for this study period, the total cost (all incidents) is divided by the total number of incidents to reach a value of $123,188 per collision. To estimate an average injury cost, the sum of total costs of each injury type is divided by the total injury counts to reach a value of $109,399 per injury. The unit cost of a fatality will remain as given, $11,960,000.

Table 6.3: Summary of North Carolina traffic collision incidents, 2013-2019.

Year	O-Incidents	C-Incidents	B-Incidents	A-Incidents	K-Incidents	**All Incidents**
2013	148938	50660	17449	1710	1180	**219937**
2014	153744	51767	17609	1763	1186	**226069**
2015	171093	58348	18676	1944	1280	**251341**
2016	183218	60718	19598	2407	1341	**267282**
2017	191868	57725	20615	3660	1292	**275160**
2018	199857	55875	21275	3682	1332	**282021**
2019	203718	54724	21867	3927	1380	**285616**
Total	1252436	389817	137089	19093	8991	**1807426**
Daily	490.0	152.5	53.6	7.5	3.5	**707.1**
Costs						
Unit	$8,710	$124,800	$228,000	$733,200	$13,106,600	
Total	$10,908,717,560	$48,649,161,600	$31,256,292,000	$13,998,987,600	$117,841,440,600	**$222,654,599,360**
Yearly	$1,558,388,223	$6,949,880,229	$4,465,184,571	$1,999,855,371	$16,834,491,514	**$31,807,799,909**
Daily	$4,267,886	$19,033,318	$12,228,596	$5,476,912	$46,103,850	**$87,110,563**

Table 6.4: Summary of North Carolina traffic casualties, 2013-2019.

Year	C-Injuries	B-Injuries	A-Injuries	K-Fatalities	**All Casualties**
2013	84360	22433	2111	1284	**110188**
2014	85876	22671	2193	1282	**112022**
2015	97267	24106	2421	1387	**125181**
2016	101874	25482	2987	1442	**131785**
2017	96316	27279	4605	1401	**129601**
2018	92613	28539	4612	1451	**127215**
2019	91063	29625	4905	1482	**127075**
Total	649369	180135	23834	9729	**863067**
Daily	254.1	70.5	9.3	3.8	**337.7**
Unit Cost	$79,552	$155,790	$571,987	$11,960,000	
Total	$51,658,602,688	$28,063,231,650	$13,632,738,158	$116,358,840,000	**$209,713,412,496**
Yearly	$7,379,800,384	$4,009,033,093	$1,947,534,023	$16,622,691,429	**$29,959,058,928**
Daily	$20,210,721	$10,979,355	$5,333,622	$45,523,803	**$82,047,501**

To review, values of $123,188 per collision, $109,399 per injury, and $11,960,000 per fatality will be used. These will be analyzed with total exposure in terms of county-days for indicator variables or county-days times mean conditional exposure for continuous variables, average outcomes per count-day, and the incident rate coefficients from the last section to estimate the changes in traffic outcomes due to weather and their total costs.

6.2 Total Collision Cost Estimates for Weather and Forecasts

A fundamental aspect of public policy is comparing the benefits and costs of a proposed action or inaction. Given the efforts behind Vision Zero, Road to Zero, and other similar projects to reduce or eliminate traffic casualties, justification for allocating public resources to traffic safety and related infrastructure and transportation projects can depend upon a viable benefit-cost analysis. This section presents a selected group of real-world weather conditions, their effect on traffic outcomes, and their associated social costs.

For all analyses below, statewide daily averages of 707.38 collisions, 333.92 injuries, and 3.808 fatalities are used, transformed into county-day averages of 7.0738, 3.3392, and 0.03808, respectively. Coefficients from Forecast Regression #4 are used to calculate the predicted change in outcomes due that condition (or conditions) being true or occurring. In particular, this study is interested in net outcomes and costs for each category of weather. Recall for this section that the collision data is statistically significant and therefore the collision method cost calculation will be more reliable (column labeled “Net Cost, Collisions”, but the casualty method total (“Net Cost, Casualties”) will be included for comparison. As a reminder, total costs are calculated using the collision rate for the “Δ Collisions” column, and the injury and fatality rate for those columns. Net costs can be interpreted as the change in total social cost due to some event or set of conditions, assuming all other factors constant.

Table 6.5: Net traffic collision outcomes and costs due to tropical cyclones and forecast effects, 2013-2019.

	Δ Collisions	Δ Injuries	Δ Fatalities	Net Cost, Collision Method	Net Cost, Casualty Method
No Storm Event, Forecast Effect Only (n = 3,038 county-days)	372	-30	-10.3	$45,842,342	($126,271,886)
No Storm Event, Forecast Effect with Line Effect (n = 212 county-days)	64	109	0.4	$7,890,851	$16,525,552
Storm Event, Forecast Effect (n = 172 county-days)	21	-41	1.4	$2,630,143	$12,667,416
Storm Event, Forecast Effect with Line Effect (n = 25 county-days)	33	17	-0.1	$4,036,877	$1,150,385
Storm Event, No Forecast Effect (n = 201 county-days)	-261	-208	-0.5	($32,179,209)	($28,734,608)
Cumulative Effect	229	-153	-9	$28,221,004	($124,663,141)
Total Cost	$28,221,004	($16,736,143)	($107,926,998)		

Broadly, Table 6.5 indicates that when a county is under the stress of an imminent tropical cyclone, but is not yet experiencing it, there is a net increase in collisions with an associated cost – this is the top two rows. Under these scenarios, precipitation is below the typical rainy day in North Carolina with a weighted average of 0.163” per county-day. When the storm arrives there are few extra collisions directly attributable to the cyclone (the third and fourth rows), though overall a net increase is expected due to the precipitation involved (1.161” per county-day). The last row, "Storm Event, No Forecast Effect" is capturing counties behind or to the side of the storm; it is likely that individuals within these counties have adapted either by driving differently or deferring travel. As there is no spillover effect, there is at least one county of separation between the cyclone eye and the county of interest. However, without being able to correlate this to traffic volumes, it is unclear if outcome rates are increasing among the people still on the road.

Adverse weather comes in everyday varieties like rain, sleet, snow, floods, thunderstorms, and wind. However, because of the frequency of these events, and their widespread distribution across the state, the cumulative effects are very large.

Table 6.6: Net traffic collision outcomes and costs due to precipitation and wind (excluding cyclones), 2013-2019.

	Δ Crashes	Δ Injuries	Δ Fatalities	Net Cost, Collision Method	Net Cost, Casualty Method
Precipitation (n = 99,111 county-days)	27549	8996	-36.0	$3,393,758,382	$553,060,424
Winter Events and Snow/Ice (n = 10,402 county-days)	23974	4087	-71.7	$2,953,326,649	($410,377,115)
Flood Events (n = 1,287 county-days)	926	412	-6.7	$114,013,923	($34,624,829)
Wind, including with Precipitation (n = 3,320 county-days)	2693	803	4.4	$331,766,128	$140,591,532
Cumulative Effect	55142	14297	-110	$6,792,865,083	$248,650,012
Total Cost	$6,792,865,083	$1,564,085,212	($1,315,435,200)		

This category represents nearly a billion dollars per year of social cost due to "normal" weather, or $2,657,615 per day on average, state-wide. In total, these categories of rain, winter weather, floods, and wind account for 3% of all collisions and 1.67% of injuries. While significant, these numbers are far below previous estimates of traffic collisions due to weather.

Table 6.7: Net traffic collision outcomes and costs due to adverse weather event lags, 2013-2019.

	Δ Crashes	Δ Injuries	Δ Fatalities	Net Cost, Collision Method	Net Cost, Casualty Method
Flood Event Lags (n = 6,541 county-days)	-2189	-787	-37.4	($269,643,200)	($533,728,947)
Wind Event Lags (n = 21,719 county-days)	-3775	-1680	10.6	($465,087,384)	($56,765,734)
Storm Event Lags (n = 1,833 county-days)	-673	-280	-8.4	($82,887,040)	($131,240,358)
Winter Event Lags (n = 15,169 county-days)	-5372	-4330	-34.5	($661,736,910)	($886,068,385)
Cumulative Effect	-12009	-7078	-70	($1,479,354,533)	($1,607,803,424)
Total Cost	($1,479,354,533)	($774,287,630)	($833,515,794)		

Of note, there appears to be a brief respite from the typical crash, injury, and fatality rates following adverse weather (the exception is increased fatalities following wind events, which may be due to downed trees or other debris on roadways). Whether these are improvements in driving skill or less cars and pedestrians on the road is unclear, but at the very least it represents less cost to society and less injuries.

Overall, there are opposite trends during adverse weather (increasing collisions and injuries) and after adverse weather (decreasing collisions and injuries). The increase in counts during adverse weather is likely due to obvious reasons such as reduced vehicle performance, congestion, poor visibility, and debris or water on the roadways. The reduction after the fact may be due to the anchoring effect, with the idea that the adverse weather event shifted drivers' expectations and now they expect hazardous conditions.

While not related to weather, two calendar fixed effects from this regression are worth discussing. Holiday effects are responsible for a dramatic reduction in collisions (-9,580) and injuries (-1,697) over the study period, with annual savings of $168 million by the collision cost method. However, holidays also explain 40 additional fatalities over the same time – using the casualty method to calculate net costs implies that holiday traffic has a social cost of over $42 million per year. Daylight savings may be responsible for an opposite effect, with 2,534 additional collisions, 1,661 additional injuries, and 23.5 fewer fatalities over the study period. Using the collision method would imply a social cost of over $44 million per year, while the casualty method reaches a savings of over $14 million per year.

As a final check, mean residuals for each category of weather variable above are compared. Nearly all residuals had a mean of zero or a mean insignificantly different than zero, which is a sign that the model and predictive coefficients are well suited. There were exceptions with slight but statistically significant offsets, including holidays and winter events with fewer crashes than predicted, and days 4-7 after a wind event or thunderstorm wind event with more crashes than predicted. Overall these offsets were less than 1 collision per county-day and likely balance out because of the number of county-days for each of the four categories, meaning that the cost estimates above remain valid. Moving ahead, the study will evaluate granular county-level data and analysis results for a handful of discovery regressions.

6.3 County-Level Use of Data and Analysis Results

The above effects are applicable to every county in the state. Counties could consider the results around precipitation and adverse weather and evaluate their transportation systems and infrastructure with the potential impacts in mind. Do any local roads become flooded or catch winds effectively? Do traffic flows change, or does visibility become an issue? Are there certain intersections or stretches of road where collisions, injuries, or fatalities frequently happen during adverse weather? If so, perhaps there are low cost and high benefit mitigation strategies that can be used to improve conditions or inform drivers of risks.

Another point to consider is that all forms of precipitation can increase congestion, providing more opportunities for marginal accidents (i.e. the accidents that occur from slower reaction times due to distraction or cognitive load) and compound accidents. This also means that the time of day weather happens can be impactful – people are generally constrained to drive places at certain times due to existing schedules, but flexibility with schools or workplaces during times of adverse weather can reduce congestion and likely reduce collisions and negative outcomes. Educating the public on the dangers of weather and travel in general, improving infrastructure to reduce flooding and puddling, and more rapidly handling injuries and clearing collisions when they do occur can also lower the social burden of traffic collisions (Lu, 2020).

To provide local governments, decision makers, and the general public with more actionable information, the following simple regressions are provided to evaluate select variables interacting with each county, controlling for date fixed effects. This part of the study compares the coefficients for baseline rates with the variable effect to calculate a relative increase in outcomes due to the presence of that factor. Due to limited observations, not all of the results presented here are significant, though collision outcomes are often significant at a $p<0.01$ or $p<0.05$, while fatality effects are significant roughly half of the time. The top twenty of each category are shown to give an idea of heterogeneity; full result tables for these following Discovery Regressions are available in Appendix A.

Table 6.8: County-Level outcome rate changes due to adverse weather events, 2013-2019.

	Count Increases during Adverse Weather Events					
rank	Collisions Increase By:		Injuries Increase By:		Fatalities Increase By:	
1	Northampton	124%	Washington	210%	Hyde	1505%
2	Davie	124%	Tyrrell	173%	Washington	765%
3	Hyde	105%	Martin	110%	Lenoir	256%
4	Chowan	97%	Chowan	100%	Greene	238%
5	Alleghany	96%	Pamlico	92%	Bladen	179%
6	Avery	94%	Northampton	84%	Avery	168%
7	Martin	93%	Bertie	73%	Alleghany	167%
8	Pamlico	88%	Granville	72%	Onslow	146%
9	Bertie	86%	Avery	70%	Gates	146%
10	Warren	76%	Perquimans	65%	Dare	141%
11	Lenoir	72%	Madison	58%	Lincoln	125%
12	Duplin	68%	Camden	57%	Edgecombe	115%
13	Richmond	68%	Duplin	55%	Beaufort	99%
14	Jackson	67%	Jones	52%	Carteret	97%
15	Alexander	66%	Hyde	48%	Northampton	95%
16	Perquimans	65%	Alexander	48%	Surry	88%
17	Granville	63%	Alleghany	44%	Chatham	79%
18	Scotland	61%	Richmond	44%	Cherokee	71%
19	Yadkin	60%	Polk	43%	Pender	69%
20	Madison	57%	Ashe	42%	Madison	65%

The large increases in traffic collision outcomes due to adverse weather events is the most significant result from this section, and as can be seen in Table 6.8, large shifts in traffic outcomes occur statewide in the presence of adverse weather events. These weather events are not entirely uncommon – most counties have between 1% and 6% of their days affected by an adverse weather event, with Coastal counties on average affected 2.2% of the year, Piedmont counties on average affected 3.3% of the year, and Mountain counties affected 4.2% of the year.

Outcome changes due to precipitation follow less of a pattern, and more detailed information on collision factors might illuminate what is driving the increases. Counties with major shifts are displayed in Table 6.9.

Table 6.9: County-Level outcome rate changes due to precipitation, 2013-2019.

Count Increases during Precipitation (calculated for 1")						
rank	Collisions Increase By:		Injuries Increase By:		Fatalities Increase By:	
1	Swain	21%	Dare	26%	Madison	143%
2	Haywood	17%	Cherokee	22%	Perquimans	131%
3	Dare	17%	Polk	21%	Clay	101%
4	Clay	17%	Clay	18%	Swain	89%
5	Granville	17%	Hoke	18%	Avery	88%
6	Wilkes	16%	Avery	16%	Rowan	86%
7	Rutherford	15%	Rutherford	16%	Macon	78%
8	Polk	15%	Swain	16%	Vance	75%
9	McDowell	15%	Granville	16%	Chowan	75%
10	Warren	14%	Haywood	15%	Lincoln	55%
11	Jackson	13%	Warren	15%	Lee	47%
12	Gaston	13%	Transylvania	14%	McDowell	40%
13	Martin	12%	Lee	13%	Franklin	39%
14	Lincoln	12%	Randolph	12%	Ashe	38%
15	Hoke	12%	Gaston	12%	Dare	37%
16	Rowan	12%	Martin	11%	Transylvania	37%
17	Scotland	11%	Tyrrell	11%	Alleghany	34%
18	Forsyth	11%	Alexander	11%	Montgomery	34%
19	Davie	11%	Jackson	10%	Cabarrus	33%
20	Randolph	11%	Scotland	10%	Duplin	32%

The study next evaluated county-level changes on days that are very hot, or with mean temperatures at or above the 95th percentile for that county. This may be due to increased pedestrian or cyclist traffic, more motorcycles, or destination effects because of local beaches, lakes, or forests. It may also be due to psychological factors, as extreme heat has been associated with anger or violence and this could play out in driving behavior or risk-taking (Anderson, 1996). It could also be more mundane, and given the pace of climate change and the increase in hot days (and hot nights), this area deserves more research.

Table 6.10: County-level outcome rate changes due to very hot days, 2013-2019.

	Count Increases on Very Hot Days					
rank	Collisions Increase By:		Injuries Increase By:		Fatalities Increase By:	
1	Dare	102%	Tyrrell	109%	Duplin	159%
2	Swain	43%	Dare	92%	Warren	119%
3	Currituck	41%	Swain	71%	Dare	116%
4	Carteret	27%	Greene	69%	Caswell	93%
5	Tyrrell	25%	Currituck	58%	Caldwell	91%
6	Macon	25%	Camden	54%	Currituck	90%
7	Graham	24%	Jones	46%	Rockingham	90%
8	Transylvania	23%	Avery	44%	Northampton	87%
9	Washington	16%	Graham	44%	Burke	77%
10	Watauga	14%	Davie	35%	Rutherford	73%
11	Northampton	14%	Warren	35%	Wilson	72%
12	Avery	13%	Washington	32%	Gates	69%
13	Brunswick	12%	Transylvania	31%	Davie	61%
14	Warren	12%	Yancey	29%	Carteret	61%
15	Haywood	12%	Perquimans	26%	Alexander	59%
16	Ashe	11%	Henderson	24%	Washington	51%
17	Bertie	11%	Northampton	22%	Alleghany	49%
18	Henderson	11%	Granville	18%	Bertie	49%
19	Richmond	10%	Macon	17%	Lincoln	49%
20	Lincoln	9%	Madison	16%	Lenoir	49%

While not an environmental factor per se, daylight savings week and holidays do have strong impacts on collisions, injuries, and fatalities. Prior studies have implicated the increase in collisions and injuries around daylight savings week with darkness and tiredness, but it could also mean more interactions with wildlife or an overlap of commuters with non-vehicle road users. Holidays also lead to significant alterations in behavior, timing of traffic, and routes taken. This shows the top ten most affected counties for each of these categories to demonstrate how fixed effect modifiers may vary in a predictable way. Results from these regressions can be seen in Table 6.11 and Table 6.12.

Table 6.11: County-level outcome rate changes due to daylight savings week, 2013-2019.

Count Increases during Daylight Savings Week						
rank	Collisions Increase By:		Injuries Increase By:		Fatalities Increase By:	
1	Perquimans	27%	Pamlico	60%	Carteret	339%
2	Person	27%	Ashe	52%	Chowan	235%
3	Greene	26%	Yadkin	44%	Dare	202%
4	Anson	23%	Montgomery	39%	Cabarrus	136%
5	Edgecombe	21%	Edgecombe	36%	Camden	129%
6	Montgomery	18%	Polk	32%	Avery	128%
7	Lee	17%	Burke	32%	Alexander	125%
8	Pamlico	17%	Cherokee	27%	Warren	123%
9	Rockingham	16%	Halifax	25%	Wilkes	120%
10	Chatham	15%	Warren	24%	Alleghany	109%

Table 6.12: County-level outcome rate changes due to holidays, 2013-2019.

Count Increases on Holidays						
rank	Collisions Increase By:		Injuries Increase By:		Fatalities Increase By:	
1	Graham	64%	Graham	83%	Hyde	378%
2	Tyrrell	50%	Tyrrell	57%	Polk	175%
3	Dare	42%	Gates	41%	Clay	162%
4	Warren	35%	Dare	35%	Person	113%
5	Pamlico	25%	Pender	34%	Transylvania	112%
6	Pender	22%	Greene	34%	Burke	111%
7	Jones	20%	Avery	33%	Edgecombe	107%
8	Northampton	19%	Perquimans	32%	Greene	106%
9	Scotland	15%	Warren	31%	Perquimans	106%
10	Currituck	14%	Transylvania	27%	Swain	106%

The above tables are not meant to draw blame towards any counties, but instead to show that the factors that affect traffic collisions in one county may be irrelevant to another nearby. Some trends present themselves based on county type (rural or urban) and topography (Mountains, Piedmont, or Coastal Plain), but there is no firm relationship. As such, county-level efforts to improve traffic safety and reduce the social cost of collisions will need to be studied and tailored to the particular risks present.

CHAPTER 7: DISCUSSION AND CONCLUSION

This section summarizes the study and concludes with a few caveats, opportunities for future research, and final thoughts.

7.1 Review of Study

Traffic collisions and the injuries and fatalities that result are a significant burden on society. Over the period of this study from January 2013 through December 2019, the total social cost of collisions in North Carolina amounted to $209.7 billion, which represents 5.68% of North Carolina's all industry total GDP over the same period (US BEA, 2023). Annual social costs increased from $27.1 billion in 2013 to $35.2 billion in 2019. Predictable factors such as month and day of week are highly correlated with outcome frequencies, and measurable environmental variables help to explain variation in the observed collisions, injuries, and fatalities for any given day. Many of the predictable factors and environmental variables are known ahead of time, either because they are set on the calendar or because modern meteorology forecasts their arrival and modern technology communicates it effectively. As such, these changes in traffic outcomes can be anticipated and potentially prevented. This adds value for society in terms of helping to mitigate harm and allocate resources to handle these changes in traffic outcomes.

This study adds to the understanding of traffic collisions by evaluating the specific ways in which weather can influence outcomes. This includes the addition of novel explanatory variables for tropical cyclone forecasts. When controlling for the presence of a tropical cyclone and other factors, forecasts alone were responsible for some 436 additional collisions between 2013 and 2019 (a rate of approximately 0.134 additional collisions per county-day of forecast cone coverage). The study also shows an increase in collisions upon tropical cyclone arrival, and a decrease in collisions as the cyclone passes by. The leading effect of an increase in collisions may be a result of stress, unusual routes or schedules, or evacuations, and is worth exploring more.

This study also evaluates more typical environmental traffic hazards such as rain, floods, wind, thunderstorms, and winter weather. While they may be commonplace, their effect is significant and likely responsible for at least 7,846 collisions per year over the study period, with an average value of $970 million (approximately 0.18% of North Carolina's GNP over the study period). These weather hazards are responsible for over 2,000 additional injuries each year, but perhaps surprisingly, 16 fewer fatalities per year. These findings could indicate a need for more public awareness building and safety campaigns revolving around improving safety for road users during typical weather, as well as a revamping of severe weather preparedness communication and planning to stress the importance of staying off roadways.

Of note, winter weather events are responsible for a bit of a duality. In analyzing specific days, seven of the ten highest daily collision totals in the state occurred during winter storms, typically involving ice or freezing rain in the Piedmont and Coastal Plain. Just these seven days caused 14,091 collisions worth an estimated $1.73 billion in losses using the collision cost method. On the other hand, winter weather on average has a significant effect in decreasing fatalities – this may be due to people staying off the road or driving cautiously. If people are staying off the road, there may be additional welfare loss due to deferred or cancelled activities or missed school or work. Two of the other top-ten collision days involved large storm fronts with heavy rain and wind, an effect accentuated by them falling on a Friday.

An interesting result to come out of this study is from a new set of explanatory variables that look at lag effects from adverse weather events. In the seven days following adverse weather events, there are 12,000 fewer collisions, 7,000 fewer injuries, and 70 fewer fatalities than expected given the conditions of the day. Evaluating all of the effects simultaneously, a pattern emerges that gives additional weight to the anchoring effect. Even with adequate forecasting, the arrival of adverse weather events including highly publicized tropical cyclones leads to an immediate increase in collisions. Once the adverse weather event has passed, there is a reduction in collisions relative to expected outcomes for the conditions. If the anchoring effect is responsible, then this is the described pattern of people reacting slowly to the arrival of adverse weather, and perhaps taking unnecessary trips or not engaging in safer driving tactics; this is followed by the anchoring effect working in the opposite direction, with people driving under normal conditions as if there were still adverse conditions that necessitated caution, route changes, or other protective strategies. This anchoring effect theory seems bolstered by the fact that the decrease in collisions, injuries, and fatalities is strongest in the first three days following an event, before returning towards baseline between days four and seven. If this is indeed the underlying mechanism for why negative traffic outcomes decrease after an adverse weather event, then a potentially valuable strategy is to use well-timed reminders of the dangers of environmental factors on traffic outcomes to “move up” the adaptive effect and potentially mitigate the adverse weather. This requires further study to understand what exactly happens with traffic and driving styles in the days after adverse weather.

Lastly, this study provides a detailed analysis of fixed effects on North Carolina traffic outcomes. These include month trends, day of week trends, and special calendar day trends around holidays and daylight savings week, all of which could inform transportation and public safety policy.

7.2 Caveats

There are two major caveats with the results of this study – the collision data may be incomplete, and the data could be more granular. Regarding the first issue, while the results obtained are indicative of serious problems, the data is only partial. To begin, the data source is filtered by emergency personnel – if no injury is reported at the time and they believe the damage is less than $1000, the collision would not be reported. However, more than two-thirds of the social costs of collisions are unrelated to property damage, and congestion, productivity loss, and general costs still accrue. This filtering may also disproportionately affect poorer communities – many older cars are valued at less $1000, possibly leading to significant underreporting that explains the underrepresentation in collision counts for rural and economically distressed areas. In addition to this, the National Highway Traffic Safety Administration believes that 57% of crashes are not reported to emergency personnel, particularly property damage only collisions and collisions that occur during inclement weather (Pisano, 2008). A separate study estimates that 24% of all injury crashes are not reported, and this may indicate why the weather-related traffic outcomes in this study (3.05% collision association) were much lower than prior estimates of 24% of collisions being weather-related (Blincoe, 2015). If this pattern holds true in North Carolina, then this study specifically evaluating weather-related traffic collisions may be seeing biased data.

Finding another way to corroborate collisions with weather events may help get past this bias. This could especially be true with winter events – as previously pointed out, the two lowest (negative) residuals for the study's data set were in the days following major winter storms in Mecklenburg County – it seems equally probable that people stayed off the roads and there truly were less collisions, or there were just as many collisions as predicted but neither party wanted to wait in the cold to report them to emergency personnel. One recent trend is to compare official police and transportation department records against hospital admissions for traffic collisions. A study from Europe found that cyclists only report between 7% (minor injuries) and 14% (serious injuries) of collisions with vehicles, and motorcyclists only report between 10% and 35%, respectively (Janstrup, 2016). Another European study found that only 42% of pedestrian and cyclist injuries were reported to police (Bauer, 2018). There may be a larger underreporting problem in rural areas (Piatkowski, 2021). There is evidence of a similar discrepancy in North Carolina – in 2019, the last year of this study, the North Carolina DOT reported 1,482 fatalities while North Carolina HHS reported 1,567 fatalities from traffic collisions. This is worth considering in light of these already stark results.

A second main shortcoming is that for practical purposes, data was not made any more geographically granular than the county level, or at smaller times of analysis than a day. Intuitively, if a major rainstorm happens at 2am on Friday versus happening at 8am on the same day, it is reasonable to expect very different effects on traffic collision, injury, and fatality counts. This may mean that the overall effect of precipitation and other adverse events are muted by the days they occur during low traffic volume times. Likewise, impacts of precipitation and adverse weather events can be heterogenous within a county; the relatively large impact of flood events on traffic collision outcomes is likely driven entirely by a few small areas where roadways are covered by water.

Lastly, the same models were used for collision, injury, and fatality outcomes. However, the frequency of excess zeros with injury and fatality data may indicate another model or different variables are more appropriate for interpreting.

7.3 Future Research

With any study like this, a standout interest is what can individuals and communities do with the resulting information. Is knowing that there is an effect sufficient to change people's behavior? In certain contexts, safety briefings are given to orient people to the dangers ahead of them. Many people have experienced such a briefing before commercial flights, while others with dangerous or high risk jobs (such as soldiers, pilots, miners, surgeons, and astronauts) have extensive routines ahead of and during their riskiest activities to get them into the proper frame of mind. Given the risks of traffic, it would be beneficial to understand if and how a similar intervention would work for drivers, pedestrians, and cyclists.

Returning to the top-ten worst collision days over the study period, seven involved major winter weather events that blanketed much of the state with snow or ice, two involved large rain storms, but one of the top-ten days did not involve adverse weather of any kind. It did rain that day across much of the state (0.34" average per county), but not enough to explain 1,650 collisions, 510 more than predicted. Instead, the only significant event to happen in the state that day was a high-stakes political rally ahead of a midterm election. Could this be behind a spike in collisions, and if so, what other social factors can affect traffic outcomes?

This study explored the correlations between weather events and environmental conditions with traffic outcomes. Given the realities of climate change and the uncertainties of what future weather will be like, how might traffic outcomes be affected? This study also evaluated spillover effects of tropical cyclone forecasts, yet these are somewhat rare. Is there a spillover effect for more common adverse weather events? Likewise, adverse weather events are not typically hyperlocal, yet within the data there is a slight but obvious positive trend between county population and frequency of adverse weather events reported – this could be a result of more insurance claims, weather stations, airports, or trained personnel in high-population counties. Using remote sensing data to set adverse weather events could provide a more accurate assessment of the effects on traffic outcomes.

An assumption made for this study was that days are uncorrelated, but what if that is not true? Communities and individuals may adapt in short- and long-term ways, and these adaptations may be heterogeneous depending on unknown factors.

Finally, accounting for which injuries and fatalities are pedestrians, cyclists, and motorcyclists, and obtaining this data from multiple sources, including hospitals and insurance claims, may allow for improved estimates of the factors in collisions, injuries, and fatalities. Correlating these outcomes to traffic volumes could also inform relative risk at a personal level.

At a larger scale, this study did not evaluate personal choices for changes in individual behavior. Evaluating behavioral trends may be informative for understanding why collisions, injuries, and fatalities occur, and how the outcome rates change based on individual characteristics for different weather events or related characteristics. As an example, driving in inclement weather has a benefit-cost tradeoff; choosing not to drive can mean forgoing income or welfare gained from being somewhere else such as at work or school, or in the case of making it home, safety or reduced spending from not staying at a hotel or sleeping in one’s car. Evaluating this study in the context of traffic surveys or logs for households and individuals would be informative for understanding the motivation behind driving or not driving or otherwise using roadways in the presence of adverse conditions.

7.4 Conclusion

Traffic collisions are a social issue that affect our quality of life and burden the state economy. While the traffic collision issue remains unsolved, getting the public to adopt alternative or energy efficient transportation methods may be impossible. Similarly, unsafe roadways fragment communities and reduce quality of life for people who would otherwise use street frontage for walking or recreation. Importantly, North Carolina is a growing state and so the total cost of traffic collisions can be expected to grow even if outcome rates are held constant. This study may inform and motivate efforts to address this issue with urgency and attention. Legislative levers such as stricter licensing requirements, stiffened penalties for traffic infractions, heightened insurance requirements around road safety training, or technological monitoring could all reduce collision and collision-related outcomes. Likewise, focusing budget priorities on counties with high rates of negative outcomes, and addressing the high rates of fatalities in economically distressed counties would reduce statewide social disparities.

Most people that drive, walk, or bicycle on public roadways can recall at least one time in their life when they were in a traffic collision or came close to being in a collision. What were the factors involved? What was different about that time that led to a collision, compared to all of the other time spent on roads without a collision? While there is certainly a random element to traffic outcomes, better understanding how weather and other predictable factors play a role in collisions can help us develop technologies, infrastructure, and policies to lower everyone’s risk of injury or death and reduce the traffic-related financial burden that society currently shoulders. Given the costs associated with loss of life, medical expenses, lost productivity, congestion, and property damage, the potential net benefits to society available by addressing this problem are substantial.

REFERENCES

Aldred, R. (2019). Motor traffic on urban minor and major roads: Impacts on pedestrian and cyclist injuries. Proceedings of the Institution of Civil Engineers. Municipal Engineer, 172(1), 3. https://doi.org/10.1680/jmuen.16.00068

Alemany, R., Ayuso, M., & Guillén, M. (2013). Impact of road traffic injuries on disability rates and long-term care costs in Spain. Accident analysis & prevention, 60, 95-102.

Algora-Buenafé, A. F., Suasnavas-Bermúdez, P. R., Merino-Salazar, P., & Gómez-García, A. R. (2017). Epidemiological study of fatal road traffic accidents in Ecuador. Australasian Medical Journal (Online), 10(3), 238.

Allison, P. D., & Waterman, R. P. (2002). Fixed-effects negative binomial regression models. Sociological Methodology, 32(1), 247-265. https://doi.org/10.1111/1467-9531.00117

Altheide, D. L. (1997). "the news media, the problem frame, and the production of fear". Sociological Quarterly, 38(4), 647-668. https://doi.org/10.1111/j.1533-8525.1997.tb00758.x

American Psychological Association. (2020). What's the difference between stress and anxiety. Apa. org. https://www. apa. org/topics/stress/anxiety-difference

Anderson, C. A., & Anderson, K. B. (1996). Violent crime rate studies in philosophical context: A destructive testing approach to heat and southern culture of violence effects. Journal of personality and social psychology, 70(4), 740.

Anowar, S., Yasmin, S., & Tay, R. (2013). Comparison of crashes during public holidays and regular weekends. Accident Analysis and Prevention, 51, 93-97. https://doi.org/10.1016/j.aap.2012.10.021

Ashley, W. S., Strader, S., Dziubla, D. C., & Haberlie, A. (2015). DRIVING BLIND: Weather-related vision hazards and fatal motor vehicle crashes. Bulletin of the American Meteorological Society, 96(5), 755-778. https://doi.org/10.1175/BAMS-D-14-00026.1

Bacon, K. (2012). Under the weather: Media induced severe storm anxiety (MISSA) and the local weather news. Presentation at the 40th American Meteorological Society Conference on Broadcast Meteorology, Boston, MA. https://ams. confex. com/ams/40BROADCAST/webprogram/Manuscript/Paper208432/MI SSA. pdf.

Baltruschat, S., Mas-Cuesta, L., Cándido, A., Maldonado, A., Verdejo-Lucas, C., Catena-Verdejo, E., & Catena, A. (2020;2021;). Repeat traffic offenders improve their performance in risky driving situations and have fewer accidents following a mindfulness-based intervention. Frontiers in Psychology, 11, 567278-567278. https://doi.org/10.3389/fpsyg.2020.567278

Bauer, R., Steiner, M., Khnelt-Leddihn, A., Rogmans, W., & Kisser, R. (2018). SM 04-1272 Under-reporting of vulnerable road users in official eu road accident statistics–implications for road safety and added value of eu idb hospital data.

Bhattachan, A., Okin, G. S., Zhang, J., Vimal, S., & Lettenmaier, D. P. (2019). Characterizing the role of wind and dust in traffic accidents in california. Geohealth, 3(10), 328-336. https://doi.org/10.1029/2019GH000212

Blincoe, L., Miller, T. R., Zaloshnja, E., & Lawrence, B. A. (2015). The economic and societal impact of motor vehicle crashes, 2010 (Revised) (No. DOT HS 812 013).

Bonsang, E., & Caroli, E. (2021). Cognitive load and occupational injuries. Industrial Relations: A Journal of Economy and Society, 60(2), 219-242.

Breznitz, S. (2013). Cry wolf: The psychology of false alarms. Psychology Press.

Broad, K., Leiserowitz, A., Weinkle, J., & Steketee, M. (2007). Misinterpretations of the “Cone of uncertainty” in florida during the 2004 hurricane season. Bulletin of the American Meteorological Society, 88(5), 651-667. https://doi.org/10.1175/BAMS-88-5-651

Cabrera-Arnau, C., Prieto Curiel, R., & Bishop, S. R. (2020). Uncovering the behaviour of road accidents in urban areas. Royal Society open science, 7(4), 191739.

Cahyanto, I., Pennington-Gray, L., Thapa, B., Srinivasan, S., Villegas, J., Matyas, C., & Kiousis, S. (2014). An empirical evaluation of the determinants of tourist's hurricane evacuation decision making. Journal of Destination Marketing & Management, 2(4), 253-265.

Cangialosi, J. (2022). National hurricane center forecast verification report, 2021 hurricane season. NOAA. (april 2022). https://www.nhc.noaa.gov/verification/pdfs/Verification_2021.pdf

Cappellari, P., & Weber, B. S. (2022). An analysis of the new york city traffic volume, vehicle collisions, and safety under COVID-19. Journal of Safety Research, 83, 57-65. https://doi.org/10.1016/j.jsr.2022.08.004

Cartwright, S., Cooper, C. L., & Barron, A. (1996). The company car driver, occupational stress as a predictor of motor vehicle accident involvement. Human Relations (New York), 49(2), 195-208. https://doi.org/10.1177/001872679604900204

Chang, L. (2005). Analysis of freeway accident frequencies: Negative binomial regression versus artificial neural network. Safety Science, 43(8), 541-557. https://doi.org/10.1016/j.ssci.2005.04.004

Clark, D. E., & Cushing, B. M. (2004). Rural and urban traffic fatalities, vehicle miles, and population density. Accident Analysis and Prevention, 36(6), 967-972. https://doi.org/10.1016/j.aap.2003.10.006

Coleman, J. S. M., Newby, K. D., Multon, K. D., & Taylor, C. L. (2014). Weathering the storm: Revisiting severe-weather phobia. Bulletin of the American Meteorological Society, 95(8), 1179-1183. https://doi.org/10.1175/BAMS-D-13-00137.1

Connelly, L. B., & Supangan, R. (2006). The economic costs of road traffic crashes: Australia, states and territories. Accident Analysis & Prevention, 38(6), 1087-1093.

Cox, A. E., & Cicchino, J. B. (2021). Continued trends in older driver crash involvement rates in the united states: Data through 2017–2018. Journal of Safety Research, 77, 288-295. https://doi.org/10.1016/j.jsr.2021.03.013

Coxe, S., West, S. G., & Aiken, L. S. (2009). The analysis of count data: A gentle introduction to poisson regression and its alternatives. Journal of Personality Assessment, 91(2), 121-136. https://doi.org/10.1080/00223890802634175

Cunningham, C. X., Nuñez, T. A., Hentati, Y., Sullender, B., Breen, C., Ganz, T. R., Kreling, S. E. S., Shively, K. A., Reese, E., Miles, J., & Prugh, L. R. (2022). Permanent daylight saving time would reduce deer-vehicle collisions. Current Biology, 32(22), 4982-4988.e4. https://doi.org/10.1016/j.cub.2022.10.007

Czajkowski, J., Simmons, K., & Sutter, D. (2011). An analysis of coastal and inland fatalities in landfalling US hurricanes. Natural Hazards (Dordrecht), 59(3), 1513-1531. https://doi.org/10.1007/s11069-011-9849-x

Czajkowski, J., Simmons, K., & Sutter, D. (2011). An analysis of coastal and inland fatalities in landfalling US hurricanes. Natural Hazards (Dordrecht), 59(3), 1513-1531. https://doi.org/10.1007/s11069-011-9849-x

Dalvi, Q. (2004). World report on road traffic injury prevention by world health organization and world bank (WHO, geneva, april 2004). Transport Reviews, 24(3), 365-376. https://doi.org/10.1080/0144164042000231404

Daniels, G. L. (2007). Conceptualizing continuous coverage: A strategic model for wall-to-wall local television weather broadcasts 1. Journal of Applied Communication Research : JACR, 35(1), 48.

Dash, N., & Gladwin, H. (2007). Evacuation decision making and behavioral responses: Individual and household. Natural hazards review, 8(3), 69-77.

Diaz-Corro, K. J., Moreno, L. C., Mitra, S., & Hernandez, S. (2021). Assessment of crash occurrence using historical crash data and a random effect negative binomial model: A case study for a rural state. Transportation Research Record, 2675(12), 38-52. https://doi.org/10.1177/03611981211027569

Ecola, L., Popper, S. W., Silberglitt, R., & Fraade-Blanar, L. (2018). The road to zero: A vision for achieving zero roadway deaths by 2050. Rand Health Quarterly, 8(2), 11-11.

Eisenberg, D. (2004). The mixed effects of precipitation on traffic crashes. Accident Analysis and Prevention, 36(4), 637-647. https://doi.org/10.1016/S0001-4575(03)00085-X

Elvik, R. (1995). An analysis of official economic valuations of traffic accident fatalities in 20 motorized countries. Accident analysis & prevention, 27(2), 237-247.

Engström, J., Ljung Aust, M., & Viström, M. (2018). Effects of cognitive load and anticipation on driver responses to a critical traffic event. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 62(1), 1584-1588. https://doi.org/10.1177/1541931218621358

Espinel, Z., Kossin, J. P., Galea, S., Richardson, A. S., & Shultz, J. M. (2019). Forecast: increasing mental health consequences from Atlantic hurricanes throughout the 21st century. Psychiatric services, 70(12), 1165-1167.

Ewing, R., & Dumbaugh, E. (2009). The built environment and traffic safety: A review of empirical evidence. Journal of Planning Literature, 23(4), 347-367. https://doi.org/10.1177/0885412209335553

GARCIA-ALTES, A., SUELVES, J. M., & BARBERIA, E. (2013;2012;). Cost savings associated with 10 years of road safety policies in catalonia, spain. Bulletin of the World Health Organization, 91(1), 28-35. https://doi.org/10.2471/BLT.12.110072

García-Herrero, S., Febres, J. D., Boulagouas, W., Gutiérrez, J. M., & Mariscal Saldaña, M. Á. (2021). Assessment of the influence of technology-based distracted driving on drivers' infractions and their subsequent impact on traffic accidents severity. International Journal of Environmental Research and Public Health, 18(13), 7155. https://doi.org/10.3390/ijerph18137155

Givi, J., & Galak, J. (2019). The “future is now” bias: Anchoring and (insufficient) adjustment when predicting the future from the present. Journal of Experimental Social Psychology, 84, 103830. https://doi.org/10.1016/j.jesp.2019.103830

Graff Zivin, J., Liao, Y., & Panassié, Y. (2023). How hurricanes sweep up housing markets: Evidence from florida. Journal of Environmental Economics and Management, 118, 102770. https://doi.org/10.1016/j.jeem.2022.102770

Green, C. P., Heywood, J. S., & Navarro, M. (2016). Traffic accidents and the london congestion charge. Journal of Public Economics, 133, 11-22. https://doi.org/10.1016/j.jpubeco.2015.10.005

Greene, W. H. 2018. Econometric Analysis. 8th ed. New York: Pearson.

Guo, Y., Gasparrini, A., Armstrong, B., Li, S., Tawatsupa, B., Tobias, A., ... & Williams, G. (2014). Global variation in the effects of ambient temperature on mortality: a systematic evaluation. Epidemiology (Cambridge, Mass.), 25(6), 781.

Harmon, T., Bahar, G. B., & Gross, F. B. (2018). Crash costs for highway safety analysis (No. FHWA-SA-17-071). United States. Federal Highway Administration. Office of Safety.

Hengen, K. M., & Alpers, G. W. (2021). Stress makes the difference: Social stress and social anxiety in decision-making under uncertainty. Frontiers in Psychology, 12, 578293-578293. https://doi.org/10.3389/fpsyg.2021.578293

Hochard, J., Li, Y., & Abashidze, N. (2022). Associations of hurricane exposure and forecasting with impaired birth outcomes. Nature Communications, 13(1), 6746-6746. https://doi.org/10.1038/s41467-022-33865-x

Janstrup, K. H., Kaplan, S., Hels, T., Lauritsen, J., & Prato, C. G. (2016). Understanding traffic crash under-reporting: linking police and medical records to individual and crash characteristics. Traffic Injury Prevention, 17(6), 580-584.

Joslyn, S., Savelli, S., & Nadav-Greenberg, L. (2011). Reducing probabilistic weather forecasts to the worst-case scenario: Anchoring effects. Journal of Experimental Psychology. Applied, 17(4), 342-353. https://doi.org/10.1037/a0025901

Kilpeläinen, M., & Summala, H. (2007). Effects of weather and weather forecasts on driver behaviour. Transportation Research. Part F, Traffic Psychology and Behaviour, 10(4), 288-299. https://doi.org/10.1016/j.trf.2006.11.002

Kousky, C. (2014). Informing climate adaptation: A review of the economic costs of natural disasters. Energy Economics, 46, 576-592. https://doi.org/10.1016/j.eneco.2013.09.029

Langley, R. L., Higgins, S. A., & Herrin, K. B. (2006). Risk factors associated with fatal animal-vehicle collisions in the united states, 1995–2004. Wilderness & Environmental Medicine, 17(4), 229-239. https://doi.org/10.1580/06-WEME-OR-001R1.1

Leard, B., & Roth, K. (2015). Weather, traffic accidents, and climate change (No. RFF DP 15-19). Resources for the Future.

LeBlanc, V. R. (2009). The effects of acute stress on performance: implications for health professions education. Academic Medicine, 84(10), S25-S33.

Legree, P. J., Heffner, T. S., Psotka, J., Martin, D. E., & Medsker, G. J. (2003). Traffic crash involvement: Experiential driving knowledge and stressful contextual antecedents. Journal of Applied Psychology, 88(1), 15-26. https://doi.org/10.1037/0021-9010.88.1.15

Levine, N., Kim, K. E., & Nitz, L. H. (1995). Daily fluctuations in Honolulu motor vehicle accidents. Accident Analysis & Prevention, 27(6), 785-796.

Lippmann, S. J., Fuhrmann, C. M., Waller, A. E., & Richardson, D. B. (2013). Ambient temperature and emergency department visits for heat-related illness in North Carolina, 2007–2008. Environmental research, 124, 35-42.

Lu, H., Chen, M., & Kuang, W. (2020). The impacts of abnormal weather and natural disasters on transport and strategies for enhancing ability for disaster prevention and mitigation. Transport Policy, 98, 2-9. https://doi.org/10.1016/j.tranpol.2019.10.006

Luo, Z., Li, J., & Zhong, M. (2017). Prediction of seasonal variation in traffic collisions on rural highways: A case study in the province of british columbia. Paper presented at the 23-26. https://doi.org/10.1109/ICTIS.2017.8047736

Martin, J. (2002). Relationship between crash rate and hourly traffic flow on interurban motorways. Accident Analysis and Prevention, 34(5), 619-629. https://doi.org/10.1016/S0001-4575(01)00061-6

Martin, J. (2002). Relationship between crash rate and hourly traffic flow on interurban motorways. Accident Analysis and Prevention, 34(5), 619-629. https://doi.org/10.1016/S0001-4575(01)00061-6

Maze, T., Agarwai, M., & Burchett, G. (2006). Whether weather matters to traffic demand, traffic safety, and traffic operations and flow. Transportation Research Record, 1948(1948), 170-176. https://doi.org/10.3141/1948-19

McCance, E. C., Baydack, R. K., Walker, D. J., & Leask, D. N. (2015). Spatial and temporal analysis of factors associated with urban deer–vehicle collisions. Human-Wildlife Interactions, 9(1), 119-131.

MCKEE, J. J., COCHRAN, D. M., Oak Ridge National Lab. (ORNL), Oak Ridge, TN (United States), & Center for Computational Sciences. (2012). The role of landscape in the distribution of deer-vehicle collisions in south mississippi. Southeastern Geographer, 52(3), 327-340. https://doi.org/10.1353/sgo.2012.0020

Merdjanoff, A. A., Abramson, D. M., Piltch-Loeb, R., Findley, P., Peek, L., Beedasy, J., Park, Y. S., Sury, J., & Meltzer, G. Y. (2022). Examining the Dose–Response relationship: Applying the disaster exposure matrix to understand the mental health impacts of hurricane sandy. Clinical Social Work Journal, 50(4), 400-413. https://doi.org/10.1007/s10615-021-00814-y

Mohan, D., Tiwari, G., Varghese, M., Bhalla, K., John, D., Saran, A., & White, H. (2020). PROTOCOL: Effectiveness of road safety interventions: An evidence and gap map. Campbell Systematic Review, 16(1), n/a. https://doi.org/10.1002/cl2.1077

Morrison, E. R., Gupta, A., Olson, L., Cook, L., & Keenan, H. (2013). Health and financial fragility: Evidence from car crashes and consumer bankruptcy. University of Chicago Coase-Sandor Institute for Law & Economics Research Paper, (655), 13-81.

Musa, M. F., Hassan, S. A., Mashros, N., & Chen, F. (2020). The impact of roadway conditions towards accident severity on federal roads in malaysia. PloS One, 15(7), e0235564-e0235564. https://doi.org/10.1371/journal.pone.0235564

Nadav-Greenberg, L., Joslyn, S. L., & Taing, M. U. (2008). The effect of uncertainty visualizations on decision making in weather forecasting. Journal of Cognitive Engineering and Decision Making, 2(1), 24-47. https://doi.org/10.1518/155534308X284354

National Center for Statistics and Analysis. (2022, June). Speeding: 2020 data (Traffic Safety Facts. Report No. DOT HS 813 320). National Highway Traffic Safety Administration.

National Highway Traffic Safety Administration. (2015). The economic and societal impact of motor vehicle crashes, 2010 (revised). Annals of Emergency Medicine, 66(2), 194-196. https://doi.org/10.1016/j.annemergmed.2015.06.011

National Weather Service. (2023). Beaufort wind scale (NOAA 2023). https://www.weather.gov/mfl/beaufort

North Carolina Department of Health and Human Services. (2021). 10 leading causes of injury deaths by age group, north carolina residents, 2019. https://injuryfreenc.dph.ncdhhs.gov/DataSurveillance/LC-InjuryDeathTable-2019.pdf

North Carolina Department of Motor Vehicles. (2023). DMV-349 instruction manual. NC DOT. https://connect.ncdot.gov/business/DMV/DMV%20Documents/DMV-349%20Instructional%20Manual.pdf

North Carolina Department of Transportation. (2020). North carolina 2019 traffic crash facts. NC DOT. https://connect.ncdot.gov/business/DMV/CrashFactsDocuments/2019%20Crash%20Facts.pdf

North Carolina Department of Transportation. (2022). North carolina 2013-2019 daily traffic collision data. NC DOT. Public records request, received 20 September 2022.

Nunn, S., & Newby, W. (2015). Landscapes of risk: The geography of fatal traffic collisions in indiana, 2003 to 2011. The Professional Geographer, 67(2), 269-281. https://doi.org/10.1080/00330124.2014.935165

O'Dea, S. (2020). Smartphone penetration rate as share of the population in the United States from 2010 to 2021.

Papadakaki, M., Stamouli, M. A., Ferraro, O. E., Orsi, C., Otte, D., Tzamalouka, G., ... & Chliaoutakis, J. (2017). Hospitalization costs and estimates of direct and indirect economic losses due to injury sustained in road traffic crashes: Results from a one-year cohort study in three European countries (The REHABILAID project). Trauma, 19(4), 264-276.

Papantoniou, P., Papadimitriou, E., & Yannis, G. (2017). Review of driving performance parameters critical for distracted driving research. Transportation research procedia, 25, 1796-1805.

Parc, C. (2019). How does fear hit the headlines?. Lexis. Journal in English Lexicology, (13).

Parks, R. M., Anderson, G. B., Nethery, R. C., Navas-Acien, A., Dominici, F., & Kioumourtzoglou, M. A. (2021). Tropical cyclone exposure is associated with increased hospitalization rates in older adults. Nature Communications, 12(1), 1545.

Parks, R. M., Benavides, J., Anderson, G. B., Nethery, R. C., Navas-Acien, A., Dominici, F., ... & Kioumourtzoglou, M. A. (2022). Association of tropical cyclones with county-level mortality in the US. JAMA, 327(10), 946-955.

Pennelly, C., Reuter, G. W., & Tjandra, S. (2018). Effects of weather on traffic collisions in edmonton, canada. Atmosphere-Ocean, 56(5), 362-371. https://doi.org/10.1080/07055900.2018.1548344

Piatkowski, D., McCully, J., & Piatkowski, M. (2021). Toward a Rural Vision Zero: A Qualitative Exploration of Bicyclist and Pedestrian Traffic Fatalities in Small-Town and Rural Nebraska. Great Plains Research, 31(1), 97-109.

Pisano, P. A., Goodwin, L. C., & Rossetti, M. (2008). 8.1 U.S. highway crashes in adverse road weather conditions. Papers from the 88th AMS Annual Meeting,

Raynham, P., Unwin, J., Khazova, M., & Tolia, S. (2020). The role of lighting in road traffic collisions. Lighting Research & Technology (London, England : 2001), 52(4), 485-494. https://doi.org/10.1177/1477153519870857

Razi-Ardakani, H., Mahmoudzadeh, A., & Kermanshah, M. (2018). A nested logit analysis of the influence of distraction on types of vehicle crashes. European Transport Research Review, 10(2), 1-14. https://doi.org/10.1186/s12544-018-0316-6

Robinson, R. M., Collins, A. J., Jordan, C. A., Foytik, P., & Khattak, A. J. (2018). Modeling the impact of traffic incidents during hurricane evacuations using a large scale microsimulation. International Journal of Disaster Risk Reduction, 31, 1159-1165. https://doi.org/10.1016/j.ijdrr.2017.09.013

Rusli, R., Haque, M. M., King, M., & Voon, W. S. (2017). Single-vehicle crashes along rural mountainous highways in malaysia: An application of random parameters negative binomial model. Accident Analysis and Prevention, 102, 153-164. https://doi.org/10.1016/j.aap.2017.03.002

Saha, S., Schramm, P., Nolan, A., & Hess, J. (2016). Adverse weather conditions and fatal motor vehicle crashes in the united states, 1994-2012. Environmental Health, 15(1), 104-104. https://doi.org/10.1186/s12940-016-0189-x

Saunier, N., Mourji, N., & Agard, B. (2011). Mining microscopic data of vehicle conflicts and collisions to investigate collision factors. Transportation Research Record, 2237(1), 41-50. https://doi.org/10.3141/2237-05

Schaeffer, K., & Van Green, T. (2022). Key facts about US voter priorities ahead of the 2022 midterm elections.

Schneider, R. J. (2020). United states pedestrian fatality trends, 1977 to 2016. Transportation Research Record, 2674(9), 1069-1083. https://doi.org/10.1177/0361198120933636

Schwebel, D. C., Hasan, R., Griffin, R., Hasan, R., Hoque, M. A., Karim, M. Y., Luo, K., & Johnston, A. (2021). Reducing distracted pedestrian behavior using bluetooth beacon technology: A crossover trial. Accident Analysis and Prevention, 159, 106253-106253. https://doi.org/10.1016/j.aap.2021.106253

Sherman-Morris, K., & Del Valle-Martinez, I. (2017). Optimistic bias and the consistency of hurricane track forecasts. Natural hazards, 88, 1523-1543.

Spencer, M. R., Hedegaard, H., & Garnet, M. (2021). Motor vehicle traffic death rates by sex, age group, and road-user type: United States, 1999-2019.

Thompson, R. R., Holman, E. A., & Silver, R. C. (2019). Media coverage, forecasted posttraumatic stress symptoms, and psychological responses before and after an approaching hurricane. JAMA Network Open, 2(1), e186228-e186228. https://doi.org/10.1001/jamanetworkopen.2018.6228

U.S. Bureau of Economic Analysis, Gross Domestic Product: All Industry Total in North Carolina [NCNGSP], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/NCNGSP, February 22, 2023.

United Nations. (2020). Resolution 74/299 improving global road safety (UN, september 2020). https://undocs.org/en/A/RES/74/299

Vandoros, S., Avendano, M., & Kawachi, I. (2018). The short-term impact of economic uncertainty on motor vehicle collisions. Preventive Medicine, 111, 87-93. https://doi.org/10.1016/j.ypmed.2018.02.005

Washington, S., Karlaftis, M., Mannering, F., & Anastasopoulos, P. (2020). Statistical and econometric methods for transportation data analysis. Chapman and Hall/CRC.

Whitehead, J. C. (2003). One million dollars per mile? the opportunity costs of hurricane evacuation. Ocean & Coastal Management, 46(11), 1069-1083. https://doi.org/10.1016/j.ocecoaman.2003.11.001

Wilkins, D. C., Kockelman, K. M., & Jiang, N. (2019). Animal-vehicle collisions in texas: How to protect travelers and animals on roadways. Accident Analysis and Prevention, 131, 157-170. https://doi.org/10.1016/j.aap.2019.05.030

WILSON, F. A., & STIMPSON, J. P. (2010). Trends in fatalities from distracted driving in the united states, 1999 to 2008. American Journal of Public Health (1971), 100(11), 2213-2219. https://doi.org/10.2105/AJPH.2009.187179

Wolf, K., & Bratton, N. (2006). Urban trees and traffic safety: Considering U.S. roadside policy and crash data. Arboriculture & Urban Forestry, 32(4), 170-179. https://doi.org/10.48044/jauf.2006.023

World Health Organization. (2021). Global plan decade of action for road safety 2021-2030 (WHO, october 2021). https://cdn.who.int/media/docs/default-source/documents/health-topics/road-traffic-injuries/global-plan-for-road-safety.pdf

Xu, Z., Hu, W., Su, H., Turner, L. R., Ye, X., Wang, J., & Tong, S. (2014). Extreme temperatures and paediatric emergency department admissions. Journal of Epidemiology and Community Health (1979), 68(4), 304-311. https://doi.org/10.1136/jech-2013-202725

Yan, M., Wilson, A., Dominici, F., Wang, Y., Al-Hamdan, M., Crosson, W., Schumacher, A., Guikema, S., Magzamen, S., Peel, J. L., Peng, R. D., & Anderson, G. B. (2021). Tropical cyclone exposures and risks of emergency medicare hospital admission for cardiorespiratory diseases in 175 urban united states counties, 1999-2010. Epidemiology (Cambridge, Mass.), 32(3), 315. https://doi.org/10.1097/EDE.0000000000001337

Yan, X., Wang, B., An, M., & Zhang, C. (2012). Distinguishing between rural and urban road segment traffic safety based on zero-inflated negative binomial regression models. Discrete Dynamics in Nature and Society, 2012, 1-11. https://doi.org/10.1155/2012/789140

Yasin, Y. J., Grivna, M., & Abu-Zidan, F. M. (2021). Global impact of COVID-19 pandemic on road traffic collisions. World Journal of Emergency Surgery, 16(1), 1-51. https://doi.org/10.1186/s13017-021-00395-8

Zhao, Q., Zhang, Y., Zhang, W., Li, S., Chen, G., Wu, Y., ... & Guo, Y. (2017). Ambient temperature and emergency department visits: Time-series analysis in 12 Chinese cities. Environmental pollution, 224, 310-316.

Zhu, J., Dai, Q., Deng, Y., Zhang, A., Zhang, Y., & Zhang, S. (2018). Indirect damage of urban flooding: Investigation of flood-induced traffic congestion using dynamic modeling. Water (Basel), 10(5), 622. https://doi.org/10.3390/w10050622

APPENDICES

Appendix A

County-specific outcomes from discovery regressions (Stata prompts and coefficient outputs for these and all other regressions are available in Appendix B).

Outcome rate changes due to selected variables, by county.
C = Collisions; I = Injuries; K = Fatalities

	Adverse Weather			**Precipitation (1")**			**Very Hot Days**		
	C	I	K	C	I	K	C	I	K
Alamance	54%	30%	-51%	9%	8%	-35%	-5%	-2%	5%
Alexander	66%	48%	-100%	7%	11%	-72%	-4%	0%	59%
Alleghany	96%	44%	167%	7%	9%	34%	-4%	-9%	49%
Anson	28%	10%	-100%	4%	7%	-79%	6%	8%	-100%
Ashe	49%	42%	37%	-1%	8%	38%	11%	-10%	-34%
Avery	94%	70%	168%	6%	16%	88%	13%	44%	-100%
Beaufort	36%	-4%	99%	-6%	7%	-27%	-4%	-8%	-30%
Bertie	86%	73%	-9%	8%	-1%	8%	11%	16%	49%
Bladen	24%	23%	179%	0%	2%	-8%	2%	2%	-10%
Brunswick	25%	6%	-68%	-5%	-2%	1%	12%	11%	11%
Buncombe	15%	10%	-27%	8%	6%	0%	8%	8%	-18%
Burke	32%	18%	51%	9%	6%	22%	-3%	4%	77%
Cabarrus	24%	16%	-51%	3%	2%	33%	-7%	-7%	-13%
Caldwell	30%	4%	-68%	3%	0%	-32%	6%	9%	91%
Camden	52%	57%	-100%	11%	-27%	-100%	7%	54%	-100%
Carteret	23%	18%	97%	-5%	-10%	-17%	27%	4%	61%
Caswell	19%	14%	-100%	6%	6%	-40%	-8%	16%	93%
Catawba	53%	26%	19%	8%	4%	-46%	0%	1%	-9%
Chatham	48%	29%	79%	3%	-8%	-56%	-16%	4%	-38%
Cherokee	28%	30%	71%	9%	22%	16%	4%	-4%	-60%
Chowan	97%	100%	-100%	0%	-4%	75%	-12%	-20%	-100%
Clay	34%	35%	-100%	17%	18%	101%	-21%	-14%	47%
Cleveland	34%	27%	9%	8%	5%	6%	-7%	-5%	8%
Columbus	22%	3%	-41%	4%	-5%	-1%	4%	5%	30%
Craven	16%	-14%	-61%	-4%	-8%	6%	1%	-4%	-23%
Cumberland	6%	-6%	-21%	6%	2%	-9%	4%	-2%	19%
Currituck	18%	9%	37%	3%	8%	-9%	41%	58%	90%
Dare	-1%	-36%	141%	17%	26%	37%	102%	92%	116%
Davidson	49%	34%	0%	8%	-1%	-34%	-2%	4%	28%
Davie	124%	35%	-100%	11%	7%	-81%	-3%	35%	61%
Duplin	68%	55%	-27%	-3%	-4%	32%	-4%	2%	159%
Durham	15%	0%	-35%	7%	2%	16%	2%	2%	45%

Edgecombe	29%	26%	115%	2%	2%	-48%	-4%	11%	-49%
Forsyth	48%	27%	-32%	11%	8%	7%	0%	-2%	0%
Franklin	46%	9%	-21%	-4%	0%	39%	1%	0%	-31%
Gaston	37%	14%	-52%	13%	12%	12%	3%	-8%	-56%
Gates	53%	21%	146%	-6%	-18%	31%	-13%	-16%	69%
Graham	23%	-32%	-100%	9%	-13%	-13%	24%	44%	-32%
Granville	63%	72%	-58%	17%	16%	12%	-5%	18%	-42%
Greene	43%	16%	238%	10%	-3%	-15%	-6%	69%	-23%
Guilford	35%	14%	55%	10%	9%	0%	-5%	-9%	-10%
Halifax	45%	25%	-60%	11%	3%	12%	6%	11%	-10%
Harnett	19%	2%	-36%	2%	2%	3%	-6%	-6%	-26%
Haywood	41%	35%	-19%	17%	15%	-63%	12%	12%	38%
Henderson	43%	33%	-41%	4%	2%	-6%	11%	24%	-58%
Hertford	47%	30%	62%	4%	-4%	21%	-5%	-27%	26%
Hoke	41%	3%	-100%	12%	18%	-43%	-3%	-5%	18%
Hyde	105%	48%	1505%	6%	-12%	10%	-4%	5%	-100%
Iredell	47%	22%	28%	8%	8%	-27%	0%	-1%	-21%
Jackson	67%	41%	-38%	13%	10%	-43%	9%	8%	5%
Johnston	32%	9%	37%	6%	1%	-12%	-4%	-14%	-61%
Jones	39%	52%	-100%	-5%	-2%	6%	6%	46%	18%
Lee	46%	12%	-9%	11%	13%	47%	-10%	-25%	4%
Lenoir	72%	22%	256%	0%	-2%	-5%	-10%	-3%	49%
Lincoln	55%	40%	125%	12%	6%	55%	9%	3%	49%
Macon	34%	3%	-41%	9%	-9%	78%	25%	17%	-24%
Madison	57%	58%	65%	11%	4%	143%	6%	16%	-100%
Martin	93%	110%	-100%	12%	11%	-29%	-11%	-8%	-100%
McDowell	42%	20%	58%	15%	10%	40%	-1%	-1%	-65%
Mecklenburg	20%	9%	-30%	8%	6%	-4%	4%	-5%	-20%
Mitchell	34%	7%	-100%	-9%	6%	-94%	-7%	16%	-100%
Montgomery	46%	32%	-25%	8%	4%	34%	-5%	-4%	32%
Moore	15%	15%	39%	4%	2%	-21%	-12%	-8%	-38%
Nash	50%	8%	-28%	8%	0%	31%	-11%	-17%	0%
New Hanover	14%	5%	-48%	-1%	-5%	5%	5%	-5%	-21%
Northampton	124%	84%	95%	6%	-3%	-18%	14%	22%	87%
Onslow	29%	26%	146%	-3%	0%	-19%	-2%	-1%	-40%
Orange	34%	4%	-66%	5%	4%	-32%	-9%	-13%	-37%
Pamlico	88%	92%	-100%	-5%	1%	-50%	-15%	12%	-100%
Pasquotank	22%	-23%	-100%	0%	-4%	-70%	0%	3%	-22%
Pender	27%	6%	69%	-5%	-9%	-34%	6%	11%	-27%
Perquimans	65%	65%	-100%	0%	-9%	131%	-7%	26%	16%
Person	52%	20%	-100%	7%	8%	-84%	-20%	-31%	-100%
Pitt	30%	7%	-39%	2%	-2%	16%	-7%	-12%	-89%
Polk	44%	43%	42%	15%	21%	-5%	1%	-9%	-100%

Randolph	28%	17%	3%	11%	12%	-33%	-10%	-8%	-46%
Richmond	68%	44%	6%	8%	4%	19%	10%	1%	-48%
Robeson	33%	18%	-13%	7%	5%	3%	1%	-1%	2%
Rockingham	33%	25%	-100%	8%	-1%	20%	-4%	12%	90%
Rowan	43%	19%	-36%	12%	5%	86%	-2%	4%	-24%
Rutherford	38%	20%	-32%	15%	16%	-18%	-4%	2%	73%
Sampson	16%	0%	23%	7%	2%	-8%	-5%	-9%	37%
Scotland	61%	28%	-28%	11%	10%	30%	8%	9%	-35%
Stanly	21%	-1%	-100%	3%	8%	-1%	-8%	-11%	32%
Stokes	42%	30%	21%	0%	-5%	-49%	-18%	-11%	39%
Surry	50%	14%	88%	4%	5%	-18%	6%	2%	-44%
Swain	5%	-44%	13%	21%	16%	89%	43%	71%	14%
Transylvania	41%	-9%	-100%	5%	14%	37%	23%	31%	-41%
Tyrrell	7%	173%	-100%	8%	11%	-97%	25%	109%	-100%
Union	16%	10%	-75%	4%	4%	-10%	-2%	-5%	1%
Vance	53%	16%	-46%	8%	0%	75%	-9%	-23%	-46%
Wake	16%	2%	37%	5%	4%	-1%	-3%	-7%	-50%
Warren	76%	-18%	35%	14%	15%	-72%	12%	35%	119%
Washington	48%	210%	765%	-3%	-17%	-64%	16%	32%	51%
Watauga	37%	11%	-100%	-2%	-10%	-71%	14%	14%	-100%
Wayne	30%	9%	34%	2%	-1%	-8%	-3%	-1%	20%
Wilkes	43%	31%	-21%	16%	10%	-8%	-4%	-15%	27%
Wilson	16%	-8%	-16%	11%	2%	-22%	1%	-3%	72%
Yadkin	60%	17%	-24%	3%	-2%	-10%	-10%	-15%	-21%
Yancey	23%	-24%	16%	0%	-3%	-96%	9%	29%	-100%

Outcome rate changes due to selected variables, by county.
C = Collisions; I = Injuries; K = Fatalities

	Holidays			**Daylight Savings**		
	C	I	K	C	I	K
Alamance	-14%	-5%	-5%	10%	15%	-60%
Alexander	-18%	-21%	-59%	2%	-6%	125%
Alleghany	11%	14%	-100%	-7%	-33%	109%
Anson	9%	-1%	93%	23%	18%	-100%
Ashe	9%	18%	67%	-2%	52%	-10%
Avery	14%	33%	-100%	-5%	-11%	128%
Beaufort	-4%	-17%	48%	13%	12%	-3%
Bertie	8%	-20%	-42%	-7%	-1%	-100%
Bladen	10%	21%	-24%	-3%	-6%	-68%

Brunswick	2%	2%	76%	-4%	-3%	-40%
Buncombe	-17%	-17%	-23%	-4%	-1%	41%
Burke	-2%	-10%	111%	-7%	32%	3%
Cabarrus	-10%	-6%	-15%	10%	24%	136%
Caldwell	-5%	-6%	-13%	2%	-4%	-26%
Camden	10%	-9%	32%	4%	9%	129%
Carteret	8%	11%	-1%	-2%	4%	339%
Caswell	9%	12%	-64%	6%	0%	-37%
Catawba	-14%	-10%	10%	2%	15%	-9%
Chatham	-10%	-5%	4%	15%	7%	-43%
Cherokee	3%	2%	-66%	3%	27%	84%
Chowan	0%	-20%	-10%	3%	0%	235%
Clay	7%	-2%	162%	-30%	-18%	-100%
Cleveland	-8%	-18%	1%	2%	7%	36%
Columbus	4%	9%	21%	0%	-17%	-82%
Craven	-9%	-5%	12%	7%	5%	-100%
Cumberland	-13%	-9%	-4%	0%	6%	-11%
Currituck	14%	20%	-3%	-9%	-22%	-100%
Dare	42%	35%	11%	-45%	-41%	202%
Davidson	-8%	-7%	12%	0%	-2%	-61%
Davie	-17%	-17%	-37%	-1%	-6%	-100%
Duplin	4%	13%	-10%	5%	-15%	29%
Durham	-19%	-11%	-16%	4%	10%	6%
Edgecombe	4%	16%	107%	21%	36%	48%
Forsyth	-19%	-13%	-30%	3%	-3%	10%
Franklin	-11%	-6%	42%	14%	3%	-34%
Gaston	-13%	-10%	57%	3%	12%	-10%
Gates	9%	41%	-34%	9%	8%	-100%
Graham	64%	83%	73%	-35%	-33%	-100%
Granville	0%	-9%	33%	12%	-4%	-17%
Greene	4%	34%	106%	26%	-9%	-100%
Guilford	-17%	-14%	-19%	6%	9%	-39%
Halifax	13%	12%	90%	3%	25%	-40%
Harnett	-10%	-5%	-19%	5%	-8%	-19%
Haywood	2%	8%	-34%	-6%	-16%	-100%
Henderson	-6%	-10%	-47%	-5%	-4%	24%
Hertford	-10%	0%	-50%	1%	2%	78%
Hoke	-7%	-3%	40%	-9%	12%	-68%
Hyde	0%	-42%	378%	-27%	-19%	-100%
Iredell	-14%	-19%	22%	-1%	-1%	-6%
Jackson	-4%	-9%	54%	-13%	16%	-51%
Johnston	-11%	-5%	-24%	4%	6%	44%
Jones	20%	25%	-4%	5%	-13%	-100%

Lee	-5%	-12%	22%	17%	10%	-13%
Lenoir	4%	3%	-41%	10%	7%	-33%
Lincoln	-23%	-20%	-33%	1%	19%	17%
Macon	-3%	19%	64%	-27%	-47%	-48%
Madison	4%	0%	-44%	2%	-31%	-3%
Martin	6%	16%	-100%	2%	-12%	-16%
McDowell	2%	-8%	-10%	-17%	3%	-100%
Mecklenburg	-22%	-19%	10%	3%	9%	25%
Mitchell	0%	-11%	-100%	-10%	6%	-100%
Montgomery	-2%	11%	17%	18%	39%	-2%
Moore	-20%	-20%	64%	11%	12%	36%
Nash	-5%	-7%	39%	12%	14%	-6%
New Hanover	-8%	-1%	35%	-2%	5%	10%
Northampton	19%	11%	61%	5%	10%	4%
Onslow	-11%	-12%	-40%	-1%	-12%	77%
Orange	-12%	-2%	13%	11%	8%	-100%
Pamlico	25%	5%	11%	17%	60%	-100%
Pasquotank	-6%	8%	-37%	6%	4%	9%
Pender	22%	34%	35%	11%	-3%	-20%
Perquimans	4%	32%	106%	27%	-20%	-100%
Person	-2%	-3%	113%	27%	-2%	36%
Pitt	-20%	-16%	-30%	8%	15%	-49%
Polk	1%	3%	175%	14%	32%	5%
Randolph	-10%	-9%	18%	7%	16%	59%
Richmond	-7%	1%	87%	6%	-10%	-64%
Robeson	5%	0%	39%	4%	6%	-1%
Rockingham	-5%	-14%	17%	16%	1%	70%
Rowan	-10%	1%	-27%	10%	14%	-11%
Rutherford	-6%	-11%	-11%	6%	7%	13%
Sampson	-1%	-1%	73%	-5%	-9%	-36%
Scotland	15%	13%	9%	10%	11%	-100%
Stanly	-16%	-24%	-10%	9%	9%	16%
Stokes	-9%	5%	-15%	6%	-10%	-53%
Surry	-10%	-8%	7%	7%	5%	-23%
Swain	6%	11%	106%	-32%	-24%	-100%
Transylvania	1%	27%	112%	-25%	0%	-16%
Tyrrell	50%	57%	-100%	1%	-22%	-100%
Union	-15%	-2%	-34%	8%	10%	-1%
Vance	13%	25%	41%	5%	6%	-24%
Wake	-25%	-20%	15%	4%	13%	-3%
Warren	35%	31%	-60%	15%	24%	123%
Washington	1%	-5%	20%	0%	-10%	-100%
Watauga	-15%	-4%	-100%	-12%	-8%	-32%

Wayne	-6%	-1%	-46%	5%	18%	-4%
Wilkes	-11%	-11%	5%	-13%	-9%	120%
Wilson	3%	15%	9%	9%	1%	-75%
Yadkin	0%	13%	-4%	8%	44%	9%
Yancey	7%	19%	-28%	-14%	-37%	26%

Appendix B

	Annual Rates Per 1000 Population, 2019		
COUNTY	Collisions	Injuries	Fatalities
Alamance	24.88	11.71	0.09
Alexander	14.06	6.48	0.05
Alleghany	15.11	6.14	0.09
Anson	36.32	18.23	0.18
Ashe	17.53	7.54	0.26
Avery	18.39	7.48	0.11
Beaufort	23.06	10.52	0.13
Bertie	22.36	11.90	0.44
Bladen	32.02	13.68	0.47
Brunswick	22.14	9.01	0.16
Buncombe	31.09	10.43	0.11
Burke	25.40	10.54	0.18
Cabarrus	26.55	10.55	0.13
Caldwell	22.16	9.99	0.15
Camden	19.01	5.95	0.00
Carteret	21.63	7.71	0.18
Caswell	20.46	7.61	0.44
Catawba	30.69	11.65	0.13
Chatham	22.10	7.70	0.21
Cherokee	18.32	7.29	0.24
Chowan	15.86	5.89	0.51
Clay	18.15	9.03	0.09
Cleveland	28.76	11.24	0.19
Columbus	29.90	15.58	0.35
Craven	23.84	10.29	0.11
Cumberland	26.37	13.06	0.17
Currituck	12.70	8.34	0.26
Dare	22.52	9.89	0.16
Davidson	21.63	9.11	0.13
Davie	20.34	10.63	0.19
Duplin	33.11	12.99	0.42
Durham	34.63	12.95	0.11
Edgecombe	26.99	13.79	0.24
Forsyth	33.59	13.31	0.09
Franklin	19.12	8.52	0.22
Gaston	28.82	11.61	0.08
Gates	16.56	8.98	0.28
Graham	20.64	10.94	0.75

Granville	21.26	9.40	0.30
Greene	23.90	9.32	0.24
Guilford	27.76	15.60	0.12
Halifax	30.44	15.13	0.31
Harnett	19.36	9.31	0.17
Haywood	21.41	9.32	0.13
Henderson	24.85	7.77	0.10
Hertford	19.91	12.16	0.23
Hoke	18.80	11.76	0.21
Hyde	16.61	3.67	0.00
Iredell	23.82	12.08	0.14
Jackson	20.99	7.29	0.30
Johnston	24.17	10.68	0.13
Jones	39.85	13.32	0.21
Lee	28.20	10.55	0.13
Lenoir	26.79	15.37	0.34
Lincoln	21.30	7.67	0.19
Macon	21.73	9.82	0.24
Madison	16.05	5.29	0.09
Martin	27.69	11.26	0.27
McDowell	26.68	9.98	0.13
Mecklenburg	36.41	17.74	0.08
Mitchell	16.65	7.99	0.00
Montgomery	25.54	7.86	0.47
Moore	24.42	9.23	0.14
Nash	25.83	12.83	0.29
New Hanover	27.26	10.15	0.15
Northampton	26.23	13.98	0.55
Onslow	21.41	8.23	0.11
Orange	21.39	9.24	0.10
Pamlico	15.93	6.18	0.16
Pasquotank	21.56	9.72	0.12
Pender	26.99	12.41	0.34
Perquimans	13.23	7.65	0.08
Person	25.88	9.01	0.08
Pitt	32.56	16.97	0.10
Polk	24.31	9.21	0.10
Randolph	23.96	9.75	0.24
Richmond	28.59	15.83	0.16
Robeson	33.48	19.00	0.36
Rockingham	23.24	8.45	0.17
Rowan	25.92	12.60	0.11
Rutherford	21.69	9.91	0.19

Sampson	27.03	11.96	0.29
Scotland	23.64	16.92	0.29
Stanly	23.27	10.55	0.13
Stokes	18.33	7.54	0.16
Surry	21.75	11.93	0.28
Swain	13.65	6.69	0.21
Transylvania	18.78	7.10	0.18
Tyrrell	28.31	6.73	0.56
Union	24.50	9.52	0.10
Vance	26.48	14.26	0.16
Wake	30.71	11.94	0.07
Warren	20.28	12.11	0.21
Washington	20.97	8.87	0.09
Watauga	25.87	8.35	0.17
Wayne	26.40	13.46	0.14
Wilkes	20.02	9.32	0.20
Wilson	33.08	15.60	0.11
Yadkin	20.24	7.62	0.30
Yancey	11.69	5.44	0.22

Appendix C

All prompts run on Stata version 17.

Stata Prompt and Results for Baseline Regression #1

```
nbreg Crashes i.Year i.MoY i.DoW, vce(robust)
estimates store Ba1C
outreg2 using Ba1, word replace ctitle(Collisions, NB) label
nbreg Injured i.Year i.MoY i.DoW, vce(robust)
estimates store Ba1I
outreg2 using Ba1, word append ctitle(Injuries, NB) label
nbreg Killed i.Year i.MoY i.DoW, vce(robust)
estimates store Ba1K
outreg2 using Ba1, word append ctitle(Fatalities, NB) label
```

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
2014	0.0253*	0.0154	-0.00163
	(0.0142)	(0.0157)	(0.0436)
2015	0.129***	0.125***	0.0775*
	(0.0143)	(0.0159)	(0.0430)
2016	0.192***	0.176***	0.114***
	(0.0144)	(0.0159)	(0.0425)
2017	0.223***	0.163***	0.0881**
	(0.0143)	(0.0158)	(0.0431)
2018	0.245***	0.141***	0.124***
	(0.0144)	(0.0160)	(0.0428)
2019	0.259***	0.140***	0.143***
	(0.0145)	(0.0159)	(0.0421)
February	0.00208	0.0590***	-0.0225
	(0.0200)	(0.0220)	(0.0603)
March	-0.00312	0.116***	0.0226
	(0.0194)	(0.0214)	(0.0587)
April	0.00206	0.168***	0.105*
	(0.0195)	(0.0214)	(0.0577)
May	0.0253	0.196***	0.206***
	(0.0192)	(0.0211)	(0.0562)
June	0.0104	0.177***	0.241***
	(0.0192)	(0.0210)	(0.0565)
July	-0.0570***	0.106***	0.101*
	(0.0189)	(0.0208)	(0.0575)
August	0.00472	0.183***	0.133**
	(0.0191)	(0.0209)	(0.0568)
September	0.0339*	0.196***	0.260***
	(0.0195)	(0.0214)	(0.0560)
October	0.184***	0.275***	0.290***
	(0.0191)	(0.0212)	(0.0555)
November	0.235***	0.230***	0.233***
	(0.0189)	(0.0217)	(0.0570)
December	0.149***	0.170***	0.101*
	(0.0194)	(0.0215)	(0.0572)
Monday	0.379***	0.265***	-0.223***
	(0.0142)	(0.0159)	(0.0430)
Tuesday	0.403***	0.272***	-0.203***
	(0.0144)	(0.0160)	(0.0422)
Wednesday	0.398***	0.269***	-0.179***

	(0.0143)	(0.0160)	(0.0422)
Thursday	0.398***	0.271***	-0.199***
	(0.0142)	(0.0158)	(0.0424)
Friday	0.551***	0.451***	-0.0114
	(0.0140)	(0.0156)	(0.0406)
Saturday	0.239***	0.230***	0.0912**
	(0.0137)	(0.0157)	(0.0397)
lnalpha	0.515***	0.962***	1.716***
	(0.00382)	(0.00427)	(0.0399)
Constant	1.395***	0.677***	-3.396***
	(0.0188)	(0.0212)	(0.0583)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Baseline Regression #2

```
nbreg Crashes i.CountyNum i.Year i.MoY i.DoW, vce(robust)
estimates store Ba2C
outreg2 using Ba2, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW, vce(robust)
estimates store Ba2I
outreg2 using Ba2, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW, vce(robust)
estimates store Ba2K
outreg2 using Ba2, word append ctitle(Fatalities, NB) label
```

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-2.013***	-2.096***	-1.265***
	(0.0189)	(0.0388)	(0.198)
Alleghany	-3.035***	-3.121***	-2.285***
	(0.0314)	(0.0615)	(0.291)
Anson	-1.731***	-1.600***	-1.321***
	(0.0176)	(0.0343)	(0.199)
Ashe	-2.136***	-2.273***	-1.481***
	(0.0212)	(0.0417)	(0.212)
Avery	-2.507***	-2.641***	-2.364***
	(0.0246)	(0.0484)	(0.302)
Beaufort	-1.385***	-1.426***	-0.860***
	(0.0155)	(0.0326)	(0.170)
Bertie	-2.220***	-2.071***	-0.896***
	(0.0218)	(0.0415)	(0.181)
Bladen	-1.497***	-1.423***	-0.467***
	(0.0163)	(0.0339)	(0.165)
Brunswick	-0.434***	-0.554***	0.0243
	(0.0118)	(0.0228)	(0.135)
Buncombe	0.615***	0.369***	0.553***
	(0.0104)	(0.0185)	(0.117)
Burke	-0.686***	-0.680***	-0.222
	(0.0135)	(0.0246)	(0.141)
Cabarrus	0.319***	0.249***	0.115
	(0.0107)	(0.0194)	(0.128)
Caldwell	-0.831***	-0.821***	-0.600***
	(0.0134)	(0.0247)	(0.161)
Camden	-3.124***	-3.413***	-2.364***
	(0.0309)	(0.0653)	(0.365)
Carteret	-1.105***	-1.235***	-0.999***

	(0.0144)	(0.0274)	(0.182)
Caswell	-2.221***	-2.273***	-1.134***
	(0.0210)	(0.0406)	(0.187)
Catawba	0.142***	0.0120	0.103
	(0.0113)	(0.0199)	(0.129)
Chatham	-1.015***	-1.318***	-0.348**
	(0.0154)	(0.0280)	(0.152)
Cherokee	-2.174***	-2.217***	-1.064***
	(0.0206)	(0.0396)	(0.187)
Chowan	-2.815***	-3.009***	-2.016***
	(0.0276)	(0.0592)	(0.272)
Clay	-3.054***	-3.259***	-2.283***
	(0.0316)	(0.0636)	(0.312)
Cleveland	-0.416***	-0.500***	0.0726
	(0.0125)	(0.0229)	(0.133)
Columbus	-0.858***	-0.686***	0.113
	(0.0133)	(0.0264)	(0.129)
Craven	-0.637***	-0.659***	-0.272*
	(0.0123)	(0.0233)	(0.143)
Cumberland	0.728***	0.761***	0.929***
	(0.0105)	(0.0180)	(0.112)
Currituck	-2.314***	-2.393***	-1.381***
	(0.0223)	(0.0462)	(0.218)
Dare	-1.587***	-1.670***	-1.515***
	(0.0197)	(0.0347)	(0.216)
Davidson	-0.120***	-0.0970***	0.431***
	(0.0116)	(0.0209)	(0.121)
Davie	-1.554***	-1.521***	-0.979***
	(0.0191)	(0.0328)	(0.187)
Duplin	-0.880***	-1.055***	-0.216
	(0.0142)	(0.0289)	(0.148)
Durham	0.907***	0.707***	0.448***
	(0.0100)	(0.0178)	(0.118)
Edgecombe	-1.147***	-1.040***	-0.573***
	(0.0147)	(0.0276)	(0.162)
Forsyth	0.917***	0.800***	0.724***
	(0.0110)	(0.0182)	(0.115)
Franklin	-1.194***	-1.158***	-0.481***
	(0.0145)	(0.0271)	(0.149)
Gaston	0.381***	0.436***	0.465***
	(0.0107)	(0.0187)	(0.119)
Gates	-2.912***	-2.852***	-1.712***
	(0.0283)	(0.0579)	(0.244)
Graham	-3.160***	-2.834***	-1.518***
	(0.0320)	(0.0509)	(0.227)
Granville	-1.224***	-1.151***	-0.297**
	(0.0155)	(0.0272)	(0.145)
Greene	-2.120***	-2.224***	-1.670***
	(0.0206)	(0.0431)	(0.239)
Guilford	1.273***	1.454***	1.179***
	(0.0102)	(0.0167)	(0.107)
Halifax	-1.017***	-0.938***	-0.397***
	(0.0144)	(0.0298)	(0.152)
Harnett	-0.535***	-0.474***	0.405***
	(0.0122)	(0.0224)	(0.122)
Haywood	-1.239***	-1.184***	-0.615***
	(0.0157)	(0.0275)	(0.161)
Henderson	-0.463***	-0.699***	-0.405***
	(0.0129)	(0.0237)	(0.146)
Hertford	-2.155***	-1.849***	-1.448***
	(0.0205)	(0.0415)	(0.204)
Hoke	-1.526***	-1.270***	-0.476***
	(0.0163)	(0.0300)	(0.159)
Hyde	-3.788***	-4.411***	-3.463***
	(0.0427)	(0.104)	(0.508)
Iredell	0.0648***	0.113***	0.267**
	(0.0118)	(0.0199)	(0.122)
Jackson	-1.589***	-1.693***	-0.899***
	(0.0182)	(0.0320)	(0.182)
Johnston	0.107***	0.122***	0.559***

	(0.0115)	(0.0199)	(0.120)
Jones	-2.459***	-2.682***	-2.075***
	(0.0229)	(0.0501)	(0.281)
Lee	-0.958***	-1.017***	-0.349**
	(0.0141)	(0.0283)	(0.152)
Lenoir	-1.001***	-0.833***	-0.506***
	(0.0145)	(0.0256)	(0.149)
Lincoln	-0.911***	-0.996***	-0.349**
	(0.0149)	(0.0268)	(0.145)
Macon	-1.704***	-1.777***	-0.957***
	(0.0172)	(0.0327)	(0.174)
Madison	-2.532***	-2.868***	-1.551***
	(0.0241)	(0.0490)	(0.220)
Martin	-1.846***	-1.897***	-1.414***
	(0.0200)	(0.0370)	(0.206)
McDowell	-1.266***	-1.496***	-0.917***
	(0.0156)	(0.0301)	(0.182)
Mecklenburg	2.177***	2.305***	1.618***
	(0.00924)	(0.0159)	(0.102)
Mitchell	-2.823***	-2.637***	-2.651***
	(0.0264)	(0.0478)	(0.411)
Montgomery	-1.850***	-2.108***	-0.879***
	(0.0185)	(0.0369)	(0.177)
Moore	-0.646***	-0.785***	-0.0826
	(0.0130)	(0.0245)	(0.138)
Nash	-0.485***	-0.377***	0.290**
	(0.0129)	(0.0231)	(0.127)
New Hanover	0.368***	0.266***	0.107
	(0.0105)	(0.0188)	(0.127)
Northampton	-2.137***	-2.140***	-0.936***
	(0.0217)	(0.0424)	(0.177)
Onslow	0.00287	-0.0755***	0.168
	(0.0110)	(0.0203)	(0.128)
Orange	-0.339***	-0.477***	-0.428***
	(0.0123)	(0.0225)	(0.151)
Pamlico	-3.044***	-3.258***	-2.209***
	(0.0293)	(0.0630)	(0.282)
Pasquotank	-1.565***	-1.684***	-1.670***
	(0.0164)	(0.0331)	(0.231)
Pender	-0.975***	-1.061***	0.000863
	(0.0137)	(0.0293)	(0.134)
Perquimans	-2.909***	-3.053***	-2.076***
	(0.0285)	(0.0615)	(0.307)
Person	-1.486***	-1.601***	-1.184***
	(0.0170)	(0.0321)	(0.191)
Pitt	0.318***	0.370***	0.171
	(0.0108)	(0.0192)	(0.127)
Polk	-2.299***	-2.437***	-1.628***
	(0.0218)	(0.0436)	(0.241)
Randolph	-0.178***	-0.236***	0.291**
	(0.0120)	(0.0209)	(0.123)
Richmond	-1.289***	-1.052***	-0.601***
	(0.0159)	(0.0284)	(0.170)
Robeson	-0.105***	0.160***	0.879***
	(0.0114)	(0.0201)	(0.114)
Rockingham	-0.663***	-0.797***	-0.306**
	(0.0128)	(0.0242)	(0.142)
Rowan	-0.158***	-0.154***	0.146
	(0.0118)	(0.0207)	(0.133)
Rutherford	-1.113***	-1.106***	-0.613***
	(0.0145)	(0.0264)	(0.156)
Sampson	-0.867***	-0.821***	-0.0527
	(0.0137)	(0.0251)	(0.137)
Scotland	-1.657***	-1.285***	-0.804***
	(0.0172)	(0.0311)	(0.172)
Stanly	-1.099***	-1.235***	-0.626***
	(0.0142)	(0.0287)	(0.166)
Stokes	-1.505***	-1.662***	-0.858***
	(0.0170)	(0.0319)	(0.176)
Surry	-0.948***	-0.856***	-0.233

	(0.0143)	(0.0254)	(0.143)
Swain	-2.929***	-3.003***	-2.076***
	(0.0276)	(0.0554)	(0.266)
Transylvania	-1.981***	-2.106***	-1.415***
	(0.0194)	(0.0377)	(0.225)
Tyrrell	-3.487***	-4.184***	-4.156***
	(0.0373)	(0.106)	(1.004)
Union	0.257***	0.147***	0.228*
	(0.0104)	(0.0194)	(0.128)
Vance	-1.086***	-0.941***	-0.644***
	(0.0148)	(0.0276)	(0.156)
Wake	2.007***	1.837***	1.316***
	(0.00971)	(0.0163)	(0.105)
Warren	-2.200***	-2.158***	-1.238***
	(0.0222)	(0.0448)	(0.230)
Washington	-2.815***	-2.984***	-2.284***
	(0.0273)	(0.0559)	(0.292)
Watauga	-1.115***	-1.439***	-1.210***
	(0.0154)	(0.0292)	(0.207)
Wayne	-0.298***	-0.196***	0.0786
	(0.0117)	(0.0215)	(0.131)
Wilkes	-1.133***	-1.053***	-0.546***
	(0.0147)	(0.0260)	(0.155)
Wilson	-0.609***	-0.590***	-0.244*
	(0.0132)	(0.0243)	(0.145)
Yadkin	-1.687***	-1.823***	-0.976***
	(0.0188)	(0.0348)	(0.178)
Yancey	-2.766***	-2.783***	-1.804***
	(0.0259)	(0.0519)	(0.246)
2014	0.0162***	0.00837	-0.000102
	(0.00451)	(0.00814)	(0.0433)
2015	0.111***	0.101***	0.0752*
	(0.00429)	(0.00804)	(0.0426)
2016	0.162***	0.144***	0.110***
	(0.00430)	(0.00798)	(0.0420)
2017	0.192***	0.132***	0.0811*
	(0.00414)	(0.00796)	(0.0425)
2018	0.214***	0.0988***	0.114***
	(0.00421)	(0.00792)	(0.0421)
2019	0.220***	0.0966***	0.143***
	(0.00407)	(0.00790)	(0.0417)
February	-0.00711	0.0510***	-0.0260
	(0.00698)	(0.0113)	(0.0593)
March	-0.0229***	0.101***	0.0258
	(0.00626)	(0.0107)	(0.0580)
April	-0.0153**	0.165***	0.113**
	(0.00603)	(0.0104)	(0.0571)
May	0.0149**	0.217***	0.208***
	(0.00592)	(0.0104)	(0.0554)
June	0.00574	0.210***	0.244***
	(0.00594)	(0.0104)	(0.0557)
July	-0.0574***	0.149***	0.113**
	(0.00597)	(0.0107)	(0.0571)
August	-0.00726	0.202***	0.142**
	(0.00593)	(0.0104)	(0.0562)
September	0.0216***	0.206***	0.272***
	(0.00608)	(0.0104)	(0.0556)
October	0.179***	0.279***	0.293***
	(0.00585)	(0.0103)	(0.0548)
November	0.248***	0.227***	0.234***
	(0.00589)	(0.0104)	(0.0561)
December	0.144***	0.162***	0.109*
	(0.00624)	(0.0105)	(0.0566)
Monday	0.337***	0.207***	-0.212***
	(0.00441)	(0.00850)	(0.0425)
Tuesday	0.344***	0.200***	-0.189***
	(0.00434)	(0.00839)	(0.0417)
Wednesday	0.341***	0.197***	-0.167***
	(0.00432)	(0.00834)	(0.0416)
Thursday	0.345***	0.209***	-0.190***

	(0.00422)	(0.00824)	(0.0416)
Friday	0.508***	0.395***	-0.00120
	(0.00428)	(0.00818)	(0.0399)
Saturday	0.222***	0.200***	0.0967**
	(0.00434)	(0.00851)	(0.0390)
lnalpha	-2.774***	-0.866***	0.875***
	(0.0182)	(0.00936)	(0.0535)
Constant	1.892***	1.188***	-3.136***
	(0.0104)	(0.0185)	(0.108)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Baseline Regression #3

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nbreg Crashes i.CountyNum i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store Ba3C
outreg2 using Ba3, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store Ba3I
outreg2 using Ba3, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store Ba3K
outreg2 using Ba3, word append ctitle(Fatalities, NB) label
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VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.533***	-0.617***	0.215
	(0.0190)	(0.0388)	(0.198)
Alleghany	-0.341***	-0.429***	0.408
	(0.0314)	(0.0615)	(0.291)
Anson	0.180***	0.308***	0.587***
	(0.0178)	(0.0344)	(0.199)
Ashe	-0.331***	-0.470***	0.324
	(0.0212)	(0.0417)	(0.212)
Avery	-0.299***	-0.435***	-0.156
	(0.0246)	(0.0484)	(0.303)
Beaufort	-0.125***	-0.168***	0.399**
	(0.0155)	(0.0325)	(0.170)
Bertie	-0.0793***	0.0668	1.244***
	(0.0217)	(0.0415)	(0.181)
Bladen	0.135***	0.205***	1.164***
	(0.0163)	(0.0338)	(0.165)
Brunswick	-0.159***	-0.279***	0.299**
	(0.0118)	(0.0228)	(0.135)
Buncombe	0.140***	-0.106***	0.0788
	(0.0104)	(0.0185)	(0.117)
Burke	-0.0786***	-0.0735***	0.385***
	(0.0135)	(0.0246)	(0.141)
Cabarrus	0.0759***	0.00737	-0.128
	(0.0107)	(0.0195)	(0.128)
Caldwell	-0.144***	-0.135***	0.0882
	(0.0134)	(0.0247)	(0.161)
Camden	-0.348***	-0.639***	0.412
	(0.0309)	(0.0654)	(0.365)
Carteret	-0.240***	-0.372***	-0.134
	(0.0145)	(0.0274)	(0.182)
Caswell	-0.277***	-0.331***	0.809***
	(0.0210)	(0.0406)	(0.187)
Catawba	0.168***	0.0362*	0.128
	(0.0114)	(0.0199)	(0.129)

Chatham	-0.192***	-0.495***	0.476***
	(0.0154)	(0.0280)	(0.152)
Cherokee	-0.423***	-0.467***	0.687***
	(0.0206)	(0.0397)	(0.187)
Chowan	-0.376***	-0.572***	0.422
	(0.0276)	(0.0592)	(0.272)
Clay	-0.363***	-0.569***	0.408
	(0.0316)	(0.0636)	(0.312)
Cleveland	0.0877***	0.00278	0.576***
	(0.0125)	(0.0229)	(0.133)
Columbus	0.242***	0.411***	1.212***
	(0.0132)	(0.0263)	(0.129)
Craven	-0.180***	-0.204***	0.183
	(0.0124)	(0.0233)	(0.143)
Cumberland	0.00678	0.0388**	0.208*
	(0.0105)	(0.0180)	(0.112)
Currituck	-0.477***	-0.557***	0.456**
	(0.0223)	(0.0462)	(0.218)
Dare	-0.0773***	-0.161***	-0.00538
	(0.0197)	(0.0347)	(0.216)
Davidson	-0.144***	-0.121***	0.407***
	(0.0116)	(0.0209)	(0.121)
Davie	-0.201***	-0.168***	0.375**
	(0.0192)	(0.0328)	(0.187)
Duplin	0.241***	0.0650**	0.906***
	(0.0142)	(0.0290)	(0.149)
Durham	0.268***	0.0665***	-0.191
	(0.0101)	(0.0178)	(0.118)
Edgecombe	-0.00649	0.0973***	0.567***
	(0.0147)	(0.0275)	(0.162)
Forsyth	0.0833***	-0.0346*	-0.110
	(0.0110)	(0.0182)	(0.116)
Franklin	-0.270***	-0.234***	0.443***
	(0.0146)	(0.0271)	(0.149)
Gaston	0.0797***	0.135***	0.164
	(0.0107)	(0.0188)	(0.119)
Gates	-0.233***	-0.175***	0.966***
	(0.0282)	(0.0578)	(0.244)
Graham	-0.193***	0.130**	1.449***
	(0.0320)	(0.0508)	(0.227)
Granville	-0.220***	-0.148***	0.707***
	(0.0155)	(0.0272)	(0.145)
Greene	-0.0691***	-0.174***	0.381
	(0.0206)	(0.0430)	(0.239)
Guilford	0.0951***	0.275***	0.000952
	(0.0102)	(0.0167)	(0.107)
Halifax	0.140***	0.216***	0.760***
	(0.0144)	(0.0297)	(0.152)
Harnett	-0.303***	-0.242***	0.637***
	(0.0122)	(0.0224)	(0.122)
Haywood	-0.261***	-0.208***	0.362**
	(0.0157)	(0.0275)	(0.161)
Henderson	-0.102***	-0.339***	-0.0449
	(0.0129)	(0.0238)	(0.146)
Hertford	-0.206***	0.0964**	0.500**
	(0.0205)	(0.0416)	(0.204)
Hoke	-0.377***	-0.122***	0.673***
	(0.0163)	(0.0300)	(0.159)
Hyde	-0.332***	-0.959***	-0.00927
	(0.0426)	(0.104)	(0.508)
Iredell	-0.0163	0.0313	0.186
	(0.0119)	(0.0199)	(0.122)
Jackson	-0.245***	-0.350***	0.445**
	(0.0182)	(0.0319)	(0.182)
Johnston	-0.0738***	-0.0569***	0.380***
	(0.0115)	(0.0199)	(0.120)
Jones	0.355***	0.130***	0.738***
	(0.0230)	(0.0500)	(0.281)
Lee	0.0222	-0.0376	0.631***
	(0.0141)	(0.0284)	(0.152)

Lenoir	0.0479***	0.214***	0.544***
	(0.0144)	(0.0256)	(0.149)
Lincoln	-0.229***	-0.314***	0.333**
	(0.0149)	(0.0268)	(0.145)
Macon	-0.187***	-0.261***	0.560***
	(0.0173)	(0.0328)	(0.174)
Madison	-0.503***	-0.840***	0.478**
	(0.0241)	(0.0490)	(0.220)
Martin	0.105***	0.0509	0.536***
	(0.0200)	(0.0370)	(0.206)
McDowell	0.0204	-0.212***	0.369**
	(0.0156)	(0.0301)	(0.182)
Mecklenburg	0.300***	0.428***	-0.261**
	(0.00923)	(0.0159)	(0.102)
Mitchell	-0.450***	-0.267***	-0.279
	(0.0264)	(0.0478)	(0.411)
Montgomery	-0.0309*	-0.291***	0.939***
	(0.0185)	(0.0369)	(0.177)
Moore	-0.110***	-0.249***	0.454***
	(0.0130)	(0.0245)	(0.138)
Nash	0.0550***	0.162***	0.830***
	(0.0129)	(0.0231)	(0.127)
New Hanover	0.0616***	-0.0407**	-0.200
	(0.0105)	(0.0189)	(0.127)
Northampton	-0.00998	-0.0157	1.189***
	(0.0217)	(0.0425)	(0.177)
Onslow	-0.191***	-0.270***	-0.0260
	(0.0111)	(0.0203)	(0.128)
Orange	-0.221***	-0.360***	-0.310**
	(0.0123)	(0.0224)	(0.152)
Pamlico	-0.491***	-0.707***	0.343
	(0.0293)	(0.0630)	(0.282)
Pasquotank	-0.167***	-0.287***	-0.272
	(0.0164)	(0.0331)	(0.231)
Pender	0.0633***	-0.0230	1.039***
	(0.0137)	(0.0294)	(0.134)
Perquimans	-0.405***	-0.552***	0.426
	(0.0284)	(0.0615)	(0.307)
Person	-0.0625***	-0.179***	0.240
	(0.0171)	(0.0321)	(0.191)
Pitt	0.269***	0.320***	0.121
	(0.0109)	(0.0192)	(0.127)
Polk	-0.194***	-0.334***	0.475**
	(0.0218)	(0.0436)	(0.241)
Randolph	-0.0562***	-0.115***	0.413***
	(0.0120)	(0.0209)	(0.123)
Richmond	0.00684	0.242***	0.694***
	(0.0159)	(0.0284)	(0.170)
Robeson	0.163***	0.425***	1.147***
	(0.0115)	(0.0201)	(0.114)
Rockingham	-0.0926***	-0.229***	0.264*
	(0.0129)	(0.0242)	(0.142)
Rowan	-0.0352***	-0.0326	0.268**
	(0.0118)	(0.0207)	(0.133)
Rutherford	-0.207***	-0.202***	0.293*
	(0.0145)	(0.0264)	(0.156)
Sampson	0.108***	0.152***	0.922***
	(0.0137)	(0.0251)	(0.137)
Scotland	-0.130***	0.241***	0.723***
	(0.0172)	(0.0311)	(0.172)
Stanly	-0.127***	-0.264***	0.346**
	(0.0143)	(0.0287)	(0.166)
Stokes	-0.232***	-0.391***	0.416**
	(0.0170)	(0.0319)	(0.176)
Surry	-0.136***	-0.0449*	0.580***
	(0.0143)	(0.0255)	(0.143)
Swain	-0.517***	-0.593***	0.336
	(0.0275)	(0.0554)	(0.266)
Transylvania	-0.389***	-0.515***	0.177
	(0.0194)	(0.0377)	(0.225)

Tyrrell	0.231***	-0.469***	-0.438
	(0.0373)	(0.106)	(1.004)
Union	-0.0705***	-0.180***	-0.0989
	(0.0104)	(0.0195)	(0.128)
Vance	0.229***	0.373***	0.670***
	(0.0148)	(0.0276)	(0.156)
Wake	0.138***	-0.0338**	-0.553***
	(0.00975)	(0.0163)	(0.105)
Warren	-0.0881***	-0.0479	0.874***
	(0.0222)	(0.0449)	(0.230)
Washington	-0.189***	-0.361***	0.341
	(0.0273)	(0.0559)	(0.292)
Watauga	-0.00764	-0.332***	-0.103
	(0.0154)	(0.0292)	(0.207)
Wayne	-0.00156	0.0993***	0.375***
	(0.0117)	(0.0215)	(0.131)
Wilkes	-0.255***	-0.178***	0.331**
	(0.0147)	(0.0260)	(0.155)
Wilson	0.104***	0.122***	0.469***
	(0.0132)	(0.0243)	(0.145)
Yadkin	-0.225***	-0.363***	0.486***
	(0.0188)	(0.0348)	(0.178)
Yancey	-0.572***	-0.590***	0.390
	(0.0259)	(0.0520)	(0.246)
2014	0.0119***	0.00583	-0.00360
	(0.00448)	(0.00808)	(0.0432)
2015	0.102***	0.0953***	0.0674
	(0.00427)	(0.00799)	(0.0426)
2016	0.145***	0.133***	0.0960**
	(0.00428)	(0.00794)	(0.0419)
2017	0.168***	0.116***	0.0605
	(0.00410)	(0.00794)	(0.0425)
2018	0.183***	0.0768***	0.0869**
	(0.00418)	(0.00790)	(0.0421)
2019	0.182***	0.0694***	0.109***
	(0.00402)	(0.00789)	(0.0417)
February	-0.00723	0.0507***	-0.0259
	(0.00698)	(0.0113)	(0.0593)
March	-0.0229***	0.101***	0.0262
	(0.00627)	(0.0107)	(0.0580)
April	-0.0153**	0.165***	0.113**
	(0.00603)	(0.0104)	(0.0571)
May	0.0148**	0.217***	0.208***
	(0.00592)	(0.0104)	(0.0554)
June	0.00558	0.210***	0.244***
	(0.00594)	(0.0104)	(0.0557)
July	-0.0575***	0.149***	0.113**
	(0.00597)	(0.0107)	(0.0571)
August	-0.00738	0.202***	0.142**
	(0.00593)	(0.0104)	(0.0562)
September	0.0216***	0.206***	0.272***
	(0.00608)	(0.0104)	(0.0556)
October	0.179***	0.279***	0.293***
	(0.00584)	(0.0103)	(0.0548)
November	0.248***	0.227***	0.234***
	(0.00589)	(0.0104)	(0.0561)
December	0.144***	0.163***	0.109*
	(0.00625)	(0.0105)	(0.0566)
Monday	0.337***	0.207***	-0.212***
	(0.00441)	(0.00850)	(0.0425)
Tuesday	0.344***	0.200***	-0.189***
	(0.00433)	(0.00839)	(0.0417)
Wednesday	0.341***	0.197***	-0.167***
	(0.00431)	(0.00834)	(0.0416)
Thursday	0.345***	0.209***	-0.190***
	(0.00421)	(0.00824)	(0.0416)
Friday	0.509***	0.395***	-0.00109
	(0.00427)	(0.00818)	(0.0399)
Saturday	0.222***	0.200***	0.0970**
	(0.00433)	(0.00852)	(0.0390)

lnalpha	-2.784***	-0.866***	0.875***
	(0.0185)	(0.00937)	(0.0536)
Constant	-10.08***	-10.79***	-15.11***
	(0.0105)	(0.0185)	(0.109)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Independent Factors Regression #1

```
nbreg Crashes i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce Vhot Vcold
c.VhotSum c.VcoldSum, vce(robust) exposure(YearPop)
estimates store In1C
outreg2 using In1, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce Vhot Vcold
c.VhotSum c.VcoldSum, vce(robust) exposure(YearPop)
estimates store In1I
outreg2 using In1, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce Vhot Vcold
c.VhotSum c.VcoldSum, vce(robust) exposure(YearPop)
estimates store In1K
outreg2 using In1, word append ctitle(Fatalities, NB) label
```

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.533***	-0.617***	0.213
	(0.0189)	(0.0388)	(0.198)
Alleghany	-0.355***	-0.431***	0.420
	(0.0313)	(0.0615)	(0.291)
Anson	0.182***	0.309***	0.584***
	(0.0177)	(0.0344)	(0.199)
Ashe	-0.345***	-0.472***	0.339
	(0.0211)	(0.0417)	(0.213)
Avery	-0.317***	-0.438***	-0.137
	(0.0245)	(0.0484)	(0.303)
Beaufort	-0.122***	-0.167***	0.395**
	(0.0155)	(0.0325)	(0.170)
Bertie	-0.0787***	0.0668	1.242***
	(0.0216)	(0.0415)	(0.181)
Bladen	0.137***	0.205***	1.159***
	(0.0162)	(0.0338)	(0.165)
Brunswick	-0.157***	-0.280***	0.292**
	(0.0117)	(0.0228)	(0.135)
Buncombe	0.139***	-0.106***	0.0822
	(0.0103)	(0.0185)	(0.117)
Burke	-0.0788***	-0.0735***	0.383***
	(0.0134)	(0.0246)	(0.141)
Cabarrus	0.0786***	0.00789	-0.132
	(0.0106)	(0.0194)	(0.128)
Caldwell	-0.144***	-0.135***	0.0866
	(0.0133)	(0.0247)	(0.161)
Camden	-0.347***	-0.639***	0.409
	(0.0308)	(0.0654)	(0.365)
Carteret	-0.239***	-0.372***	-0.142
	(0.0144)	(0.0274)	(0.182)
Caswell	-0.279***	-0.331***	0.810***
	(0.0209)	(0.0406)	(0.187)
Catawba	0.169***	0.0369*	0.126
	(0.0111)	(0.0199)	(0.129)

Chatham	-0.193***	-0.495***	0.475***
	(0.0151)	(0.0280)	(0.152)
Cherokee	-0.426***	-0.468***	0.687***
	(0.0205)	(0.0396)	(0.187)
Chowan	-0.375***	-0.573***	0.420
	(0.0275)	(0.0592)	(0.272)
Clay	-0.366***	-0.569***	0.409
	(0.0316)	(0.0636)	(0.312)
Cleveland	0.0897***	0.00318	0.573***
	(0.0123)	(0.0229)	(0.133)
Columbus	0.246***	0.411***	1.205***
	(0.0131)	(0.0263)	(0.129)
Craven	-0.177***	-0.204***	0.177
	(0.0123)	(0.0233)	(0.142)
Cumberland	0.00942	0.0391**	0.204*
	(0.0103)	(0.0180)	(0.112)
Currituck	-0.477***	-0.557***	0.454**
	(0.0223)	(0.0462)	(0.218)
Dare	-0.0769***	-0.162***	-0.0101
	(0.0196)	(0.0347)	(0.216)
Davidson	-0.142***	-0.121***	0.407***
	(0.0114)	(0.0209)	(0.121)
Davie	-0.201***	-0.167***	0.374**
	(0.0189)	(0.0328)	(0.187)
Duplin	0.243***	0.0648**	0.902***
	(0.0141)	(0.0290)	(0.149)
Durham	0.267***	0.0662***	-0.191
	(0.00987)	(0.0178)	(0.118)
Edgecombe	-0.00590	0.0970***	0.565***
	(0.0146)	(0.0275)	(0.162)
Forsyth	0.0829***	-0.0348*	-0.111
	(0.0108)	(0.0181)	(0.115)
Franklin	-0.270***	-0.234***	0.442***
	(0.0145)	(0.0271)	(0.149)
Gaston	0.0835***	0.136***	0.160
	(0.0106)	(0.0188)	(0.119)
Gates	-0.234***	-0.175***	0.966***
	(0.0282)	(0.0579)	(0.244)
Graham	-0.197***	0.130**	1.450***
	(0.0320)	(0.0508)	(0.227)
Granville	-0.221***	-0.148***	0.706***
	(0.0152)	(0.0272)	(0.145)
Greene	-0.0687***	-0.175***	0.378
	(0.0205)	(0.0430)	(0.239)
Guilford	0.0965***	0.275***	-0.000509
	(0.00995)	(0.0167)	(0.107)
Halifax	0.139***	0.216***	0.760***
	(0.0142)	(0.0298)	(0.152)
Harnett	-0.301***	-0.242***	0.634***
	(0.0121)	(0.0224)	(0.122)
Haywood	-0.268***	-0.208***	0.370**
	(0.0156)	(0.0274)	(0.161)
Henderson	-0.107***	-0.340***	-0.0440
	(0.0127)	(0.0238)	(0.146)
Hertford	-0.207***	0.0961**	0.501**
	(0.0204)	(0.0415)	(0.204)
Hoke	-0.376***	-0.122***	0.669***
	(0.0161)	(0.0300)	(0.159)
Hyde	-0.331***	-0.960***	-0.0142
	(0.0425)	(0.104)	(0.508)
Iredell	-0.0167	0.0312	0.185
	(0.0116)	(0.0199)	(0.122)
Jackson	-0.249***	-0.350***	0.449**
	(0.0181)	(0.0319)	(0.182)
Johnston	-0.0735***	-0.0568***	0.376***
	(0.0113)	(0.0199)	(0.120)
Jones	0.356***	0.129***	0.733***
	(0.0230)	(0.0500)	(0.281)
Lee	0.0236*	-0.0374	0.628***
	(0.0139)	(0.0284)	(0.152)

Lenoir	0.0491***	0.214***	0.539***
	(0.0143)	(0.0256)	(0.149)
Lincoln	-0.228***	-0.313***	0.331**
	(0.0147)	(0.0268)	(0.145)
Macon	-0.190***	-0.262***	0.560***
	(0.0172)	(0.0327)	(0.174)
Madison	-0.510***	-0.840***	0.488**
	(0.0241)	(0.0490)	(0.220)
Martin	0.104***	0.0501	0.533***
	(0.0198)	(0.0370)	(0.206)
McDowell	0.0175	-0.213***	0.366**
	(0.0154)	(0.0301)	(0.182)
Mecklenburg	0.304***	0.428***	-0.266***
	(0.00906)	(0.0159)	(0.102)
Mitchell	-0.457***	-0.267***	-0.271
	(0.0264)	(0.0478)	(0.411)
Montgomery	-0.0301	-0.291***	0.938***
	(0.0184)	(0.0368)	(0.177)
Moore	-0.109***	-0.249***	0.452***
	(0.0129)	(0.0245)	(0.138)
Nash	0.0543***	0.161***	0.828***
	(0.0127)	(0.0231)	(0.127)
New Hanover	0.0638***	-0.0407**	-0.208
	(0.0104)	(0.0189)	(0.127)
Northampton	-0.0109	-0.0164	1.188***
	(0.0216)	(0.0425)	(0.177)
Onslow	-0.189***	-0.271***	-0.0328
	(0.0110)	(0.0203)	(0.128)
Orange	-0.221***	-0.360***	-0.310**
	(0.0122)	(0.0224)	(0.152)
Pamlico	-0.488***	-0.708***	0.335
	(0.0293)	(0.0630)	(0.282)
Pasquotank	-0.166***	-0.287***	-0.274
	(0.0163)	(0.0331)	(0.231)
Pender	0.0647***	-0.0227	1.033***
	(0.0137)	(0.0294)	(0.134)
Perquimans	-0.404***	-0.552***	0.424
	(0.0283)	(0.0615)	(0.307)
Person	-0.0644***	-0.180***	0.241
	(0.0170)	(0.0321)	(0.191)
Pitt	0.269***	0.320***	0.118
	(0.0107)	(0.0192)	(0.127)
Polk	-0.195***	-0.335***	0.470*
	(0.0217)	(0.0436)	(0.241)
Randolph	-0.0571***	-0.115***	0.414***
	(0.0118)	(0.0209)	(0.124)
Richmond	0.00850	0.242***	0.691***
	(0.0157)	(0.0284)	(0.170)
Robeson	0.167***	0.426***	1.140***
	(0.0113)	(0.0201)	(0.114)
Rockingham	-0.0934***	-0.229***	0.264*
	(0.0127)	(0.0242)	(0.142)
Rowan	-0.0342***	-0.0324	0.266**
	(0.0116)	(0.0206)	(0.133)
Rutherford	-0.205***	-0.202***	0.289*
	(0.0143)	(0.0264)	(0.156)
Sampson	0.111***	0.153***	0.918***
	(0.0135)	(0.0251)	(0.137)
Scotland	-0.128***	0.241***	0.719***
	(0.0170)	(0.0311)	(0.172)
Stanly	-0.125***	-0.263***	0.343**
	(0.0141)	(0.0287)	(0.166)
Stokes	-0.233***	-0.390***	0.417**
	(0.0169)	(0.0319)	(0.176)
Surry	-0.138***	-0.0449*	0.581***
	(0.0141)	(0.0255)	(0.143)
Swain	-0.529***	-0.595***	0.345
	(0.0275)	(0.0554)	(0.266)
Transylvania	-0.397***	-0.518***	0.178
	(0.0193)	(0.0376)	(0.225)

Tyrrell	0.231***	-0.469***	-0.442
	(0.0372)	(0.106)	(1.004)
Union	-0.0662***	-0.179***	-0.103
	(0.0103)	(0.0195)	(0.128)
Vance	0.227***	0.373***	0.671***
	(0.0146)	(0.0276)	(0.156)
Wake	0.139***	-0.0337**	-0.554***
	(0.00950)	(0.0163)	(0.105)
Warren	-0.0885***	-0.0478	0.874***
	(0.0221)	(0.0449)	(0.230)
Washington	-0.189***	-0.362***	0.338
	(0.0272)	(0.0559)	(0.292)
Watauga	-0.0262*	-0.335***	-0.0823
	(0.0153)	(0.0292)	(0.207)
Wayne	-0.000431	0.0991***	0.371***
	(0.0116)	(0.0215)	(0.131)
Wilkes	-0.258***	-0.179***	0.332**
	(0.0145)	(0.0260)	(0.155)
Wilson	0.104***	0.121***	0.467***
	(0.0130)	(0.0243)	(0.145)
Yadkin	-0.226***	-0.363***	0.486***
	(0.0186)	(0.0348)	(0.178)
Yancey	-0.581***	-0.591***	0.400
	(0.0259)	(0.0520)	(0.246)
2014	0.00996**	0.00826	0.00405
	(0.00439)	(0.00812)	(0.0432)
2015	0.101***	0.0972***	0.0710*
	(0.00421)	(0.00801)	(0.0429)
2016	0.148***	0.135***	0.0945**
	(0.00423)	(0.00800)	(0.0423)
2017	0.173***	0.117***	0.0551
	(0.00407)	(0.00795)	(0.0426)
2018	0.181***	0.0776***	0.0893**
	(0.00412)	(0.00795)	(0.0423)
2019	0.186***	0.0692***	0.101**
	(0.00403)	(0.00796)	(0.0422)
February	0.00498	0.0556***	-0.0277
	(0.00695)	(0.0116)	(0.0614)
March	0.00185	0.0938***	-0.0191
	(0.00623)	(0.0113)	(0.0604)
April	0.0145**	0.150***	0.0367
	(0.00665)	(0.0122)	(0.0648)
May	0.0474***	0.203***	0.128**
	(0.00671)	(0.0124)	(0.0645)
June	0.0383***	0.196***	0.159**
	(0.00681)	(0.0126)	(0.0656)
July	-0.0206***	0.136***	0.0234
	(0.00716)	(0.0134)	(0.0701)
August	0.0278***	0.188***	0.0543
	(0.00682)	(0.0126)	(0.0663)
September	0.0526***	0.191***	0.189***
	(0.00684)	(0.0125)	(0.0648)
October	0.212***	0.265***	0.212***
	(0.00664)	(0.0123)	(0.0640)
November	0.274***	0.213***	0.165***
	(0.00657)	(0.0122)	(0.0639)
December	0.167***	0.152***	0.0530
	(0.00648)	(0.0114)	(0.0609)
Monday	0.337***	0.205***	-0.212***
	(0.00435)	(0.00850)	(0.0425)
Tuesday	0.344***	0.198***	-0.190***
	(0.00429)	(0.00840)	(0.0417)
Wednesday	0.342***	0.197***	-0.163***
	(0.00427)	(0.00834)	(0.0417)
Thursday	0.349***	0.211***	-0.188***
	(0.00421)	(0.00825)	(0.0416)
Friday	0.510***	0.394***	0.000219
	(0.00424)	(0.00819)	(0.0399)
Saturday	0.223***	0.200***	0.0958**
	(0.00430)	(0.00852)	(0.0390)

Precipitation (inches)	0.0673***	0.0338***	0.0173
	(0.00315)	(0.00542)	(0.0291)
Rain After 3 or more Dry Days	0.0674***	0.0548***	-0.0496
	(0.00398)	(0.00716)	(0.0403)
Snow or Ice Conditions	0.163***	0.0279*	-0.257***
	(0.0103)	(0.0156)	(0.0867)
Very Hot Day (95th percentile)	0.0276***	0.0294**	-0.151**
	(0.00668)	(0.0144)	(0.0749)
Very Cold Day (5th percentile)	0.00460	-0.0262**	0.00270
	(0.00804)	(0.0132)	(0.0724)
Sum of Very Hot Days (3 to 1 days ago)	-0.0124***	-0.00914*	0.0442*
	(0.00231)	(0.00492)	(0.0242)
Sum of Very Cold Days (30 to 3 days ago)	-0.000188	-0.00247**	-0.00729
	(0.000649)	(0.00125)	(0.00606)
lnalpha	-2.820***	-0.868***	0.872***
	(0.0181)	(0.00940)	(0.0536)
Constant	-10.13***	-10.79***	-15.03***
	(0.0108)	(0.0198)	(0.114)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Independent Factors Regression #2

nbreg Crashes i.CountyNum i.Year i.MoY i.DoW FloodEv WindEv TStormEv StormEv WinterEv, vce(robust) exposure(YearPop)
estimates store In2C
outreg2 using In2, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW FloodEv WindEv TStormEv StormEv WinterEv, vce(robust) exposure(YearPop)
estimates store In2I
outreg2 using In2, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW FloodEv WindEv TStormEv StormEv WinterEv, vce(robust) exposure(YearPop)
estimates store In2K
outreg2 using In2, word append ctitle(Fatalities, NB) label

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.531***	-0.617***	0.216
	(0.0185)	(0.0388)	(0.198)
Alleghany	-0.338***	-0.427***	0.406
	(0.0310)	(0.0615)	(0.291)
Anson	0.190***	0.313***	0.585***
	(0.0174)	(0.0344)	(0.199)
Ashe	-0.332***	-0.471***	0.319
	(0.0206)	(0.0416)	(0.212)
Avery	-0.322***	-0.445***	-0.152
	(0.0240)	(0.0483)	(0.302)
Beaufort	-0.114***	-0.162***	0.397**
	(0.0151)	(0.0325)	(0.170)
Bertie	-0.0715***	0.0701*	1.242***
	(0.0213)	(0.0414)	(0.181)
Bladen	0.147***	0.211***	1.162***
	(0.0158)	(0.0338)	(0.165)
Brunswick	-0.147***	-0.273***	0.295**
	(0.0114)	(0.0227)	(0.135)
Buncombe	0.136***	-0.109***	0.0799
	(0.00996)	(0.0184)	(0.117)

Burke	-0.0857***	-0.0776***	0.387***
	(0.0129)	(0.0245)	(0.141)
Cabarrus	0.0808***	0.00905	-0.130
	(0.0102)	(0.0194)	(0.128)
Caldwell	-0.151***	-0.138***	0.0884
	(0.0128)	(0.0247)	(0.161)
Camden	-0.339***	-0.634***	0.408
	(0.0307)	(0.0653)	(0.365)
Carteret	-0.228***	-0.366***	-0.138
	(0.0141)	(0.0274)	(0.182)
Caswell	-0.269***	-0.328***	0.808***
	(0.0208)	(0.0406)	(0.187)
Catawba	0.170***	0.0367*	0.128
	(0.0105)	(0.0198)	(0.129)
Chatham	-0.186***	-0.493***	0.475***
	(0.0149)	(0.0280)	(0.152)
Cherokee	-0.411***	-0.462***	0.685***
	(0.0203)	(0.0396)	(0.187)
Chowan	-0.367***	-0.568***	0.420
	(0.0273)	(0.0591)	(0.272)
Clay	-0.349***	-0.562***	0.406
	(0.0315)	(0.0636)	(0.312)
Cleveland	0.0948***	0.00494	0.576***
	(0.0119)	(0.0227)	(0.133)
Columbus	0.255***	0.417***	1.209***
	(0.0128)	(0.0263)	(0.129)
Craven	-0.168***	-0.198***	0.181
	(0.0120)	(0.0233)	(0.143)
Cumberland	0.0166*	0.0437**	0.205*
	(0.0100)	(0.0180)	(0.112)
Currituck	-0.469***	-0.552***	0.453**
	(0.0221)	(0.0462)	(0.218)
Dare	-0.0659***	-0.155***	-0.00979
	(0.0194)	(0.0347)	(0.216)
Davidson	-0.141***	-0.121***	0.407***
	(0.0108)	(0.0208)	(0.121)
Davie	-0.200***	-0.168***	0.375**
	(0.0182)	(0.0327)	(0.187)
Duplin	0.252***	0.0699**	0.903***
	(0.0134)	(0.0289)	(0.148)
Durham	0.273***	0.0687***	-0.193
	(0.00958)	(0.0178)	(0.118)
Edgecombe	0.000816	0.101***	0.565***
	(0.0143)	(0.0275)	(0.162)
Forsyth	0.0836***	-0.0350*	-0.110
	(0.0101)	(0.0180)	(0.115)
Franklin	-0.264***	-0.231***	0.442***
	(0.0141)	(0.0271)	(0.149)
Gaston	0.0873***	0.138***	0.163
	(0.0101)	(0.0187)	(0.119)
Gates	-0.225***	-0.171***	0.965***
	(0.0279)	(0.0578)	(0.244)
Graham	-0.199***	0.128**	1.450***
	(0.0319)	(0.0509)	(0.227)
Granville	-0.216***	-0.147***	0.706***
	(0.0149)	(0.0271)	(0.145)
Greene	-0.0567***	-0.168***	0.379
	(0.0203)	(0.0430)	(0.239)
Guilford	0.0940***	0.274***	-0.000359
	(0.00937)	(0.0167)	(0.107)
Halifax	0.145***	0.218***	0.759***
	(0.0138)	(0.0297)	(0.152)
Harnett	-0.296***	-0.239***	0.636***
	(0.0118)	(0.0224)	(0.122)
Haywood	-0.274***	-0.214***	0.366**
	(0.0154)	(0.0274)	(0.161)
Henderson	-0.105***	-0.341***	-0.0452
	(0.0122)	(0.0237)	(0.146)
Hertford	-0.198***	0.100**	0.499**
	(0.0202)	(0.0415)	(0.204)

Hoke	-0.366***	-0.116***	0.670***
	(0.0159)	(0.0300)	(0.159)
Hyde	-0.319***	-0.953***	-0.0125
	(0.0424)	(0.104)	(0.508)
Iredell	-0.0164	0.0308	0.187
	(0.0109)	(0.0198)	(0.122)
Jackson	-0.252***	-0.353***	0.447**
	(0.0177)	(0.0319)	(0.182)
Johnston	-0.0711***	-0.0556***	0.378***
	(0.0108)	(0.0199)	(0.120)
Jones	0.368***	0.136***	0.736***
	(0.0227)	(0.0500)	(0.281)
Lee	0.0290**	-0.0344	0.629***
	(0.0136)	(0.0284)	(0.152)
Lenoir	0.0594***	0.220***	0.541***
	(0.0139)	(0.0255)	(0.149)
Lincoln	-0.224***	-0.312***	0.332**
	(0.0142)	(0.0267)	(0.145)
Macon	-0.188***	-0.261***	0.560***
	(0.0170)	(0.0328)	(0.174)
Madison	-0.518***	-0.848***	0.482**
	(0.0238)	(0.0489)	(0.220)
Martin	0.115***	0.0551	0.533***
	(0.0196)	(0.0369)	(0.206)
McDowell	0.0157	-0.214***	0.369**
	(0.0151)	(0.0300)	(0.182)
Mecklenburg	0.304***	0.429***	-0.261**
	(0.00867)	(0.0158)	(0.102)
Mitchell	-0.473***	-0.276***	-0.275
	(0.0262)	(0.0478)	(0.411)
Montgomery	-0.0219	-0.287***	0.938***
	(0.0182)	(0.0369)	(0.177)
Moore	-0.102***	-0.246***	0.454***
	(0.0126)	(0.0245)	(0.138)
Nash	0.0594***	0.164***	0.828***
	(0.0122)	(0.0231)	(0.127)
New Hanover	0.0731***	-0.0346*	-0.205
	(0.0100)	(0.0189)	(0.127)
Northampton	-0.00371	-0.0133	1.188***
	(0.0212)	(0.0424)	(0.177)
Onslow	-0.180***	-0.264***	-0.0286
	(0.0104)	(0.0202)	(0.128)
Orange	-0.220***	-0.359***	-0.310**
	(0.0118)	(0.0224)	(0.152)
Pamlico	-0.478***	-0.701***	0.340
	(0.0291)	(0.0630)	(0.282)
Pasquotank	-0.158***	-0.282***	-0.275
	(0.0161)	(0.0331)	(0.231)
Pender	0.0745***	-0.0172	1.036***
	(0.0133)	(0.0294)	(0.134)
Perquimans	-0.396***	-0.548***	0.424
	(0.0282)	(0.0614)	(0.307)
Person	-0.0622***	-0.179***	0.240
	(0.0165)	(0.0321)	(0.191)
Pitt	0.280***	0.326***	0.119
	(0.0104)	(0.0192)	(0.127)
Polk	-0.193***	-0.334***	0.475**
	(0.0216)	(0.0435)	(0.241)
Randolph	-0.0523***	-0.113***	0.412***
	(0.0115)	(0.0209)	(0.123)
Richmond	0.0163	0.246***	0.692***
	(0.0154)	(0.0283)	(0.170)
Robeson	0.174***	0.431***	1.145***
	(0.0110)	(0.0200)	(0.114)
Rockingham	-0.0890***	-0.228***	0.262*
	(0.0123)	(0.0242)	(0.142)
Rowan	-0.0319***	-0.0317	0.269**
	(0.0111)	(0.0206)	(0.133)
Rutherford	-0.207***	-0.203***	0.293*
	(0.0140)	(0.0263)	(0.156)

Sampson	0.116***	0.156***	0.919***
	(0.0133)	(0.0251)	(0.137)
Scotland	-0.119***	0.246***	0.720***
	(0.0168)	(0.0311)	(0.172)
Stanly	-0.119***	-0.260***	0.343**
	(0.0138)	(0.0287)	(0.166)
Stokes	-0.227***	-0.390***	0.414**
	(0.0165)	(0.0318)	(0.176)
Surry	-0.133***	-0.0433*	0.578***
	(0.0136)	(0.0254)	(0.143)
Swain	-0.528***	-0.597***	0.338
	(0.0275)	(0.0554)	(0.266)
Transylvania	-0.391***	-0.516***	0.176
	(0.0191)	(0.0377)	(0.225)
Tyrrell	0.244***	-0.462***	-0.441
	(0.0371)	(0.106)	(1.004)
Union	-0.0603***	-0.176***	-0.101
	(0.00995)	(0.0194)	(0.128)
Vance	0.233***	0.375***	0.669***
	(0.0142)	(0.0276)	(0.156)
Wake	0.141***	-0.0333**	-0.554***
	(0.00916)	(0.0163)	(0.105)
Warren	-0.0833***	-0.0455	0.872***
	(0.0218)	(0.0449)	(0.230)
Washington	-0.177***	-0.356***	0.339
	(0.0270)	(0.0558)	(0.292)
Watauga	-0.00928	-0.333***	-0.108
	(0.0149)	(0.0292)	(0.207)
Wayne	0.00610	0.103***	0.372***
	(0.0111)	(0.0214)	(0.131)
Wilkes	-0.251***	-0.177***	0.329**
	(0.0141)	(0.0259)	(0.155)
Wilson	0.112***	0.126***	0.467***
	(0.0128)	(0.0243)	(0.145)
Yadkin	-0.218***	-0.360***	0.484***
	(0.0184)	(0.0348)	(0.178)
Yancey	-0.594***	-0.598***	0.394
	(0.0259)	(0.0521)	(0.246)
2014	0.00211	0.00167	-0.00135
	(0.00429)	(0.00806)	(0.0432)
2015	0.0962***	0.0930***	0.0685
	(0.00414)	(0.00798)	(0.0426)
2016	0.143***	0.133***	0.0954**
	(0.00414)	(0.00792)	(0.0419)
2017	0.170***	0.116***	0.0612
	(0.00403)	(0.00793)	(0.0425)
2018	0.177***	0.0749***	0.0860**
	(0.00407)	(0.00789)	(0.0422)
2019	0.186***	0.0710***	0.109***
	(0.00398)	(0.00788)	(0.0417)
February	-0.00690	0.0498***	-0.0266
	(0.00625)	(0.0112)	(0.0593)
March	0.000816	0.111***	0.0212
	(0.00579)	(0.0107)	(0.0580)
April	0.0224***	0.181***	0.105*
	(0.00564)	(0.0104)	(0.0571)
May	0.0530***	0.233***	0.201***
	(0.00553)	(0.0104)	(0.0555)
June	0.0394***	0.224***	0.239***
	(0.00558)	(0.0105)	(0.0559)
July	-0.0233***	0.163***	0.107*
	(0.00561)	(0.0107)	(0.0574)
August	0.0304***	0.218***	0.136**
	(0.00554)	(0.0104)	(0.0562)
September	0.0589***	0.223***	0.261***
	(0.00570)	(0.0105)	(0.0558)
October	0.217***	0.297***	0.282***
	(0.00545)	(0.0103)	(0.0548)
November	0.284***	0.243***	0.227***
	(0.00554)	(0.0104)	(0.0561)

December	0.174***	0.176***	0.103*
	(0.00587)	(0.0105)	(0.0566)
Monday	0.336***	0.205***	-0.211***
	(0.00426)	(0.00847)	(0.0425)
Tuesday	0.339***	0.196***	-0.187***
	(0.00420)	(0.00838)	(0.0417)
Wednesday	0.337***	0.193***	-0.165***
	(0.00420)	(0.00833)	(0.0416)
Thursday	0.347***	0.209***	-0.189***
	(0.00415)	(0.00824)	(0.0416)
Friday	0.509***	0.394***	-0.000793
	(0.00417)	(0.00817)	(0.0399)
Saturday	0.222***	0.200***	0.0968**
	(0.00429)	(0.00851)	(0.0390)
Flood Event	0.167***	0.0829***	0.120
	(0.0146)	(0.0258)	(0.128)
Wind Event	0.101***	0.0320	0.198
	(0.0203)	(0.0418)	(0.202)
Thunderstorm Wind Event	0.107***	0.0908***	-0.0882
	(0.00791)	(0.0170)	(0.0976)
Storm Event (Tropical Cyclone)	-0.0662	-0.184***	0.0631
	(0.0420)	(0.0578)	(0.237)
Winter Event	0.610***	0.325***	-0.189
	(0.0179)	(0.0224)	(0.123)
lnalpha	-2.873***	-0.870***	0.874***
	(0.0162)	(0.00936)	(0.0536)
Constant	-10.12***	-10.81***	-15.10***
	(0.00976)	(0.0185)	(0.109)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Independent Factors Regression #3

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nbreg Crashes i.CountyNum i.Year i.MoY i.DoW Holiday DST, vce(robust) exposure(YearPop)
estimates store In3C
outreg2 using In3, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW Holiday DST, vce(robust) exposure(YearPop)
estimates store In3I
outreg2 using In3, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW Holiday DST, vce(robust) exposure(YearPop)
estimates store In3K
outreg2 using In3, word append ctitle(Fatalities, NB) label
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VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.533***	-0.617***	0.216
	(0.0189)	(0.0388)	(0.198)
Alleghany	-0.341***	-0.429***	0.409
	(0.0314)	(0.0615)	(0.291)
Anson	0.180***	0.308***	0.587***
	(0.0178)	(0.0344)	(0.199)
Ashe	-0.331***	-0.470***	0.324
	(0.0212)	(0.0417)	(0.212)
Avery	-0.299***	-0.435***	-0.156
	(0.0246)	(0.0484)	(0.303)
Beaufort	-0.125***	-0.168***	0.399**
	(0.0155)	(0.0325)	(0.170)
Bertie	-0.0792***	0.0666	1.244***
	(0.0217)	(0.0414)	(0.181)
Bladen	0.135***	0.206***	1.164***

	(0.0163)	(0.0338)	(0.165)
Brunswick	-0.159***	-0.279***	0.299**
	(0.0118)	(0.0227)	(0.135)
Buncombe	0.140***	-0.106***	0.0794
	(0.0104)	(0.0185)	(0.117)
Burke	-0.0785***	-0.0738***	0.385***
	(0.0135)	(0.0246)	(0.141)
Cabarrus	0.0758***	0.00717	-0.128
	(0.0107)	(0.0194)	(0.128)
Caldwell	-0.143***	-0.135***	0.0883
	(0.0134)	(0.0247)	(0.161)
Camden	-0.348***	-0.639***	0.412
	(0.0309)	(0.0653)	(0.365)
Carteret	-0.240***	-0.372***	-0.134
	(0.0145)	(0.0274)	(0.182)
Caswell	-0.277***	-0.331***	0.809***
	(0.0210)	(0.0406)	(0.187)
Catawba	0.168***	0.0360*	0.129
	(0.0113)	(0.0199)	(0.129)
Chatham	-0.192***	-0.495***	0.476***
	(0.0154)	(0.0280)	(0.152)
Cherokee	-0.423***	-0.467***	0.687***
	(0.0206)	(0.0396)	(0.188)
Chowan	-0.376***	-0.572***	0.423
	(0.0276)	(0.0592)	(0.272)
Clay	-0.363***	-0.569***	0.408
	(0.0316)	(0.0636)	(0.312)
Cleveland	0.0877***	0.00252	0.577***
	(0.0125)	(0.0229)	(0.133)
Columbus	0.242***	0.411***	1.212***
	(0.0132)	(0.0263)	(0.129)
Craven	-0.180***	-0.204***	0.183
	(0.0124)	(0.0233)	(0.142)
Cumberland	0.00671	0.0388**	0.208*
	(0.0105)	(0.0180)	(0.112)
Currituck	-0.477***	-0.557***	0.456**
	(0.0223)	(0.0462)	(0.218)
Dare	-0.0772***	-0.161***	-0.00522
	(0.0197)	(0.0347)	(0.216)
Davidson	-0.144***	-0.121***	0.407***
	(0.0116)	(0.0209)	(0.121)
Davie	-0.201***	-0.168***	0.375**
	(0.0191)	(0.0328)	(0.187)
Duplin	0.242***	0.0651**	0.906***
	(0.0142)	(0.0290)	(0.149)
Durham	0.268***	0.0663***	-0.191
	(0.0100)	(0.0178)	(0.118)
Edgecombe	-0.00640	0.0971***	0.567***
	(0.0147)	(0.0275)	(0.162)
Forsyth	0.0831***	-0.0347*	-0.109
	(0.0110)	(0.0181)	(0.116)
Franklin	-0.270***	-0.234***	0.443***
	(0.0145)	(0.0271)	(0.149)
Gaston	0.0796***	0.135***	0.164
	(0.0107)	(0.0187)	(0.119)
Gates	-0.233***	-0.175***	0.966***
	(0.0282)	(0.0579)	(0.244)
Graham	-0.193***	0.130**	1.449***
	(0.0320)	(0.0508)	(0.227)
Granville	-0.220***	-0.148***	0.707***
	(0.0155)	(0.0272)	(0.145)
Greene	-0.0691***	-0.174***	0.381
	(0.0206)	(0.0430)	(0.239)
Guilford	0.0949***	0.275***	0.00122
	(0.0102)	(0.0167)	(0.107)
Halifax	0.140***	0.216***	0.760***
	(0.0144)	(0.0296)	(0.152)
Harnett	-0.303***	-0.241***	0.638***
	(0.0122)	(0.0224)	(0.122)
Haywood	-0.261***	-0.208***	0.363**

	(0.0157)	(0.0274)	(0.161)
Henderson	-0.102***	-0.339***	-0.0445
	(0.0129)	(0.0237)	(0.146)
Hertford	-0.206***	0.0964**	0.500**
	(0.0205)	(0.0415)	(0.204)
Hoke	-0.377***	-0.122***	0.673***
	(0.0163)	(0.0300)	(0.159)
Hyde	-0.332***	-0.959***	-0.00921
	(0.0426)	(0.104)	(0.508)
Iredell	-0.0163	0.0313	0.186
	(0.0118)	(0.0199)	(0.122)
Jackson	-0.245***	-0.350***	0.445**
	(0.0182)	(0.0319)	(0.182)
Johnston	-0.0739***	-0.0570***	0.380***
	(0.0115)	(0.0199)	(0.120)
Jones	0.355***	0.130***	0.738***
	(0.0230)	(0.0500)	(0.281)
Lee	0.0222	-0.0378	0.631***
	(0.0141)	(0.0283)	(0.152)
Lenoir	0.0481***	0.214***	0.544***
	(0.0144)	(0.0255)	(0.149)
Lincoln	-0.229***	-0.314***	0.333**
	(0.0149)	(0.0268)	(0.145)
Macon	-0.187***	-0.261***	0.560***
	(0.0173)	(0.0328)	(0.174)
Madison	-0.503***	-0.840***	0.478**
	(0.0241)	(0.0490)	(0.220)
Martin	0.105***	0.0510	0.536***
	(0.0200)	(0.0370)	(0.206)
McDowell	0.0204	-0.212***	0.369**
	(0.0156)	(0.0301)	(0.182)
Mecklenburg	0.299***	0.427***	-0.260**
	(0.00919)	(0.0158)	(0.102)
Mitchell	-0.450***	-0.267***	-0.279
	(0.0264)	(0.0478)	(0.411)
Montgomery	-0.0308*	-0.291***	0.939***
	(0.0185)	(0.0368)	(0.177)
Moore	-0.110***	-0.249***	0.454***
	(0.0130)	(0.0245)	(0.138)
Nash	0.0550***	0.162***	0.830***
	(0.0129)	(0.0231)	(0.127)
New Hanover	0.0616***	-0.0407**	-0.200
	(0.0105)	(0.0189)	(0.127)
Northampton	-0.00989	-0.0158	1.189***
	(0.0218)	(0.0425)	(0.177)
Onslow	-0.191***	-0.270***	-0.0253
	(0.0110)	(0.0203)	(0.128)
Orange	-0.221***	-0.360***	-0.310**
	(0.0123)	(0.0224)	(0.151)
Pamlico	-0.491***	-0.707***	0.343
	(0.0293)	(0.0630)	(0.282)
Pasquotank	-0.167***	-0.287***	-0.272
	(0.0164)	(0.0331)	(0.231)
Pender	0.0635***	-0.0228	1.039***
	(0.0138)	(0.0294)	(0.134)
Perquimans	-0.405***	-0.552***	0.427
	(0.0284)	(0.0615)	(0.307)
Person	-0.0625***	-0.179***	0.240
	(0.0171)	(0.0321)	(0.191)
Pitt	0.269***	0.320***	0.122
	(0.0108)	(0.0192)	(0.127)
Polk	-0.194***	-0.334***	0.475**
	(0.0218)	(0.0436)	(0.241)
Randolph	-0.0562***	-0.115***	0.413***
	(0.0120)	(0.0209)	(0.123)
Richmond	0.00683	0.242***	0.694***
	(0.0159)	(0.0284)	(0.170)
Robeson	0.164***	0.425***	1.147***
	(0.0115)	(0.0200)	(0.114)
Rockingham	-0.0926***	-0.229***	0.264*

	(0.0128)	(0.0242)	(0.142)
Rowan	-0.0352***	-0.0326	0.269**
	(0.0118)	(0.0206)	(0.133)
Rutherford	-0.207***	-0.202***	0.293*
	(0.0145)	(0.0264)	(0.156)
Sampson	0.108***	0.152***	0.922***
	(0.0137)	(0.0251)	(0.137)
Scotland	-0.130***	0.241***	0.723***
	(0.0172)	(0.0311)	(0.172)
Stanly	-0.128***	-0.264***	0.346**
	(0.0142)	(0.0287)	(0.166)
Stokes	-0.232***	-0.391***	0.416**
	(0.0170)	(0.0319)	(0.176)
Surry	-0.136***	-0.0450*	0.580***
	(0.0142)	(0.0254)	(0.143)
Swain	-0.517***	-0.593***	0.336
	(0.0275)	(0.0554)	(0.266)
Transylvania	-0.389***	-0.515***	0.177
	(0.0194)	(0.0376)	(0.225)
Tyrrell	0.231***	-0.469***	-0.438
	(0.0373)	(0.106)	(1.004)
Union	-0.0705***	-0.180***	-0.0986
	(0.0104)	(0.0194)	(0.128)
Vance	0.229***	0.373***	0.670***
	(0.0148)	(0.0276)	(0.156)
Wake	0.138***	-0.0341**	-0.553***
	(0.00971)	(0.0163)	(0.105)
Warren	-0.0880***	-0.0479	0.874***
	(0.0222)	(0.0449)	(0.230)
Washington	-0.189***	-0.361***	0.341
	(0.0273)	(0.0559)	(0.292)
Watauga	-0.00766	-0.332***	-0.103
	(0.0154)	(0.0292)	(0.207)
Wayne	-0.00150	0.0992***	0.375***
	(0.0117)	(0.0215)	(0.131)
Wilkes	-0.255***	-0.178***	0.331**
	(0.0147)	(0.0260)	(0.155)
Wilson	0.104***	0.122***	0.469***
	(0.0132)	(0.0243)	(0.145)
Yadkin	-0.225***	-0.363***	0.486***
	(0.0188)	(0.0348)	(0.178)
Yancey	-0.572***	-0.590***	0.390
	(0.0259)	(0.0519)	(0.246)
2014	0.0121***	0.00597	-0.00368
	(0.00448)	(0.00808)	(0.0432)
2015	0.102***	0.0953***	0.0676
	(0.00426)	(0.00799)	(0.0426)
2016	0.145***	0.133***	0.0960**
	(0.00427)	(0.00794)	(0.0419)
2017	0.168***	0.116***	0.0606
	(0.00410)	(0.00794)	(0.0425)
2018	0.183***	0.0766***	0.0873**
	(0.00417)	(0.00790)	(0.0421)
2019	0.181***	0.0694***	0.110***
	(0.00402)	(0.00789)	(0.0417)
February	-0.00967	0.0498***	-0.0235
	(0.00697)	(0.0113)	(0.0593)
March	-0.0320***	0.0898***	0.0424
	(0.00636)	(0.0109)	(0.0598)
April	-0.0177***	0.164***	0.116**
	(0.00602)	(0.0104)	(0.0571)
May	0.0276***	0.222***	0.196***
	(0.00595)	(0.0105)	(0.0563)
June	0.00529	0.210***	0.244***
	(0.00593)	(0.0104)	(0.0557)
July	-0.0510***	0.151***	0.108*
	(0.00597)	(0.0107)	(0.0573)
August	-0.00664	0.202***	0.142**
	(0.00593)	(0.0104)	(0.0562)
September	0.0266***	0.208***	0.268***

	(0.00607)	(0.0104)	(0.0557)
October	0.182***	0.280***	0.292***
	(0.00584)	(0.0103)	(0.0548)
November	0.244***	0.217***	0.247***
	(0.00610)	(0.0109)	(0.0582)
December	0.149***	0.164***	0.105*
	(0.00622)	(0.0105)	(0.0568)
Monday	0.335***	0.205***	-0.211***
	(0.00440)	(0.00849)	(0.0425)
Tuesday	0.338***	0.197***	-0.184***
	(0.00435)	(0.00843)	(0.0419)
Wednesday	0.336***	0.195***	-0.162***
	(0.00433)	(0.00836)	(0.0418)
Thursday	0.341***	0.207***	-0.187***
	(0.00422)	(0.00826)	(0.0417)
Friday	0.506***	0.393***	0.00176
	(0.00428)	(0.00819)	(0.0400)
Saturday	0.219***	0.199***	0.0998**
	(0.00433)	(0.00853)	(0.0390)
Holiday	-0.0860***	-0.0308***	0.0677
	(0.00529)	(0.00964)	(0.0454)
Daylight Savings Time week	0.0294***	0.0464***	-0.0629
	(0.00605)	(0.0126)	(0.0655)
lnalpha	-2.798***	-0.867***	0.875***
	(0.0187)	(0.00937)	(0.0536)
Constant	-10.07***	-10.79***	-15.12***
	(0.0104)	(0.0185)	(0.109)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Independent Factors Regression #4

```
nbreg Crashes Urban i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store In4C
outreg2 using In4, word replace ctitle(Collisions, NB) label
nbreg Injured Urban i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store In4I
outreg2 using In4, word append ctitle(Injuries, NB) label
nbreg Killed Urban i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store In4K
outreg2 using In4, word append ctitle(Fatalities, NB) label
```

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Urban (1 or 0)	0.0922***	0.0661***	-0.478***
	(0.00232)	(0.00420)	(0.0228)
2014	0.0116**	0.00653	-0.00385
	(0.00462)	(0.00821)	(0.0444)
2015	0.0995***	0.0937***	0.0657
	(0.00444)	(0.00813)	(0.0438)
2016	0.142***	0.132***	0.0934**
	(0.00447)	(0.00807)	(0.0432)
2017	0.164***	0.114***	0.0604
	(0.00430)	(0.00808)	(0.0439)
2018	0.178***	0.0764***	0.0836*
	(0.00437)	(0.00805)	(0.0435)
2019	0.176***	0.0670***	0.105**
	(0.00422)	(0.00802)	(0.0430)
February	-0.00770	0.0506***	-0.0263
	(0.00716)	(0.0115)	(0.0610)

March	-0.0240***	0.101***	0.0246
	(0.00649)	(0.0110)	(0.0597)
April	-0.0161**	0.163***	0.119**
	(0.00629)	(0.0107)	(0.0587)
May	0.0143**	0.212***	0.216***
	(0.00616)	(0.0106)	(0.0573)
June	0.00673	0.206***	0.253***
	(0.00618)	(0.0106)	(0.0575)
July	-0.0547***	0.143***	0.125**
	(0.00620)	(0.0108)	(0.0590)
August	-0.00739	0.197***	0.147**
	(0.00618)	(0.0106)	(0.0579)
September	0.0210***	0.200***	0.283***
	(0.00632)	(0.0106)	(0.0573)
October	0.177***	0.273***	0.301***
	(0.00608)	(0.0104)	(0.0566)
November	0.247***	0.222***	0.239***
	(0.00612)	(0.0106)	(0.0578)
December	0.143***	0.161***	0.117**
	(0.00645)	(0.0107)	(0.0584)
Monday	0.327***	0.202***	-0.213***
	(0.00455)	(0.00864)	(0.0439)
Tuesday	0.333***	0.194***	-0.189***
	(0.00450)	(0.00851)	(0.0430)
Wednesday	0.330***	0.191***	-0.168***
	(0.00448)	(0.00845)	(0.0430)
Thursday	0.335***	0.203***	-0.190***
	(0.00436)	(0.00836)	(0.0430)
Friday	0.496***	0.387***	0.00387
	(0.00442)	(0.00832)	(0.0413)
Saturday	0.218***	0.198***	0.101**
	(0.00445)	(0.00866)	(0.0403)
lnalpha	-2.397***	-0.696***	1.031***
	(0.0128)	(0.00827)	(0.0531)
Constant	-10.14***	-10.87***	-14.59***
	(0.00682)	(0.0115)	(0.0603)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Independent Factors Regression #5

nbreg Crashes Mountains Piedmont Coastal i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store In5C
outreg2 using In5, word replace ctitle(Collisions, NB) label
nbreg Injured Mountains Piedmont Coastal i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store In5I
outreg2 using In5, word append ctitle(Injuries, NB) label
nbreg Killed Mountains Piedmont Coastal i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store In5K
outreg2 using In5, word append ctitle(Fatalities, NB) label

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Mountains County	-0.131***	-0.275***	-0.241***
	(0.00367)	(0.00676)	(0.0373)
Piedmont County	0.0320***	-0.0412***	-0.395***
	(0.00254)	(0.00471)	(0.0252)
Coastal Plains County = o,	-	-	-

2014	0.0117**	0.00574	-0.00203
	(0.00462)	(0.00815)	(0.0450)
2015	0.0995***	0.0928***	0.0687
	(0.00443)	(0.00806)	(0.0445)
2016	0.142***	0.131***	0.0959**
	(0.00447)	(0.00801)	(0.0438)
2017	0.164***	0.113***	0.0601
	(0.00430)	(0.00802)	(0.0445)
2018	0.178***	0.0761***	0.0849*
	(0.00436)	(0.00800)	(0.0441)
2019	0.176***	0.0665***	0.106**
	(0.00422)	(0.00796)	(0.0437)
February	-0.00751	0.0504***	-0.0268
	(0.00713)	(0.0114)	(0.0618)
March	-0.0238***	0.100***	0.0272
	(0.00646)	(0.0109)	(0.0606)
April	-0.0156**	0.162***	0.123**
	(0.00628)	(0.0106)	(0.0596)
May	0.0151**	0.212***	0.223***
	(0.00616)	(0.0105)	(0.0582)
June	0.00739	0.206***	0.258***
	(0.00617)	(0.0105)	(0.0584)
July	-0.0535***	0.144***	0.125**
	(0.00620)	(0.0107)	(0.0597)
August	-0.00611	0.198***	0.152***
	(0.00619)	(0.0105)	(0.0588)
September	0.0219***	0.201***	0.289***
	(0.00632)	(0.0105)	(0.0583)
October	0.177***	0.274***	0.306***
	(0.00607)	(0.0104)	(0.0574)
November	0.246***	0.222***	0.243***
	(0.00607)	(0.0105)	(0.0587)
December	0.143***	0.161***	0.120**
	(0.00642)	(0.0106)	(0.0593)
Monday	0.327***	0.203***	-0.215***
	(0.00453)	(0.00857)	(0.0445)
Tuesday	0.333***	0.196***	-0.187***
	(0.00449)	(0.00843)	(0.0437)
Wednesday	0.330***	0.193***	-0.168***
	(0.00446)	(0.00838)	(0.0436)
Thursday	0.335***	0.204***	-0.191***
	(0.00435)	(0.00829)	(0.0436)
Friday	0.495***	0.388***	0.00351
	(0.00441)	(0.00824)	(0.0419)
Saturday	0.217***	0.198***	0.105**
	(0.00442)	(0.00857)	(0.0410)
lnalpha	-2.386***	-0.712***	1.069***
	(0.0126)	(0.00822)	(0.0534)
Constant	-10.09***	-10.78***	-14.62***
	(0.00682)	(0.0116)	(0.0617)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Independent Factors Regression #6

```
nbreg Crashes DistMost Distress DistLeast i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store In6C
outreg2 using In6, word replace ctitle(Collisions, NB) label
nbreg Injured DistMost Distress DistLeast i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store In6I
outreg2 using In6, word append ctitle(Injuries, NB) label
nbreg Killed DistMost Distress DistLeast i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
```

estimates store In6K
outreg2 using In6, word append ctitle(Fatalities, NB) label

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Most Distressed County	-0.0657***	0.0878***	0.714***
	(0.00314)	(0.00574)	(0.0304)
Distressed County	-0.0872***	-0.00727	0.358***
	(0.00262)	(0.00450)	(0.0262)
Least Distressed County = o,	-	-	-
2014	0.00946**	0.00603	0.00812
	(0.00461)	(0.00806)	(0.0442)
2015	0.0993***	0.0941***	0.0710
	(0.00443)	(0.00798)	(0.0437)
2016	0.140***	0.133***	0.116***
	(0.00446)	(0.00792)	(0.0430)
2017	0.164***	0.117***	0.0771*
	(0.00429)	(0.00793)	(0.0437)
2018	0.180***	0.0803***	0.0968**
	(0.00437)	(0.00791)	(0.0434)
2019	0.176***	0.0635***	0.0799*
	(0.00422)	(0.00786)	(0.0429)
February	-0.00754	0.0504***	-0.0269
	(0.00717)	(0.0113)	(0.0608)
March	-0.0238***	0.101***	0.0277
	(0.00649)	(0.0108)	(0.0595)
April	-0.0160**	0.162***	0.119**
	(0.00630)	(0.0105)	(0.0585)
May	0.0140**	0.209***	0.217***
	(0.00616)	(0.0104)	(0.0571)
June	0.00639	0.203***	0.252***
	(0.00617)	(0.0104)	(0.0572)
July	-0.0551***	0.141***	0.124**
	(0.00619)	(0.0106)	(0.0588)
August	-0.00751	0.195***	0.148**
	(0.00618)	(0.0104)	(0.0576)
September	0.0207***	0.198***	0.283***
	(0.00631)	(0.0104)	(0.0571)
October	0.176***	0.271***	0.301***
	(0.00608)	(0.0103)	(0.0563)
November	0.246***	0.220***	0.240***
	(0.00610)	(0.0104)	(0.0575)
December	0.142***	0.160***	0.118**
	(0.00644)	(0.0105)	(0.0582)
Monday	0.327***	0.203***	-0.214***
	(0.00453)	(0.00846)	(0.0437)
Tuesday	0.332***	0.195***	-0.189***
	(0.00448)	(0.00834)	(0.0429)
Wednesday	0.329***	0.192***	-0.168***
	(0.00446)	(0.00828)	(0.0428)
Thursday	0.334***	0.204***	-0.190***
	(0.00435)	(0.00819)	(0.0429)
Friday	0.495***	0.386***	0.000294
	(0.00441)	(0.00815)	(0.0411)
Saturday	0.217***	0.197***	0.0985**
	(0.00443)	(0.00847)	(0.0402)
lnalpha	-2.388***	-0.696***	0.998***
	(0.0128)	(0.00806)	(0.0538)
Constant	-10.04***	-10.86***	-15.16***
	(0.00676)	(0.0113)	(0.0611)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Independent Factors Regression #7

```
nbreg Crashes i.CountyNum i.Year i.MoY i.DoW Cone SpOver Line StormEv RecFalPos
RecHurLan PostMatt PostFlor, vce(robust) exposure(YearPop)
estimates store In7C
outreg2 using In7, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW Cone SpOver Line StormEv RecFalPos
RecHurLan PostMatt PostFlor, vce(robust) exposure(YearPop)
estimates store In7I
outreg2 using In7, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW Cone SpOver Line StormEv RecFalPos
RecHurLan PostMatt PostFlor, vce(robust) exposure(YearPop)
estimates store In7K
outreg2 using In7, word append ctitle(Fatalities, NB) label
```

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.531***	-0.618***	0.218
	(0.0190)	(0.0388)	(0.198)
Alleghany	-0.340***	-0.430***	0.412
	(0.0314)	(0.0615)	(0.291)
Anson	0.179***	0.308***	0.586***
	(0.0177)	(0.0344)	(0.199)
Ashe	-0.329***	-0.471***	0.328
	(0.0212)	(0.0417)	(0.212)
Avery	-0.297***	-0.435***	-0.153
	(0.0246)	(0.0484)	(0.302)
Beaufort	-0.125***	-0.167***	0.398**
	(0.0155)	(0.0325)	(0.170)
Bertie	-0.0802***	0.0671	1.242***
	(0.0217)	(0.0415)	(0.181)
Bladen	0.134***	0.206***	1.162***
	(0.0162)	(0.0338)	(0.165)
Brunswick	-0.159***	-0.279***	0.299**
	(0.0118)	(0.0228)	(0.135)
Buncombe	0.142***	-0.107***	0.0812
	(0.0104)	(0.0185)	(0.117)
Burke	-0.0778***	-0.0739***	0.387***
	(0.0135)	(0.0246)	(0.141)
Cabarrus	0.0761***	0.00727	-0.128
	(0.0107)	(0.0195)	(0.128)
Caldwell	-0.142***	-0.136***	0.0912
	(0.0134)	(0.0247)	(0.161)
Camden	-0.349***	-0.639***	0.410
	(0.0309)	(0.0653)	(0.365)
Carteret	-0.240***	-0.371***	-0.135
	(0.0145)	(0.0274)	(0.182)
Caswell	-0.277***	-0.331***	0.808***
	(0.0210)	(0.0406)	(0.187)
Catawba	0.168***	0.0356*	0.130
	(0.0114)	(0.0199)	(0.129)
Chatham	-0.192***	-0.495***	0.475***
	(0.0154)	(0.0280)	(0.152)
Cherokee	-0.422***	-0.468***	0.690***
	(0.0206)	(0.0397)	(0.188)
Chowan	-0.376***	-0.572***	0.420
	(0.0276)	(0.0592)	(0.272)
Clay	-0.362***	-0.569***	0.411
	(0.0316)	(0.0636)	(0.312)
Cleveland	0.0881***	0.00255	0.577***

	(0.0125)	(0.0229)	(0.133)
Columbus	0.241***	0.411***	1.210***
	(0.0132)	(0.0263)	(0.129)
Craven	-0.180***	-0.203***	0.182
	(0.0124)	(0.0233)	(0.143)
Cumberland	0.00608	0.0392**	0.205*
	(0.0105)	(0.0180)	(0.112)
Currituck	-0.478***	-0.556***	0.454**
	(0.0223)	(0.0462)	(0.218)
Dare	-0.0781***	-0.161***	-0.00896
	(0.0197)	(0.0347)	(0.216)
Davidson	-0.144***	-0.121***	0.408***
	(0.0116)	(0.0209)	(0.121)
Davie	-0.200***	-0.168***	0.377**
	(0.0192)	(0.0328)	(0.187)
Duplin	0.241***	0.0653**	0.903***
	(0.0142)	(0.0290)	(0.148)
Durham	0.268***	0.0663***	-0.191
	(0.0100)	(0.0178)	(0.118)
Edgecombe	-0.00747	0.0977***	0.564***
	(0.0147)	(0.0275)	(0.162)
Forsyth	0.0844***	-0.0351*	-0.106
	(0.0110)	(0.0182)	(0.116)
Franklin	-0.270***	-0.233***	0.442***
	(0.0146)	(0.0271)	(0.149)
Gaston	0.0802***	0.135***	0.165
	(0.0107)	(0.0188)	(0.119)
Gates	-0.234***	-0.174***	0.964***
	(0.0282)	(0.0579)	(0.244)
Graham	-0.192***	0.130**	1.451***
	(0.0320)	(0.0508)	(0.227)
Granville	-0.220***	-0.148***	0.707***
	(0.0155)	(0.0272)	(0.145)
Greene	-0.0697***	-0.174***	0.379
	(0.0206)	(0.0430)	(0.239)
Guilford	0.0952***	0.275***	0.000112
	(0.0102)	(0.0167)	(0.107)
Halifax	0.139***	0.216***	0.757***
	(0.0144)	(0.0297)	(0.152)
Harnett	-0.303***	-0.242***	0.637***
	(0.0122)	(0.0224)	(0.122)
Haywood	-0.260***	-0.209***	0.365**
	(0.0157)	(0.0275)	(0.161)
Henderson	-0.101***	-0.339***	-0.0420
	(0.0129)	(0.0238)	(0.146)
Hertford	-0.207***	0.0965**	0.498**
	(0.0205)	(0.0416)	(0.204)
Hoke	-0.377***	-0.121***	0.672***
	(0.0163)	(0.0300)	(0.159)
Hyde	-0.333***	-0.959***	-0.0111
	(0.0426)	(0.104)	(0.508)
Iredell	-0.0155	0.0309	0.188
	(0.0118)	(0.0199)	(0.122)
Jackson	-0.244***	-0.350***	0.448**
	(0.0182)	(0.0320)	(0.182)
Johnston	-0.0746***	-0.0565***	0.377***
	(0.0115)	(0.0199)	(0.120)
Jones	0.354***	0.130***	0.737***
	(0.0230)	(0.0500)	(0.281)
Lee	0.0222	-0.0375	0.630***
	(0.0141)	(0.0284)	(0.152)
Lenoir	0.0473***	0.215***	0.541***
	(0.0144)	(0.0256)	(0.149)
Lincoln	-0.228***	-0.314***	0.335**
	(0.0149)	(0.0268)	(0.145)
Macon	-0.186***	-0.262***	0.563***
	(0.0173)	(0.0328)	(0.174)
Madison	-0.501***	-0.841***	0.481**
	(0.0241)	(0.0490)	(0.220)
Martin	0.104***	0.0510	0.534***

	(0.0200)	(0.0370)	(0.206)
McDowell	0.0217	-0.212***	0.372**
	(0.0156)	(0.0301)	(0.182)
Mecklenburg	0.300***	0.427***	-0.260**
	(0.00923)	(0.0159)	(0.102)
Mitchell	-0.449***	-0.267***	-0.276
	(0.0264)	(0.0478)	(0.411)
Montgomery	-0.0307*	-0.291***	0.939***
	(0.0185)	(0.0369)	(0.177)
Moore	-0.110***	-0.248***	0.454***
	(0.0130)	(0.0245)	(0.138)
Nash	0.0539***	0.162***	0.827***
	(0.0129)	(0.0231)	(0.127)
New Hanover	0.0622***	-0.0409**	-0.199
	(0.0105)	(0.0189)	(0.127)
Northampton	-0.0110	-0.0153	1.187***
	(0.0217)	(0.0425)	(0.177)
Onslow	-0.191***	-0.270***	-0.0260
	(0.0110)	(0.0203)	(0.128)
Orange	-0.220***	-0.360***	-0.310**
	(0.0123)	(0.0225)	(0.152)
Pamlico	-0.492***	-0.706***	0.341
	(0.0293)	(0.0630)	(0.282)
Pasquotank	-0.168***	-0.287***	-0.274
	(0.0164)	(0.0331)	(0.231)
Pender	0.0638***	-0.0233	1.040***
	(0.0137)	(0.0294)	(0.134)
Perquimans	-0.405***	-0.551***	0.424
	(0.0284)	(0.0615)	(0.307)
Person	-0.0621***	-0.179***	0.240
	(0.0171)	(0.0321)	(0.191)
Pitt	0.268***	0.320***	0.120
	(0.0109)	(0.0192)	(0.127)
Polk	-0.193***	-0.335***	0.479**
	(0.0218)	(0.0436)	(0.241)
Randolph	-0.0564***	-0.115***	0.413***
	(0.0120)	(0.0209)	(0.123)
Richmond	0.00661	0.242***	0.693***
	(0.0159)	(0.0284)	(0.170)
Robeson	0.163***	0.426***	1.148***
	(0.0115)	(0.0201)	(0.114)
Rockingham	-0.0921***	-0.229***	0.265*
	(0.0129)	(0.0242)	(0.142)
Rowan	-0.0346***	-0.0331	0.270**
	(0.0118)	(0.0207)	(0.133)
Rutherford	-0.206***	-0.203***	0.296*
	(0.0145)	(0.0264)	(0.156)
Sampson	0.107***	0.152***	0.921***
	(0.0137)	(0.0251)	(0.137)
Scotland	-0.131***	0.241***	0.722***
	(0.0172)	(0.0311)	(0.172)
Stanly	-0.127***	-0.264***	0.347**
	(0.0143)	(0.0287)	(0.166)
Stokes	-0.231***	-0.392***	0.418**
	(0.0170)	(0.0319)	(0.176)
Surry	-0.135***	-0.0457*	0.582***
	(0.0143)	(0.0255)	(0.143)
Swain	-0.515***	-0.594***	0.339
	(0.0275)	(0.0554)	(0.266)
Transylvania	-0.388***	-0.516***	0.180
	(0.0194)	(0.0377)	(0.225)
Tyrrell	0.231***	-0.468***	-0.439
	(0.0373)	(0.106)	(1.004)
Union	-0.0702***	-0.180***	-0.0988
	(0.0104)	(0.0195)	(0.128)
Vance	0.229***	0.372***	0.670***
	(0.0147)	(0.0276)	(0.156)
Wake	0.138***	-0.0338**	-0.553***
	(0.00975)	(0.0163)	(0.105)
Warren	-0.0883***	-0.0479	0.874***

	(0.0222)	(0.0449)	(0.230)
Washington	-0.190***	-0.361***	0.339
	(0.0273)	(0.0559)	(0.292)
Watauga	-0.00593	-0.333***	-0.0988
	(0.0154)	(0.0292)	(0.207)
Wayne	-0.00266	0.0994***	0.372***
	(0.0117)	(0.0215)	(0.131)
Wilkes	-0.254***	-0.179***	0.334**
	(0.0147)	(0.0260)	(0.154)
Wilson	0.103***	0.123***	0.466***
	(0.0132)	(0.0243)	(0.145)
Yadkin	-0.223***	-0.363***	0.489***
	(0.0188)	(0.0349)	(0.178)
Yancey	-0.571***	-0.591***	0.392
	(0.0259)	(0.0520)	(0.246)
2014	0.0206***	0.00410	0.0139
	(0.00477)	(0.00851)	(0.0455)
2015	0.105***	0.0939***	0.0746*
	(0.00431)	(0.00806)	(0.0430)
2016	0.155***	0.135***	0.120***
	(0.00477)	(0.00879)	(0.0461)
2017	0.190***	0.121***	0.130
	(0.00849)	(0.0160)	(0.0849)
2018	0.199***	0.0836***	0.201**
	(0.00915)	(0.0172)	(0.0910)
2019	0.192***	0.0830***	0.336***
	(0.0118)	(0.0227)	(0.120)
February	-0.00731	0.0507***	-0.0260
	(0.00698)	(0.0113)	(0.0593)
March	-0.0229***	0.101***	0.0263
	(0.00627)	(0.0107)	(0.0580)
April	-0.0154**	0.165***	0.113**
	(0.00604)	(0.0104)	(0.0571)
May	0.0128**	0.217***	0.205***
	(0.00594)	(0.0104)	(0.0556)
June	0.000462	0.213***	0.231***
	(0.00602)	(0.0106)	(0.0565)
July	-0.0571***	0.153***	0.106*
	(0.00617)	(0.0110)	(0.0589)
August	-0.00135	0.205***	0.147**
	(0.00623)	(0.0109)	(0.0589)
September	0.0253***	0.213***	0.281***
	(0.00661)	(0.0114)	(0.0609)
October	0.179***	0.289***	0.310***
	(0.00646)	(0.0116)	(0.0613)
November	0.248***	0.236***	0.249***
	(0.00640)	(0.0115)	(0.0614)
December	0.141***	0.166***	0.132**
	(0.00642)	(0.0110)	(0.0593)
Monday	0.337***	0.206***	-0.212***
	(0.00441)	(0.00850)	(0.0425)
Tuesday	0.344***	0.200***	-0.189***
	(0.00433)	(0.00839)	(0.0417)
Wednesday	0.341***	0.196***	-0.166***
	(0.00431)	(0.00834)	(0.0416)
Thursday	0.345***	0.209***	-0.189***
	(0.00421)	(0.00824)	(0.0416)
Friday	0.508***	0.395***	-0.000804
	(0.00427)	(0.00818)	(0.0399)
Saturday	0.222***	0.200***	0.0969**
	(0.00433)	(0.00851)	(0.0390)
Cone, Any Arrival Timing	0.0174	0.00794	-0.0531
	(0.0110)	(0.0204)	(0.111)
Spillover, Any Arrival Time	0.0438*	0.0190	-0.210
	(0.0224)	(0.0394)	(0.198)
Forecast Line over County	0.0561	0.175***	0.0977
	(0.0408)	(0.0664)	(0.379)
Storm Event (Tropical Cyclone)	-0.0248	-0.175***	0.142
	(0.0411)	(0.0575)	(0.241)
Recent Storm Event False Positive	0.0161***	-0.00926	0.0430

	(0.00323)	(0.00641)	(0.0333)
Recent Hurricane Landfall, USA	-0.0215***	-0.00437	-0.0261
	(0.00395)	(0.00804)	(0.0420)
Post Hurricane Matthew (1 or 0)	-0.0143*	-0.00297	-0.0590
	(0.00757)	(0.0143)	(0.0758)
Post Hurricane Florence (1 or 0)	0.0138**	-0.0103	-0.152**
	(0.00695)	(0.0138)	(0.0725)
lnalpha	-2.785***	-0.866***	0.874***
	(0.0185)	(0.00937)	(0.0535)
Constant	-10.09***	-10.79***	-15.13***
	(0.0105)	(0.0186)	(0.109)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Independent Factors Regression #8

nbreg Crashes i.CountyNum i.Year i.MoY i.DoW Cone01 Cone234 SpOver01 SpOver234 Line StormEv RecFalPos RecHurLan PostMatt PostFlor, vce(robust) exposure(YearPop)
estimates store In8C
outreg2 using In8, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW Cone01 Cone234 SpOver01 SpOver234 Line StormEv RecFalPos RecHurLan PostMatt PostFlor, vce(robust) exposure(YearPop)
estimates store In8I
outreg2 using In8, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW Cone01 Cone234 SpOver01 SpOver234 Line StormEv RecFalPos RecHurLan PostMatt PostFlor, vce(robust) exposure(YearPop)
estimates store In8K
outreg2 using In8, word append ctitle(Fatalities, NB) label

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.531***	-0.618***	0.218
	(0.0190)	(0.0388)	(0.198)
Alleghany	-0.340***	-0.429***	0.412
	(0.0314)	(0.0615)	(0.291)
Anson	0.179***	0.308***	0.586***
	(0.0177)	(0.0344)	(0.199)
Ashe	-0.329***	-0.470***	0.328
	(0.0212)	(0.0417)	(0.212)
Avery	-0.297***	-0.435***	-0.153
	(0.0246)	(0.0484)	(0.302)
Beaufort	-0.125***	-0.167***	0.397**
	(0.0155)	(0.0325)	(0.170)
Bertie	-0.0804***	0.0672	1.242***
	(0.0217)	(0.0415)	(0.181)
Bladen	0.134***	0.206***	1.161***
	(0.0163)	(0.0338)	(0.165)
Brunswick	-0.159***	-0.279***	0.300**
	(0.0118)	(0.0228)	(0.135)
Buncombe	0.141***	-0.107***	0.0813
	(0.0104)	(0.0185)	(0.117)
Burke	-0.0776***	-0.0739***	0.387***
	(0.0135)	(0.0246)	(0.141)
Cabarrus	0.0760***	0.00718	-0.128
	(0.0107)	(0.0195)	(0.128)
Caldwell	-0.142***	-0.136***	0.0910
	(0.0134)	(0.0247)	(0.161)
Camden	-0.349***	-0.639***	0.410

	(0.0309)	(0.0654)	(0.365)
Carteret	-0.241***	-0.371***	-0.135
	(0.0145)	(0.0274)	(0.182)
Caswell	-0.278***	-0.331***	0.807***
	(0.0210)	(0.0406)	(0.187)
Catawba	0.169***	0.0358*	0.130
	(0.0114)	(0.0199)	(0.129)
Chatham	-0.192***	-0.495***	0.475***
	(0.0154)	(0.0280)	(0.152)
Cherokee	-0.422***	-0.468***	0.690***
	(0.0206)	(0.0397)	(0.188)
Chowan	-0.376***	-0.572***	0.420
	(0.0276)	(0.0592)	(0.272)
Clay	-0.362***	-0.569***	0.411
	(0.0316)	(0.0636)	(0.312)
Cleveland	0.0882***	0.00266	0.577***
	(0.0125)	(0.0229)	(0.133)
Columbus	0.241***	0.411***	1.210***
	(0.0132)	(0.0263)	(0.129)
Craven	-0.181***	-0.203***	0.182
	(0.0124)	(0.0233)	(0.143)
Cumberland	0.00571	0.0390**	0.206*
	(0.0105)	(0.0180)	(0.112)
Currituck	-0.478***	-0.557***	0.454**
	(0.0223)	(0.0462)	(0.218)
Dare	-0.0783***	-0.161***	-0.00845
	(0.0197)	(0.0347)	(0.216)
Davidson	-0.144***	-0.121***	0.408***
	(0.0116)	(0.0209)	(0.121)
Davie	-0.200***	-0.168***	0.376**
	(0.0191)	(0.0328)	(0.187)
Duplin	0.241***	0.0654**	0.903***
	(0.0142)	(0.0290)	(0.149)
Durham	0.268***	0.0662***	-0.192
	(0.0100)	(0.0178)	(0.118)
Edgecombe	-0.00743	0.0978***	0.564***
	(0.0147)	(0.0275)	(0.162)
Forsyth	0.0844***	-0.0349*	-0.107
	(0.0110)	(0.0182)	(0.116)
Franklin	-0.270***	-0.233***	0.442***
	(0.0146)	(0.0271)	(0.149)
Gaston	0.0801***	0.135***	0.165
	(0.0107)	(0.0188)	(0.119)
Gates	-0.234***	-0.174***	0.964***
	(0.0282)	(0.0579)	(0.244)
Graham	-0.192***	0.130**	1.451***
	(0.0320)	(0.0508)	(0.227)
Granville	-0.220***	-0.148***	0.707***
	(0.0155)	(0.0272)	(0.145)
Greene	-0.0697***	-0.174***	0.379
	(0.0206)	(0.0430)	(0.239)
Guilford	0.0950***	0.275***	4.98e-05
	(0.0102)	(0.0167)	(0.107)
Halifax	0.139***	0.216***	0.757***
	(0.0144)	(0.0297)	(0.152)
Harnett	-0.303***	-0.242***	0.637***
	(0.0122)	(0.0224)	(0.122)
Haywood	-0.260***	-0.209***	0.365**
	(0.0157)	(0.0275)	(0.161)
Henderson	-0.101***	-0.340***	-0.0422
	(0.0129)	(0.0238)	(0.146)
Hertford	-0.207***	0.0966**	0.498**
	(0.0205)	(0.0416)	(0.204)
Hoke	-0.377***	-0.121***	0.672***
	(0.0163)	(0.0300)	(0.159)
Hyde	-0.333***	-0.959***	-0.0112
	(0.0426)	(0.104)	(0.508)
Iredell	-0.0155	0.0311	0.187
	(0.0118)	(0.0199)	(0.122)
Jackson	-0.244***	-0.350***	0.448**

	(0.0182)	(0.0320)	(0.182)
Johnston	-0.0747***	-0.0565***	0.377***
	(0.0115)	(0.0199)	(0.120)
Jones	0.353***	0.130***	0.736***
	(0.0230)	(0.0500)	(0.281)
Lee	0.0221	-0.0375	0.630***
	(0.0141)	(0.0284)	(0.152)
Lenoir	0.0470***	0.215***	0.541***
	(0.0144)	(0.0256)	(0.149)
Lincoln	-0.228***	-0.314***	0.335**
	(0.0149)	(0.0268)	(0.145)
Macon	-0.186***	-0.262***	0.563***
	(0.0173)	(0.0328)	(0.174)
Madison	-0.501***	-0.841***	0.481**
	(0.0241)	(0.0490)	(0.220)
Martin	0.104***	0.0510	0.533***
	(0.0200)	(0.0370)	(0.206)
McDowell	0.0215	-0.212***	0.371**
	(0.0156)	(0.0301)	(0.182)
Mecklenburg	0.300***	0.427***	-0.260**
	(0.00923)	(0.0159)	(0.102)
Mitchell	-0.449***	-0.267***	-0.276
	(0.0264)	(0.0478)	(0.411)
Montgomery	-0.0308*	-0.291***	0.939***
	(0.0185)	(0.0369)	(0.177)
Moore	-0.110***	-0.248***	0.454***
	(0.0130)	(0.0246)	(0.138)
Nash	0.0539***	0.163***	0.827***
	(0.0129)	(0.0231)	(0.127)
New Hanover	0.0616***	-0.0412**	-0.198
	(0.0105)	(0.0189)	(0.127)
Northampton	-0.0111	-0.0153	1.187***
	(0.0217)	(0.0425)	(0.177)
Onslow	-0.191***	-0.270***	-0.0256
	(0.0110)	(0.0203)	(0.128)
Orange	-0.220***	-0.360***	-0.310**
	(0.0123)	(0.0224)	(0.152)
Pamlico	-0.492***	-0.707***	0.341
	(0.0293)	(0.0630)	(0.282)
Pasquotank	-0.168***	-0.287***	-0.274
	(0.0164)	(0.0331)	(0.231)
Pender	0.0632***	-0.0236	1.041***
	(0.0138)	(0.0294)	(0.134)
Perquimans	-0.405***	-0.551***	0.424
	(0.0284)	(0.0615)	(0.307)
Person	-0.0622***	-0.179***	0.240
	(0.0171)	(0.0321)	(0.191)
Pitt	0.268***	0.320***	0.119
	(0.0109)	(0.0192)	(0.127)
Polk	-0.193***	-0.335***	0.479**
	(0.0218)	(0.0436)	(0.241)
Randolph	-0.0565***	-0.115***	0.412***
	(0.0120)	(0.0209)	(0.123)
Richmond	0.00654	0.242***	0.693***
	(0.0159)	(0.0284)	(0.170)
Robeson	0.163***	0.426***	1.147***
	(0.0115)	(0.0201)	(0.114)
Rockingham	-0.0922***	-0.229***	0.265*
	(0.0129)	(0.0242)	(0.142)
Rowan	-0.0346***	-0.0330	0.270**
	(0.0118)	(0.0207)	(0.133)
Rutherford	-0.206***	-0.203***	0.295*
	(0.0145)	(0.0264)	(0.156)
Sampson	0.107***	0.152***	0.920***
	(0.0137)	(0.0251)	(0.137)
Scotland	-0.131***	0.241***	0.721***
	(0.0172)	(0.0311)	(0.172)
Stanly	-0.127***	-0.264***	0.347**
	(0.0143)	(0.0287)	(0.166)
Stokes	-0.231***	-0.391***	0.418**

	(0.0170)	(0.0319)	(0.176)
Surry	-0.134***	-0.0454*	0.582***
	(0.0143)	(0.0255)	(0.143)
Swain	-0.515***	-0.594***	0.339
	(0.0275)	(0.0554)	(0.266)
Transylvania	-0.388***	-0.516***	0.179
	(0.0194)	(0.0377)	(0.225)
Tyrrell	0.230***	-0.468***	-0.439
	(0.0373)	(0.106)	(1.004)
Union	-0.0702***	-0.180***	-0.0989
	(0.0104)	(0.0195)	(0.128)
Vance	0.229***	0.372***	0.670***
	(0.0147)	(0.0276)	(0.156)
Wake	0.138***	-0.0335**	-0.553***
	(0.00975)	(0.0163)	(0.105)
Warren	-0.0882***	-0.0478	0.873***
	(0.0222)	(0.0449)	(0.230)
Washington	-0.190***	-0.361***	0.339
	(0.0273)	(0.0559)	(0.292)
Watauga	-0.00600	-0.333***	-0.0988
	(0.0154)	(0.0292)	(0.207)
Wayne	-0.00280	0.0994***	0.371***
	(0.0117)	(0.0215)	(0.131)
Wilkes	-0.254***	-0.179***	0.333**
	(0.0147)	(0.0260)	(0.154)
Wilson	0.103***	0.123***	0.466***
	(0.0132)	(0.0243)	(0.145)
Yadkin	-0.223***	-0.363***	0.488***
	(0.0188)	(0.0349)	(0.178)
Yancey	-0.571***	-0.591***	0.392
	(0.0259)	(0.0519)	(0.246)
2014	0.0205***	0.00409	0.0141
	(0.00477)	(0.00851)	(0.0455)
2015	0.105***	0.0939***	0.0749*
	(0.00431)	(0.00806)	(0.0430)
2016	0.155***	0.135***	0.119***
	(0.00476)	(0.00879)	(0.0461)
2017	0.191***	0.121***	0.128
	(0.00849)	(0.0160)	(0.0849)
2018	0.201***	0.0850***	0.199**
	(0.00915)	(0.0172)	(0.0910)
2019	0.195***	0.0855***	0.333***
	(0.0118)	(0.0227)	(0.120)
February	-0.00730	0.0507***	-0.0260
	(0.00698)	(0.0113)	(0.0593)
March	-0.0229***	0.101***	0.0263
	(0.00627)	(0.0107)	(0.0580)
April	-0.0153**	0.165***	0.113**
	(0.00604)	(0.0104)	(0.0571)
May	0.0126**	0.217***	0.206***
	(0.00594)	(0.0104)	(0.0556)
June	-0.000300	0.212***	0.231***
	(0.00601)	(0.0106)	(0.0565)
July	-0.0571***	0.153***	0.106*
	(0.00617)	(0.0110)	(0.0589)
August	-0.00123	0.205***	0.147**
	(0.00623)	(0.0109)	(0.0589)
September	0.0271***	0.214***	0.280***
	(0.00661)	(0.0114)	(0.0610)
October	0.180***	0.290***	0.309***
	(0.00646)	(0.0116)	(0.0613)
November	0.248***	0.236***	0.250***
	(0.00640)	(0.0115)	(0.0615)
December	0.142***	0.166***	0.131**
	(0.00642)	(0.0110)	(0.0593)
Monday	0.337***	0.207***	-0.213***
	(0.00440)	(0.00850)	(0.0425)
Tuesday	0.344***	0.200***	-0.189***
	(0.00433)	(0.00839)	(0.0417)
Wednesday	0.341***	0.196***	-0.166***

	(0.00431)	(0.00834)	(0.0416)
Thursday	0.345***	0.209***	-0.190***
	(0.00420)	(0.00824)	(0.0416)
Friday	0.509***	0.395***	-0.00129
	(0.00427)	(0.00818)	(0.0399)
Saturday	0.222***	0.200***	0.0969**
	(0.00433)	(0.00852)	(0.0390)
Cone, Arrival <48 hours	0.170***	0.130***	-0.203
	(0.0279)	(0.0449)	(0.221)
Cone, Arrival >48 hours	-0.0197*	-0.0205	-0.0158
	(0.0112)	(0.0221)	(0.123)
Spillover, Arrival <48 hours	0.148***	0.0183	0.0912
	(0.0388)	(0.0606)	(0.262)
Spillover, Arrival >48 hours	-0.0556**	-0.0316	-0.159
	(0.0222)	(0.0458)	(0.213)
Forecast Line over County	0.0186	0.140**	0.150
	(0.0406)	(0.0652)	(0.370)
Storm Event (Tropical Cyclone)	-0.0950**	-0.219***	0.139
	(0.0412)	(0.0591)	(0.247)
Recent Storm Event False Positive	0.0158***	-0.00915	0.0426
	(0.00323)	(0.00641)	(0.0333)
Recent Hurricane Landfall, USA	-0.0212***	-0.00409	-0.0271
	(0.00395)	(0.00803)	(0.0420)
Post Hurricane Matthew (1 or 0)	-0.0149**	-0.00369	-0.0570
	(0.00757)	(0.0143)	(0.0758)
Post Hurricane Florence (1 or 0)	0.0118*	-0.0119	-0.151**
	(0.00694)	(0.0138)	(0.0725)
lnalpha	-2.787***	-0.867***	0.874***
	(0.0185)	(0.00937)	(0.0535)
Constant	-10.09***	-10.79***	-15.13***
	(0.0105)	(0.0186)	(0.109)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Independent Factors Regression #9

nbreg Crashes i.CountyNum i.Year i.MoY i.DoW FloodEv WindEv TStormEv StormEv WinterEv FlEvLag123 FlEvLag4567 WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567 WntEvLag123 WntEvLag4567, vce(robust) exposure(YearPop)
estimates store In9C
outreg2 using In9, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW FloodEv WindEv TStormEv StormEv WinterEv FlEvLag123 FlEvLag4567 WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567 WntEvLag123 WntEvLag4567, vce(robust) exposure(YearPop)
estimates store In9I
outreg2 using In9, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW FloodEv WindEv TStormEv StormEv WinterEv FlEvLag123 FlEvLag4567 WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567 WntEvLag123 WntEvLag4567, vce(robust) exposure(YearPop)
estimates store In9K
outreg2 using In9, word append ctitle(Fatalities, NB) label

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.532***	-0.616***	0.213
	(0.0185)	(0.0388)	(0.198)
Alleghany	-0.338***	-0.429***	0.400

	(0.0310)	(0.0615)	(0.291)
Anson	0.189***	0.310***	0.583***
	(0.0174)	(0.0344)	(0.199)
Ashe	-0.330***	-0.470***	0.315
	(0.0206)	(0.0416)	(0.213)
Avery	-0.321***	-0.438***	-0.143
	(0.0240)	(0.0483)	(0.303)
Beaufort	-0.114***	-0.165***	0.395**
	(0.0150)	(0.0325)	(0.170)
Bertie	-0.0727***	0.0672	1.238***
	(0.0213)	(0.0414)	(0.181)
Bladen	0.146***	0.208***	1.159***
	(0.0158)	(0.0337)	(0.165)
Brunswick	-0.147***	-0.276***	0.295**
	(0.0114)	(0.0227)	(0.135)
Buncombe	0.137***	-0.104***	0.0873
	(0.00995)	(0.0184)	(0.117)
Burke	-0.0836***	-0.0722***	0.394***
	(0.0129)	(0.0245)	(0.141)
Cabarrus	0.0810***	0.00889	-0.129
	(0.0102)	(0.0194)	(0.128)
Caldwell	-0.150***	-0.134***	0.0947
	(0.0128)	(0.0247)	(0.161)
Camden	-0.340***	-0.638***	0.405
	(0.0307)	(0.0653)	(0.365)
Carteret	-0.228***	-0.368***	-0.139
	(0.0141)	(0.0273)	(0.182)
Caswell	-0.270***	-0.330***	0.804***
	(0.0208)	(0.0406)	(0.187)
Catawba	0.170***	0.0374*	0.128
	(0.0105)	(0.0198)	(0.129)
Chatham	-0.186***	-0.494***	0.472***
	(0.0149)	(0.0280)	(0.152)
Cherokee	-0.413***	-0.467***	0.678***
	(0.0203)	(0.0396)	(0.187)
Chowan	-0.369***	-0.572***	0.416
	(0.0273)	(0.0591)	(0.272)
Clay	-0.352***	-0.568***	0.398
	(0.0315)	(0.0636)	(0.312)
Cleveland	0.0939***	0.00350	0.571***
	(0.0119)	(0.0227)	(0.133)
Columbus	0.254***	0.414***	1.206***
	(0.0128)	(0.0263)	(0.129)
Craven	-0.168***	-0.200***	0.179
	(0.0119)	(0.0232)	(0.142)
Cumberland	0.0168*	0.0418**	0.206*
	(0.0100)	(0.0179)	(0.112)
Currituck	-0.470***	-0.555***	0.451**
	(0.0221)	(0.0461)	(0.218)
Dare	-0.0656***	-0.157***	-0.0107
	(0.0194)	(0.0347)	(0.216)
Davidson	-0.141***	-0.121***	0.406***
	(0.0108)	(0.0208)	(0.121)
Davie	-0.201***	-0.168***	0.373**
	(0.0182)	(0.0327)	(0.187)
Duplin	0.251***	0.0666**	0.899***
	(0.0134)	(0.0289)	(0.149)
Durham	0.274***	0.0694***	-0.191
	(0.00958)	(0.0178)	(0.118)
Edgecombe	0.000283	0.0983***	0.563***
	(0.0143)	(0.0274)	(0.162)
Forsyth	0.0841***	-0.0337*	-0.110
	(0.0101)	(0.0180)	(0.115)
Franklin	-0.265***	-0.232***	0.439***
	(0.0141)	(0.0271)	(0.149)
Gaston	0.0866***	0.137***	0.158
	(0.0101)	(0.0187)	(0.119)
Gates	-0.226***	-0.174***	0.961***
	(0.0279)	(0.0578)	(0.244)
Graham	-0.200***	0.129**	1.450***

	(0.0319)	(0.0508)	(0.227)
Granville	-0.217***	-0.148***	0.703***
	(0.0149)	(0.0271)	(0.145)
Greene	-0.0580***	-0.172***	0.374
	(0.0203)	(0.0430)	(0.239)
Guilford	0.0957***	0.277***	0.00743
	(0.00936)	(0.0166)	(0.107)
Halifax	0.145***	0.217***	0.756***
	(0.0138)	(0.0296)	(0.152)
Harnett	-0.296***	-0.240***	0.637***
	(0.0117)	(0.0223)	(0.122)
Haywood	-0.275***	-0.211***	0.368**
	(0.0153)	(0.0273)	(0.161)
Henderson	-0.104***	-0.339***	-0.0390
	(0.0122)	(0.0236)	(0.146)
Hertford	-0.199***	0.0972**	0.495**
	(0.0202)	(0.0415)	(0.204)
Hoke	-0.367***	-0.120***	0.668***
	(0.0159)	(0.0300)	(0.159)
Hyde	-0.320***	-0.956***	-0.0151
	(0.0424)	(0.104)	(0.507)
Iredell	-0.0161	0.0326*	0.186
	(0.0109)	(0.0197)	(0.122)
Jackson	-0.253***	-0.352***	0.447**
	(0.0177)	(0.0319)	(0.182)
Johnston	-0.0699***	-0.0549***	0.380***
	(0.0108)	(0.0199)	(0.120)
Jones	0.366***	0.131***	0.731***
	(0.0227)	(0.0500)	(0.281)
Lee	0.0283**	-0.0362	0.627***
	(0.0136)	(0.0284)	(0.152)
Lenoir	0.0583***	0.216***	0.538***
	(0.0138)	(0.0255)	(0.149)
Lincoln	-0.225***	-0.313***	0.328**
	(0.0142)	(0.0266)	(0.145)
Macon	-0.189***	-0.262***	0.559***
	(0.0169)	(0.0328)	(0.174)
Madison	-0.517***	-0.843***	0.486**
	(0.0238)	(0.0488)	(0.220)
Martin	0.114***	0.0515	0.529**
	(0.0196)	(0.0369)	(0.206)
McDowell	0.0170	-0.211***	0.372**
	(0.0151)	(0.0300)	(0.182)
Mecklenburg	0.306***	0.430***	-0.256**
	(0.00866)	(0.0158)	(0.102)
Mitchell	-0.472***	-0.269***	-0.267
	(0.0262)	(0.0478)	(0.411)
Montgomery	-0.0230	-0.290***	0.934***
	(0.0182)	(0.0369)	(0.177)
Moore	-0.102***	-0.247***	0.452***
	(0.0126)	(0.0244)	(0.138)
Nash	0.0592***	0.163***	0.825***
	(0.0122)	(0.0230)	(0.127)
New Hanover	0.0742***	-0.0371**	-0.202
	(0.0100)	(0.0188)	(0.127)
Northampton	-0.00515	-0.0159	1.185***
	(0.0212)	(0.0424)	(0.177)
Onslow	-0.180***	-0.267***	-0.0273
	(0.0104)	(0.0202)	(0.128)
Orange	-0.219***	-0.358***	-0.309**
	(0.0118)	(0.0224)	(0.152)
Pamlico	-0.479***	-0.705***	0.336
	(0.0291)	(0.0629)	(0.282)
Pasquotank	-0.159***	-0.285***	-0.279
	(0.0161)	(0.0331)	(0.231)
Pender	0.0743***	-0.0200	1.036***
	(0.0133)	(0.0293)	(0.134)
Perquimans	-0.398***	-0.551***	0.421
	(0.0282)	(0.0614)	(0.307)
Person	-0.0621***	-0.179***	0.239

	(0.0164)	(0.0320)	(0.191)
Pitt	0.279***	0.322***	0.114
	(0.0103)	(0.0192)	(0.127)
Polk	-0.194***	-0.335***	0.474**
	(0.0216)	(0.0435)	(0.241)
Randolph	-0.0519***	-0.113***	0.413***
	(0.0115)	(0.0209)	(0.123)
Richmond	0.0153	0.244***	0.690***
	(0.0154)	(0.0283)	(0.170)
Robeson	0.174***	0.429***	1.140***
	(0.0110)	(0.0200)	(0.114)
Rockingham	-0.0882***	-0.228***	0.262*
	(0.0122)	(0.0242)	(0.142)
Rowan	-0.0321***	-0.0313	0.269**
	(0.0111)	(0.0206)	(0.134)
Rutherford	-0.207***	-0.201***	0.291*
	(0.0140)	(0.0263)	(0.156)
Sampson	0.116***	0.154***	0.917***
	(0.0133)	(0.0251)	(0.137)
Scotland	-0.120***	0.243***	0.717***
	(0.0168)	(0.0311)	(0.172)
Stanly	-0.119***	-0.262***	0.341**
	(0.0138)	(0.0287)	(0.165)
Stokes	-0.227***	-0.390***	0.411**
	(0.0164)	(0.0317)	(0.176)
Surry	-0.133***	-0.0440*	0.574***
	(0.0136)	(0.0254)	(0.142)
Swain	-0.528***	-0.595***	0.341
	(0.0274)	(0.0554)	(0.266)
Transylvania	-0.391***	-0.515***	0.182
	(0.0191)	(0.0377)	(0.225)
Tyrrell	0.243***	-0.467***	-0.446
	(0.0371)	(0.106)	(1.004)
Union	-0.0609***	-0.178***	-0.103
	(0.00994)	(0.0194)	(0.128)
Vance	0.232***	0.373***	0.665***
	(0.0142)	(0.0276)	(0.156)
Wake	0.144***	-0.0293*	-0.545***
	(0.00916)	(0.0163)	(0.105)
Warren	-0.0841***	-0.0468	0.870***
	(0.0218)	(0.0449)	(0.230)
Washington	-0.178***	-0.360***	0.334
	(0.0270)	(0.0558)	(0.292)
Watauga	-0.00702	-0.332***	-0.108
	(0.0149)	(0.0291)	(0.207)
Wayne	0.00557	0.100***	0.369***
	(0.0111)	(0.0214)	(0.131)
Wilkes	-0.251***	-0.178***	0.326**
	(0.0141)	(0.0259)	(0.155)
Wilson	0.111***	0.124***	0.465***
	(0.0128)	(0.0243)	(0.145)
Yadkin	-0.218***	-0.362***	0.479***
	(0.0183)	(0.0348)	(0.178)
Yancey	-0.593***	-0.591***	0.402
	(0.0259)	(0.0521)	(0.246)
2014	0.00260	0.00432	0.000190
	(0.00429)	(0.00806)	(0.0432)
2015	0.0963***	0.0941***	0.0684
	(0.00413)	(0.00798)	(0.0426)
2016	0.145***	0.134***	0.0967**
	(0.00414)	(0.00793)	(0.0420)
2017	0.169***	0.116***	0.0574
	(0.00403)	(0.00793)	(0.0425)
2018	0.180***	0.0792***	0.0949**
	(0.00408)	(0.00791)	(0.0423)
2019	0.186***	0.0703***	0.106**
	(0.00398)	(0.00788)	(0.0418)
February	-0.00680	0.0494***	-0.0315
	(0.00624)	(0.0112)	(0.0594)
March	-0.000858	0.105***	0.00801

	(0.00584)	(0.0107)	(0.0582)
April	0.0205***	0.169***	0.0865
	(0.00576)	(0.0106)	(0.0580)
May	0.0510***	0.221***	0.184***
	(0.00567)	(0.0106)	(0.0565)
June	0.0402***	0.215***	0.227***
	(0.00578)	(0.0108)	(0.0577)
July	-0.0222***	0.155***	0.0977*
	(0.00584)	(0.0111)	(0.0593)
August	0.0288***	0.206***	0.122**
	(0.00569)	(0.0106)	(0.0574)
September	0.0601***	0.213***	0.254***
	(0.00584)	(0.0107)	(0.0570)
October	0.217***	0.285***	0.273***
	(0.00559)	(0.0105)	(0.0559)
November	0.281***	0.229***	0.210***
	(0.00565)	(0.0105)	(0.0567)
December	0.171***	0.165***	0.0872
	(0.00592)	(0.0106)	(0.0570)
Monday	0.336***	0.204***	-0.211***
	(0.00425)	(0.00847)	(0.0425)
Tuesday	0.339***	0.196***	-0.186***
	(0.00420)	(0.00839)	(0.0417)
Wednesday	0.337***	0.194***	-0.162***
	(0.00420)	(0.00834)	(0.0416)
Thursday	0.347***	0.209***	-0.184***
	(0.00415)	(0.00825)	(0.0417)
Friday	0.509***	0.394***	0.00398
	(0.00417)	(0.00818)	(0.0399)
Saturday	0.222***	0.200***	0.0996**
	(0.00429)	(0.00851)	(0.0389)
Flood Event	0.189***	0.107***	0.123
	(0.0147)	(0.0263)	(0.133)
Wind Event	0.0997***	0.0297	0.172
	(0.0201)	(0.0418)	(0.203)
Thunderstorm Wind Event	0.107***	0.0901***	-0.0869
	(0.00791)	(0.0170)	(0.0975)
Storm Event (Tropical Cyclone)	-0.0116	-0.146**	0.0711
	(0.0422)	(0.0602)	(0.242)
Winter Event	0.626***	0.368***	-0.0714
	(0.0187)	(0.0230)	(0.128)
Flood Event, 1-3 Day Lag	-0.0348***	-0.0521***	0.0821
	(0.00925)	(0.0182)	(0.0888)
Flood Event, 4-7 Day Lag	-0.0222***	-0.000996	-0.349***
	(0.00718)	(0.0155)	(0.0902)
Wind Event, 1-3 Day Lag	-0.0228*	-0.0152	0.124
	(0.0131)	(0.0263)	(0.130)
Wind Event, 4-7 Day Lag	-0.0226**	-0.0111	-0.000769
	(0.0108)	(0.0222)	(0.121)
Thunderstorm Wind Event, 1-3 Day Lag	-0.0180***	-0.0105	-0.0306
	(0.00503)	(0.0108)	(0.0561)
Thunderstorm Wind Event, 4-7 Day Lag	-0.00872*	-0.0286***	0.00912
	(0.00451)	(0.00966)	(0.0508)
Storm Event (Tropical Cyclone), 1-3 Day Lag	-0.144***	-0.0845**	-0.0333
	(0.0226)	(0.0418)	(0.173)
Storm Event (Tropical Cyclone), 4-7 Day Lag	-0.0345**	-0.0549*	-0.275
	(0.0143)	(0.0312)	(0.189)
Winter Event, 1-3 Day Lag	-0.0509***	-0.139***	-0.359***
	(0.0100)	(0.0159)	(0.103)
Winter Event, 4-7 Day Lag	0.00659	-0.0267**	0.0665
	(0.00726)	(0.0134)	(0.0693)
lnalpha	-2.877***	-0.872***	0.869***
	(0.0162)	(0.00937)	(0.0537)
Constant	-10.12***	-10.79***	-15.08***
	(0.00983)	(0.0186)	(0.109)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Explanatory Regression #1

```
nbreg Crashes i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce FloodEv WindEv
TStormEv StormEv WinterEv Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Exp1C
outreg2 using Exp1, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce FloodEv WindEv
TStormEv StormEv WinterEv Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Exp1I
outreg2 using Exp1, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce FloodEv WindEv
TStormEv StormEv WinterEv Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Exp1K
outreg2 using Exp1, word append ctitle(Fatalities, NB) label
```

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.532***	-0.618***	0.214
	(0.0185)	(0.0387)	(0.198)
Alleghany	-0.344***	-0.425***	0.418
	(0.0310)	(0.0614)	(0.292)
Anson	0.190***	0.312***	0.583***
	(0.0174)	(0.0344)	(0.199)
Ashe	-0.337***	-0.467***	0.334
	(0.0207)	(0.0416)	(0.212)
Avery	-0.328***	-0.442***	-0.136
	(0.0240)	(0.0483)	(0.303)
Beaufort	-0.114***	-0.163***	0.394**
	(0.0151)	(0.0325)	(0.170)
Bertie	-0.0720***	0.0697*	1.240***
	(0.0213)	(0.0414)	(0.181)
Bladen	0.146***	0.210***	1.158***
	(0.0159)	(0.0337)	(0.165)
Brunswick	-0.148***	-0.275***	0.290**
	(0.0114)	(0.0227)	(0.135)
Buncombe	0.136***	-0.108***	0.0827
	(0.00988)	(0.0184)	(0.117)
Burke	-0.0855***	-0.0780***	0.384***
	(0.0129)	(0.0245)	(0.141)
Cabarrus	0.0816***	0.00831	-0.133
	(0.0101)	(0.0194)	(0.128)
Caldwell	-0.150***	-0.138***	0.0864
	(0.0128)	(0.0247)	(0.161)
Camden	-0.339***	-0.635***	0.407
	(0.0307)	(0.0653)	(0.365)
Carteret	-0.230***	-0.367***	-0.143
	(0.0141)	(0.0274)	(0.182)
Caswell	-0.271***	-0.328***	0.810***
	(0.0208)	(0.0406)	(0.187)
Catawba	0.170***	0.0368*	0.126
	(0.0104)	(0.0197)	(0.129)
Chatham	-0.187***	-0.493***	0.475***
	(0.0148)	(0.0280)	(0.152)
Cherokee	-0.414***	-0.463***	0.687***
	(0.0203)	(0.0396)	(0.187)
Chowan	-0.368***	-0.569***	0.418
	(0.0273)	(0.0591)	(0.272)

Clay	-0.352***	-0.562***	0.408
	(0.0315)	(0.0636)	(0.312)
Cleveland	0.0947***	0.00423	0.573***
	(0.0118)	(0.0227)	(0.133)
Columbus	0.255***	0.416***	1.204***
	(0.0128)	(0.0263)	(0.129)
Craven	-0.169***	-0.199***	0.176
	(0.0119)	(0.0233)	(0.142)
Cumberland	0.0169*	0.0429**	0.202*
	(0.00995)	(0.0179)	(0.112)
Currituck	-0.470***	-0.553***	0.452**
	(0.0221)	(0.0461)	(0.218)
Dare	-0.0671***	-0.156***	-0.0124
	(0.0194)	(0.0346)	(0.216)
Davidson	-0.140***	-0.120***	0.406***
	(0.0108)	(0.0208)	(0.121)
Davie	-0.200***	-0.168***	0.374**
	(0.0182)	(0.0327)	(0.187)
Duplin	0.252***	0.0691**	0.901***
	(0.0135)	(0.0289)	(0.149)
Durham	0.272***	0.0686***	-0.192
	(0.00949)	(0.0178)	(0.118)
Edgecombe	0.000474	0.100***	0.564***
	(0.0143)	(0.0275)	(0.162)
Forsyth	0.0830***	-0.0353**	-0.110
	(0.0100)	(0.0180)	(0.115)
Franklin	-0.265***	-0.231***	0.442***
	(0.0141)	(0.0271)	(0.149)
Gaston	0.0880***	0.137***	0.159
	(0.0100)	(0.0187)	(0.119)
Gates	-0.226***	-0.171***	0.965***
	(0.0279)	(0.0578)	(0.244)
Graham	-0.201***	0.129**	1.451***
	(0.0319)	(0.0509)	(0.227)
Granville	-0.217***	-0.147***	0.706***
	(0.0149)	(0.0271)	(0.145)
Greene	-0.0582***	-0.169***	0.377
	(0.0203)	(0.0430)	(0.239)
Guilford	0.0950***	0.274***	-0.00137
	(0.00926)	(0.0166)	(0.107)
Halifax	0.145***	0.218***	0.759***
	(0.0138)	(0.0296)	(0.152)
Harnett	-0.296***	-0.239***	0.634***
	(0.0117)	(0.0223)	(0.122)
Haywood	-0.276***	-0.212***	0.371**
	(0.0153)	(0.0273)	(0.161)
Henderson	-0.107***	-0.340***	-0.0440
	(0.0121)	(0.0236)	(0.146)
Hertford	-0.199***	0.100**	0.501**
	(0.0201)	(0.0415)	(0.204)
Hoke	-0.366***	-0.117***	0.667***
	(0.0158)	(0.0299)	(0.159)
Hyde	-0.321***	-0.954***	-0.0154
	(0.0424)	(0.104)	(0.508)
Iredell	-0.0171	0.0304	0.186
	(0.0108)	(0.0197)	(0.122)
Jackson	-0.253***	-0.352***	0.449**
	(0.0177)	(0.0319)	(0.182)
Johnston	-0.0715***	-0.0560***	0.375***
	(0.0107)	(0.0198)	(0.120)
Jones	0.367***	0.134***	0.732***
	(0.0228)	(0.0500)	(0.281)
Lee	0.0290**	-0.0351	0.627***
	(0.0135)	(0.0283)	(0.152)
Lenoir	0.0587***	0.219***	0.539***
	(0.0138)	(0.0255)	(0.149)
Lincoln	-0.224***	-0.311***	0.331**
	(0.0141)	(0.0266)	(0.145)
Macon	-0.190***	-0.261***	0.560***
	(0.0169)	(0.0327)	(0.174)

Madison	-0.518***	-0.845***	0.489**
	(0.0238)	(0.0489)	(0.220)
Martin	0.114***	0.0541	0.533***
	(0.0195)	(0.0369)	(0.206)
McDowell	0.0136	-0.215***	0.366**
	(0.0150)	(0.0300)	(0.182)
Mecklenburg	0.305***	0.428***	-0.265***
	(0.00856)	(0.0158)	(0.102)
Mitchell	-0.473***	-0.274***	-0.270
	(0.0262)	(0.0478)	(0.411)
Montgomery	-0.0224	-0.287***	0.937***
	(0.0181)	(0.0368)	(0.177)
Moore	-0.102***	-0.246***	0.452***
	(0.0125)	(0.0245)	(0.138)
Nash	0.0583***	0.163***	0.826***
	(0.0122)	(0.0230)	(0.127)
New Hanover	0.0723***	-0.0361*	-0.210*
	(0.01000)	(0.0188)	(0.127)
Northampton	-0.00494	-0.0139	1.188***
	(0.0212)	(0.0424)	(0.177)
Onslow	-0.181***	-0.266***	-0.0332
	(0.0104)	(0.0201)	(0.128)
Orange	-0.220***	-0.359***	-0.311**
	(0.0117)	(0.0224)	(0.152)
Pamlico	-0.479***	-0.703***	0.334
	(0.0291)	(0.0629)	(0.282)
Pasquotank	-0.158***	-0.282***	-0.276
	(0.0160)	(0.0331)	(0.231)
Pender	0.0736***	-0.0180	1.032***
	(0.0134)	(0.0294)	(0.134)
Perquimans	-0.397***	-0.548***	0.423
	(0.0282)	(0.0615)	(0.307)
Person	-0.0635***	-0.179***	0.241
	(0.0164)	(0.0320)	(0.191)
Pitt	0.279***	0.325***	0.117
	(0.0103)	(0.0191)	(0.127)
Polk	-0.195***	-0.336***	0.470*
	(0.0215)	(0.0435)	(0.241)
Randolph	-0.0530***	-0.113***	0.414***
	(0.0114)	(0.0209)	(0.124)
Richmond	0.0160	0.246***	0.691***
	(0.0153)	(0.0283)	(0.170)
Robeson	0.175***	0.430***	1.140***
	(0.0109)	(0.0200)	(0.114)
Rockingham	-0.0895***	-0.228***	0.263*
	(0.0122)	(0.0242)	(0.142)
Rowan	-0.0319***	-0.0316	0.268**
	(0.0110)	(0.0205)	(0.133)
Rutherford	-0.207***	-0.204***	0.289*
	(0.0139)	(0.0263)	(0.156)
Sampson	0.117***	0.156***	0.915***
	(0.0132)	(0.0251)	(0.137)
Scotland	-0.119***	0.245***	0.717***
	(0.0167)	(0.0311)	(0.172)
Stanly	-0.119***	-0.260***	0.341**
	(0.0138)	(0.0287)	(0.166)
Stokes	-0.228***	-0.389***	0.416**
	(0.0165)	(0.0318)	(0.176)
Surry	-0.134***	-0.0425*	0.580***
	(0.0136)	(0.0254)	(0.143)
Swain	-0.532***	-0.596***	0.346
	(0.0274)	(0.0554)	(0.266)
Transylvania	-0.396***	-0.517***	0.177
	(0.0191)	(0.0377)	(0.225)
Tyrrell	0.242***	-0.464***	-0.442
	(0.0371)	(0.106)	(1.004)
Union	-0.0594***	-0.176***	-0.104
	(0.00987)	(0.0194)	(0.128)
Vance	0.232***	0.376***	0.671***
	(0.0142)	(0.0276)	(0.156)

Wake	0.141***	-0.0334**	-0.555***
	(0.00903)	(0.0163)	(0.105)
Warren	-0.0840***	-0.0453	0.873***
	(0.0218)	(0.0449)	(0.230)
Washington	-0.178***	-0.357***	0.337
	(0.0270)	(0.0558)	(0.292)
Watauga	-0.0156	-0.328***	-0.0877
	(0.0148)	(0.0292)	(0.207)
Wayne	0.00564	0.102***	0.370***
	(0.0111)	(0.0214)	(0.131)
Wilkes	-0.253***	-0.177***	0.330**
	(0.0141)	(0.0259)	(0.155)
Wilson	0.111***	0.125***	0.466***
	(0.0127)	(0.0243)	(0.145)
Yadkin	-0.219***	-0.359***	0.485***
	(0.0183)	(0.0348)	(0.178)
Yancey	-0.596***	-0.596***	0.401
	(0.0259)	(0.0521)	(0.246)
2014	0.00263	0.00278	-0.000209
	(0.00427)	(0.00806)	(0.0432)
2015	0.0971***	0.0940***	0.0674
	(0.00413)	(0.00801)	(0.0429)
2016	0.147***	0.134***	0.0917**
	(0.00414)	(0.00799)	(0.0423)
2017	0.172***	0.117***	0.0577
	(0.00399)	(0.00793)	(0.0425)
2018	0.176***	0.0744***	0.0837**
	(0.00404)	(0.00790)	(0.0423)
2019	0.189***	0.0716***	0.104**
	(0.00396)	(0.00793)	(0.0420)
February	-0.00469	0.0477***	-0.0383
	(0.00624)	(0.0112)	(0.0594)
March	-0.00270	0.0928***	0.0107
	(0.00584)	(0.0109)	(0.0602)
April	0.0266***	0.171***	0.0706
	(0.00557)	(0.0106)	(0.0580)
May	0.0751***	0.231***	0.152***
	(0.00551)	(0.0106)	(0.0572)
June	0.0502***	0.217***	0.196***
	(0.00560)	(0.0108)	(0.0577)
July	0.000835	0.162***	0.0532
	(0.00602)	(0.0116)	(0.0630)
August	0.0445***	0.213***	0.0894
	(0.00561)	(0.0108)	(0.0585)
September	0.0737***	0.218***	0.217***
	(0.00564)	(0.0106)	(0.0570)
October	0.231***	0.292***	0.242***
	(0.00541)	(0.0104)	(0.0558)
November	0.286***	0.226***	0.211***
	(0.00568)	(0.0109)	(0.0588)
December	0.184***	0.171***	0.0715
	(0.00580)	(0.0106)	(0.0572)
Monday	0.334***	0.202***	-0.209***
	(0.00423)	(0.00847)	(0.0425)
Tuesday	0.333***	0.192***	-0.183***
	(0.00420)	(0.00842)	(0.0419)
Wednesday	0.334***	0.192***	-0.157***
	(0.00421)	(0.00836)	(0.0418)
Thursday	0.346***	0.208***	-0.183***
	(0.00416)	(0.00826)	(0.0418)
Friday	0.507***	0.392***	0.00368
	(0.00417)	(0.00819)	(0.0400)
Saturday	0.219***	0.198***	0.0986**
	(0.00428)	(0.00853)	(0.0390)
Precipitation (inches)	0.0564***	0.0312***	0.00793
	(0.00319)	(0.00560)	(0.0304)
Rain After 3 or more Dry Days	0.0552***	0.0493***	-0.0454
	(0.00382)	(0.00715)	(0.0404)
Snow or Ice Conditions	0.0578***	-0.0461***	-0.250***
	(0.00928)	(0.0135)	(0.0739)

Flood Event	0.0971***	0.0440*	0.113
	(0.0153)	(0.0263)	(0.133)
Wind Event	0.0835***	0.0216	0.190
	(0.0209)	(0.0418)	(0.203)
Thunderstorm Wind Event	0.106***	0.0875***	-0.0829
	(0.00790)	(0.0170)	(0.0978)
Storm Event (Tropical Cyclone)	-0.126***	-0.215***	0.0482
	(0.0448)	(0.0590)	(0.238)
Winter Event	0.565***	0.334***	-0.0808
	(0.0188)	(0.0233)	(0.127)
Holiday	-0.0891***	-0.0318***	0.0671
	(0.00524)	(0.00963)	(0.0455)
Daylight Savings Time week	0.0348***	0.0477***	-0.0674
	(0.00573)	(0.0126)	(0.0655)
Very Hot Day (95th percentile)	0.0232***	0.0271*	-0.151**
	(0.00664)	(0.0144)	(0.0750)
Sum of Very Hot Days (3 to 1 days ago)	-0.0140***	-0.0104**	0.0460*
	(0.00229)	(0.00492)	(0.0242)
lnalpha	-2.907***	-0.873***	0.871***
	(0.0166)	(0.00939)	(0.0536)
Constant	-10.14***	-10.81***	-15.07***
	(0.00968)	(0.0186)	(0.109)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Explanatory Regression #2

nbreg Crashes i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce FloodEv WindEv TStormEv StormEv WinterEv FlEvLag123 FlEvLag4567 WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567 WntEvLag123 WntEvLag4567 Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Exp2C
outreg2 using Exp2, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce FloodEv WindEv TStormEv StormEv WinterEv FlEvLag123 FlEvLag4567 WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567 WntEvLag123 WntEvLag4567 Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Exp2I
outreg2 using Exp2, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce FloodEv WindEv TStormEv StormEv WinterEv FlEvLag123 FlEvLag4567 WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567 WntEvLag123 WntEvLag4567 Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Exp2K
outreg2 using Exp2, word append ctitle(Fatalities, NB) label

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.533***	-0.617***	0.212
	(0.0185)	(0.0387)	(0.198)
Alleghany	-0.346***	-0.429***	0.410
	(0.0310)	(0.0615)	(0.291)
Anson	0.189***	0.310***	0.582***
	(0.0174)	(0.0344)	(0.199)
Ashe	-0.337***	-0.469***	0.326

	(0.0207)	(0.0416)	(0.213)
Avery	-0.327***	-0.438***	-0.134
	(0.0240)	(0.0483)	(0.303)
Beaufort	-0.115***	-0.165***	0.394**
	(0.0150)	(0.0325)	(0.170)
Bertie	-0.0737***	0.0667	1.237***
	(0.0213)	(0.0413)	(0.181)
Bladen	0.145***	0.207***	1.157***
	(0.0159)	(0.0337)	(0.165)
Brunswick	-0.148***	-0.277***	0.292**
	(0.0114)	(0.0227)	(0.135)
Buncombe	0.137***	-0.103***	0.0881
	(0.00985)	(0.0183)	(0.117)
Burke	-0.0828***	-0.0725***	0.392***
	(0.0128)	(0.0245)	(0.141)
Cabarrus	0.0820***	0.00861	-0.130
	(0.0101)	(0.0193)	(0.128)
Caldwell	-0.149***	-0.134***	0.0924
	(0.0128)	(0.0247)	(0.161)
Camden	-0.341***	-0.638***	0.405
	(0.0307)	(0.0653)	(0.365)
Carteret	-0.229***	-0.369***	-0.142
	(0.0141)	(0.0273)	(0.182)
Caswell	-0.273***	-0.330***	0.806***
	(0.0207)	(0.0406)	(0.187)
Catawba	0.170***	0.0376*	0.126
	(0.0104)	(0.0197)	(0.129)
Chatham	-0.188***	-0.494***	0.473***
	(0.0148)	(0.0279)	(0.152)
Cherokee	-0.418***	-0.468***	0.680***
	(0.0203)	(0.0396)	(0.187)
Chowan	-0.370***	-0.572***	0.415
	(0.0273)	(0.0591)	(0.272)
Clay	-0.356***	-0.568***	0.401
	(0.0315)	(0.0636)	(0.312)
Cleveland	0.0936***	0.00290	0.570***
	(0.0118)	(0.0227)	(0.133)
Columbus	0.254***	0.413***	1.204***
	(0.0128)	(0.0263)	(0.129)
Craven	-0.169***	-0.201***	0.177
	(0.0119)	(0.0232)	(0.142)
Cumberland	0.0169*	0.0414**	0.206*
	(0.00991)	(0.0179)	(0.112)
Currituck	-0.471***	-0.556***	0.450**
	(0.0221)	(0.0461)	(0.218)
Dare	-0.0673***	-0.159***	-0.0119
	(0.0194)	(0.0346)	(0.216)
Davidson	-0.141***	-0.120***	0.406***
	(0.0107)	(0.0207)	(0.121)
Davie	-0.201***	-0.168***	0.372**
	(0.0181)	(0.0326)	(0.187)
Duplin	0.250***	0.0660**	0.899***
	(0.0134)	(0.0289)	(0.149)
Durham	0.273***	0.0693***	-0.189
	(0.00948)	(0.0177)	(0.118)
Edgecombe	-0.000405	0.0978***	0.563***
	(0.0143)	(0.0274)	(0.162)
Forsyth	0.0835***	-0.0340*	-0.110
	(0.00998)	(0.0179)	(0.115)
Franklin	-0.266***	-0.232***	0.439***
	(0.0141)	(0.0270)	(0.148)
Gaston	0.0873***	0.136***	0.156
	(0.0100)	(0.0186)	(0.119)
Gates	-0.229***	-0.174***	0.962***
	(0.0279)	(0.0579)	(0.244)
Graham	-0.202***	0.129**	1.450***
	(0.0319)	(0.0508)	(0.227)
Granville	-0.219***	-0.148***	0.703***
	(0.0148)	(0.0270)	(0.145)
Greene	-0.0602***	-0.173***	0.374

	(0.0203)	(0.0430)	(0.239)
Guilford	0.0972***	0.277***	0.00688
	(0.00923)	(0.0166)	(0.107)
Halifax	0.144***	0.216***	0.757***
	(0.0138)	(0.0295)	(0.152)
Harnett	-0.297***	-0.240***	0.636***
	(0.0117)	(0.0223)	(0.122)
Haywood	-0.276***	-0.210***	0.370**
	(0.0153)	(0.0273)	(0.161)
Henderson	-0.107***	-0.339***	-0.0387
	(0.0121)	(0.0236)	(0.146)
Hertford	-0.202***	0.0968**	0.497**
	(0.0201)	(0.0415)	(0.204)
Hoke	-0.368***	-0.120***	0.667***
	(0.0158)	(0.0299)	(0.159)
Hyde	-0.322***	-0.957***	-0.0165
	(0.0424)	(0.104)	(0.507)
Iredell	-0.0167	0.0321	0.185
	(0.0108)	(0.0197)	(0.122)
Jackson	-0.254***	-0.352***	0.448**
	(0.0176)	(0.0318)	(0.182)
Johnston	-0.0702***	-0.0550***	0.379***
	(0.0107)	(0.0198)	(0.120)
Jones	0.364***	0.130***	0.729***
	(0.0227)	(0.0500)	(0.281)
Lee	0.0279**	-0.0368	0.626***
	(0.0135)	(0.0283)	(0.152)
Lenoir	0.0568***	0.215***	0.537***
	(0.0138)	(0.0255)	(0.149)
Lincoln	-0.225***	-0.313***	0.327**
	(0.0141)	(0.0266)	(0.145)
Macon	-0.191***	-0.262***	0.559***
	(0.0169)	(0.0327)	(0.174)
Madison	-0.519***	-0.842***	0.490**
	(0.0238)	(0.0488)	(0.220)
Martin	0.111***	0.0502	0.529**
	(0.0195)	(0.0369)	(0.207)
McDowell	0.0149	-0.212***	0.370**
	(0.0150)	(0.0300)	(0.182)
Mecklenburg	0.307***	0.430***	-0.259**
	(0.00855)	(0.0157)	(0.102)
Mitchell	-0.472***	-0.269***	-0.265
	(0.0262)	(0.0478)	(0.411)
Montgomery	-0.0241	-0.290***	0.934***
	(0.0181)	(0.0368)	(0.177)
Moore	-0.103***	-0.248***	0.452***
	(0.0125)	(0.0244)	(0.138)
Nash	0.0578***	0.162***	0.824***
	(0.0122)	(0.0230)	(0.127)
New Hanover	0.0732***	-0.0381**	-0.205
	(0.00998)	(0.0188)	(0.127)
Northampton	-0.00699	-0.0167	1.186***
	(0.0212)	(0.0424)	(0.177)
Onslow	-0.181***	-0.268***	-0.0301
	(0.0104)	(0.0201)	(0.128)
Orange	-0.219***	-0.358***	-0.309**
	(0.0117)	(0.0224)	(0.151)
Pamlico	-0.481***	-0.707***	0.332
	(0.0291)	(0.0629)	(0.282)
Pasquotank	-0.160***	-0.286***	-0.279
	(0.0160)	(0.0331)	(0.231)
Pender	0.0729***	-0.0206	1.034***
	(0.0134)	(0.0294)	(0.134)
Perquimans	-0.398***	-0.551***	0.420
	(0.0281)	(0.0614)	(0.307)
Person	-0.0636***	-0.179***	0.240
	(0.0164)	(0.0320)	(0.191)
Pitt	0.276***	0.321***	0.114
	(0.0102)	(0.0191)	(0.127)
Polk	-0.196***	-0.337***	0.470*

	(0.0215)	(0.0435)	(0.241)
Randolph	-0.0530***	-0.113***	0.415***
	(0.0114)	(0.0208)	(0.124)
Richmond	0.0146	0.243***	0.689***
	(0.0153)	(0.0283)	(0.170)
Robeson	0.174***	0.428***	1.138***
	(0.0109)	(0.0200)	(0.114)
Rockingham	-0.0889***	-0.227***	0.264*
	(0.0122)	(0.0241)	(0.142)
Rowan	-0.0322***	-0.0313	0.268**
	(0.0110)	(0.0205)	(0.133)
Rutherford	-0.206***	-0.202***	0.288*
	(0.0139)	(0.0263)	(0.156)
Sampson	0.117***	0.154***	0.915***
	(0.0132)	(0.0251)	(0.137)
Scotland	-0.121***	0.242***	0.715***
	(0.0167)	(0.0310)	(0.172)
Stanly	-0.119***	-0.262***	0.341**
	(0.0138)	(0.0286)	(0.165)
Stokes	-0.229***	-0.390***	0.413**
	(0.0164)	(0.0317)	(0.176)
Surry	-0.135***	-0.0438*	0.576***
	(0.0135)	(0.0254)	(0.142)
Swain	-0.534***	-0.595***	0.345
	(0.0274)	(0.0554)	(0.266)
Transylvania	-0.396***	-0.517***	0.182
	(0.0191)	(0.0376)	(0.225)
Tyrrell	0.239***	-0.468***	-0.446
	(0.0371)	(0.106)	(1.004)
Union	-0.0600***	-0.178***	-0.105
	(0.00986)	(0.0194)	(0.128)
Vance	0.230***	0.374***	0.666***
	(0.0142)	(0.0276)	(0.156)
Wake	0.145***	-0.0291*	-0.546***
	(0.00901)	(0.0162)	(0.105)
Warren	-0.0852***	-0.0470	0.871***
	(0.0218)	(0.0449)	(0.230)
Washington	-0.181***	-0.361***	0.334
	(0.0270)	(0.0558)	(0.292)
Watauga	-0.0153	-0.330***	-0.0923
	(0.0148)	(0.0292)	(0.208)
Wayne	0.00480	0.0995***	0.368***
	(0.0111)	(0.0213)	(0.131)
Wilkes	-0.253***	-0.178***	0.327**
	(0.0140)	(0.0259)	(0.155)
Wilson	0.110***	0.123***	0.465***
	(0.0127)	(0.0243)	(0.145)
Yadkin	-0.220***	-0.362***	0.481***
	(0.0183)	(0.0348)	(0.178)
Yancey	-0.595***	-0.590***	0.405*
	(0.0259)	(0.0521)	(0.246)
2014	0.00351	0.00521	-5.71e-05
	(0.00426)	(0.00806)	(0.0432)
2015	0.0973***	0.0948***	0.0669
	(0.00411)	(0.00801)	(0.0429)
2016	0.149***	0.135***	0.0938**
	(0.00413)	(0.00799)	(0.0423)
2017	0.172***	0.117***	0.0547
	(0.00398)	(0.00793)	(0.0425)
2018	0.180***	0.0788***	0.0925**
	(0.00404)	(0.00792)	(0.0425)
2019	0.189***	0.0714***	0.103**
	(0.00396)	(0.00793)	(0.0421)
February	-0.00372	0.0490***	-0.0393
	(0.00621)	(0.0112)	(0.0595)
March	-0.00294	0.0905***	0.00656
	(0.00588)	(0.0109)	(0.0603)
April	0.0258***	0.164***	0.0662
	(0.00567)	(0.0107)	(0.0587)
May	0.0743***	0.224***	0.150***

	(0.00562)	(0.0108)	(0.0580)
June	0.0524***	0.214***	0.200***
	(0.00576)	(0.0111)	(0.0592)
July	0.00344	0.159***	0.0611
	(0.00619)	(0.0119)	(0.0644)
August	0.0440***	0.206***	0.0910
	(0.00572)	(0.0110)	(0.0594)
September	0.0764***	0.213***	0.225***
	(0.00575)	(0.0108)	(0.0580)
October	0.232***	0.285***	0.247***
	(0.00552)	(0.0106)	(0.0567)
November	0.282***	0.216***	0.205***
	(0.00578)	(0.0110)	(0.0593)
December	0.181***	0.164***	0.0660
	(0.00583)	(0.0106)	(0.0576)
Monday	0.333***	0.201***	-0.209***
	(0.00422)	(0.00846)	(0.0425)
Tuesday	0.332***	0.192***	-0.181***
	(0.00420)	(0.00842)	(0.0419)
Wednesday	0.334***	0.192***	-0.155***
	(0.00421)	(0.00836)	(0.0418)
Thursday	0.345***	0.208***	-0.179***
	(0.00416)	(0.00827)	(0.0418)
Friday	0.507***	0.392***	0.00825
	(0.00417)	(0.00819)	(0.0400)
Saturday	0.219***	0.198***	0.102***
	(0.00428)	(0.00853)	(0.0390)
Precipitation (inches)	0.0630***	0.0365***	0.00403
	(0.00315)	(0.00568)	(0.0308)
Rain After 3 or more Dry Days	0.0515***	0.0456***	-0.0476
	(0.00382)	(0.00716)	(0.0405)
Snow or Ice Conditions	0.0782***	-0.0147	-0.187**
	(0.00967)	(0.0141)	(0.0775)
Flood Event	0.120***	0.0661**	0.123
	(0.0152)	(0.0268)	(0.138)
Wind Event	0.0810***	0.0190	0.167
	(0.0206)	(0.0418)	(0.203)
Thunderstorm Wind Event	0.106***	0.0872***	-0.0799
	(0.00789)	(0.0170)	(0.0978)
Storm Event (Tropical Cyclone)	-0.0652	-0.177***	0.0659
	(0.0447)	(0.0612)	(0.243)
Winter Event	0.581***	0.362***	-0.00845
	(0.0191)	(0.0235)	(0.130)
Flood Event, 1-3 Day Lag	-0.0549***	-0.0634***	0.0736
	(0.00920)	(0.0183)	(0.0894)
Flood Event, 4-7 Day Lag	-0.0174**	0.00218	-0.345***
	(0.00712)	(0.0156)	(0.0903)
Wind Event, 1-3 Day Lag	-0.0351***	-0.0202	0.125
	(0.0133)	(0.0263)	(0.130)
Wind Event, 4-7 Day Lag	-0.0205*	-0.00839	0.000436
	(0.0107)	(0.0222)	(0.121)
Thunderstorm Wind Event, 1-3 Day Lag	-0.0226***	-0.0128	-0.0432
	(0.00507)	(0.0109)	(0.0567)
Thunderstorm Wind Event, 4-7 Day Lag	-0.00843*	-0.0282***	0.0110
	(0.00448)	(0.00966)	(0.0508)
Storm Event (Tropical Cyclone), 1-3 Day Lag	-0.179***	-0.101**	-0.0437
	(0.0233)	(0.0423)	(0.174)
Storm Event (Tropical Cyclone), 4-7 Day Lag	-0.0257*	-0.0480	-0.264
	(0.0143)	(0.0313)	(0.190)
Winter Event, 1-3 Day Lag	-0.0816***	-0.135***	-0.301***
	(0.0104)	(0.0166)	(0.107)
Winter Event, 4-7 Day Lag	0.0107	-0.0270**	0.0644
	(0.00725)	(0.0135)	(0.0694)
Holiday	-0.0891***	-0.0324***	0.0650
	(0.00523)	(0.00963)	(0.0455)
Daylight Savings Time week	0.0358***	0.0495***	-0.0653
	(0.00575)	(0.0125)	(0.0655)
Very Hot Day (95th percentile)	0.0213***	0.0263*	-0.151**
	(0.00664)	(0.0144)	(0.0751)
Sum of Very Hot Days (3 to 1 days ago)	-0.0136***	-0.0103**	0.0442*

	(0.00230)	(0.00495)	(0.0244)
lnalpha	-2.915***	-0.874***	0.867***
	(0.0165)	(0.00940)	(0.0537)
Constant	-10.14***	-10.80***	-15.06***
	(0.00972)	(0.0187)	(0.110)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Explanatory Regression #3

```
nbreg Crashes i.CountyNum i.Year i.MoY i.DoW Ppt3day SnowIce c.Precip##(WindEv
TStormEv StormEv) FloodEv WinterEv FlEvLag123 FlEvLag4567 WiEvLag123 WiEvLag4567
TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567 WntEvLag123 WntEvLag4567
Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Exp3C
outreg2 using Exp3, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW Ppt3day SnowIce c.Precip##(WindEv
TStormEv StormEv) FloodEv WinterEv FlEvLag123 FlEvLag4567 WiEvLag123 WiEvLag4567
TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567 WntEvLag123 WntEvLag4567
Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Exp3I
outreg2 using Exp3, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW Ppt3day SnowIce c.Precip##(WindEv
TStormEv StormEv) FloodEv WinterEv FlEvLag123 FlEvLag4567 WiEvLag123 WiEvLag4567
TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567 WntEvLag123 WntEvLag4567
Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Exp3K
outreg2 using Exp3, word append ctitle(Fatalities, NB) label
```

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.533***	-0.618***	0.212
	(0.0185)	(0.0387)	(0.198)
Alleghany	-0.347***	-0.430***	0.409
	(0.0310)	(0.0615)	(0.292)
Anson	0.189***	0.310***	0.583***
	(0.0174)	(0.0344)	(0.199)
Ashe	-0.338***	-0.470***	0.324
	(0.0207)	(0.0416)	(0.213)
Avery	-0.328***	-0.438***	-0.133
	(0.0240)	(0.0483)	(0.303)
Beaufort	-0.115***	-0.165***	0.394**
	(0.0150)	(0.0324)	(0.170)
Bertie	-0.0734***	0.0670	1.238***
	(0.0213)	(0.0413)	(0.181)
Bladen	0.145***	0.207***	1.156***
	(0.0159)	(0.0337)	(0.165)
Brunswick	-0.148***	-0.278***	0.294**
	(0.0114)	(0.0227)	(0.135)
Buncombe	0.137***	-0.103***	0.0870
	(0.00985)	(0.0183)	(0.117)
Burke	-0.0831***	-0.0727***	0.390***
	(0.0128)	(0.0245)	(0.140)
Cabarrus	0.0819***	0.00866	-0.130
	(0.0101)	(0.0193)	(0.128)

Caldwell	-0.149***	-0.134***	0.0924
	(0.0128)	(0.0247)	(0.161)
Camden	-0.341***	-0.638***	0.405
	(0.0307)	(0.0653)	(0.365)
Carteret	-0.229***	-0.369***	-0.142
	(0.0141)	(0.0273)	(0.182)
Caswell	-0.273***	-0.330***	0.806***
	(0.0207)	(0.0406)	(0.187)
Catawba	0.170***	0.0375*	0.127
	(0.0104)	(0.0197)	(0.129)
Chatham	-0.188***	-0.494***	0.473***
	(0.0148)	(0.0279)	(0.152)
Cherokee	-0.418***	-0.468***	0.680***
	(0.0203)	(0.0396)	(0.187)
Chowan	-0.369***	-0.572***	0.416
	(0.0273)	(0.0591)	(0.272)
Clay	-0.356***	-0.568***	0.401
	(0.0315)	(0.0636)	(0.312)
Cleveland	0.0936***	0.00299	0.568***
	(0.0118)	(0.0227)	(0.133)
Columbus	0.254***	0.413***	1.205***
	(0.0128)	(0.0263)	(0.129)
Craven	-0.169***	-0.201***	0.176
	(0.0119)	(0.0232)	(0.142)
Cumberland	0.0168*	0.0413**	0.206*
	(0.00991)	(0.0179)	(0.112)
Currituck	-0.471***	-0.556***	0.451**
	(0.0221)	(0.0461)	(0.218)
Dare	-0.0677***	-0.159***	-0.0111
	(0.0194)	(0.0346)	(0.216)
Davidson	-0.141***	-0.120***	0.405***
	(0.0107)	(0.0207)	(0.121)
Davie	-0.201***	-0.168***	0.372**
	(0.0181)	(0.0326)	(0.187)
Duplin	0.251***	0.0664**	0.895***
	(0.0134)	(0.0289)	(0.149)
Durham	0.273***	0.0692***	-0.190
	(0.00948)	(0.0177)	(0.118)
Edgecombe	-0.000656	0.0975***	0.564***
	(0.0143)	(0.0274)	(0.162)
Forsyth	0.0834***	-0.0341*	-0.111
	(0.00998)	(0.0179)	(0.115)
Franklin	-0.266***	-0.232***	0.439***
	(0.0141)	(0.0270)	(0.148)
Gaston	0.0874***	0.136***	0.156
	(0.0100)	(0.0186)	(0.119)
Gates	-0.229***	-0.174***	0.963***
	(0.0279)	(0.0579)	(0.244)
Graham	-0.203***	0.129**	1.450***
	(0.0319)	(0.0508)	(0.227)
Granville	-0.219***	-0.148***	0.703***
	(0.0148)	(0.0270)	(0.145)
Greene	-0.0600***	-0.173***	0.372
	(0.0203)	(0.0430)	(0.239)
Guilford	0.0972***	0.277***	0.00607
	(0.00922)	(0.0165)	(0.107)
Halifax	0.143***	0.216***	0.757***
	(0.0138)	(0.0295)	(0.152)
Harnett	-0.297***	-0.240***	0.636***
	(0.0117)	(0.0223)	(0.122)
Haywood	-0.276***	-0.210***	0.370**
	(0.0153)	(0.0273)	(0.161)
Henderson	-0.108***	-0.339***	-0.0383
	(0.0121)	(0.0236)	(0.146)
Hertford	-0.202***	0.0968**	0.497**
	(0.0201)	(0.0415)	(0.204)
Hoke	-0.368***	-0.121***	0.668***
	(0.0158)	(0.0299)	(0.159)
Hyde	-0.322***	-0.957***	-0.0156
	(0.0424)	(0.104)	(0.508)

Iredell	-0.0167	0.0322	0.186
	(0.0108)	(0.0197)	(0.122)
Jackson	-0.254***	-0.352***	0.448**
	(0.0176)	(0.0318)	(0.182)
Johnston	-0.0703***	-0.0551***	0.379***
	(0.0107)	(0.0198)	(0.120)
Jones	0.365***	0.130***	0.726***
	(0.0227)	(0.0500)	(0.281)
Lee	0.0277**	-0.0369	0.627***
	(0.0135)	(0.0284)	(0.152)
Lenoir	0.0574***	0.216***	0.533***
	(0.0138)	(0.0254)	(0.149)
Lincoln	-0.225***	-0.313***	0.328**
	(0.0141)	(0.0266)	(0.145)
Macon	-0.192***	-0.262***	0.559***
	(0.0169)	(0.0327)	(0.174)
Madison	-0.518***	-0.842***	0.490**
	(0.0238)	(0.0488)	(0.220)
Martin	0.111***	0.0501	0.529**
	(0.0195)	(0.0368)	(0.207)
McDowell	0.0144	-0.213***	0.370**
	(0.0150)	(0.0300)	(0.182)
Mecklenburg	0.308***	0.430***	-0.258**
	(0.00855)	(0.0157)	(0.102)
Mitchell	-0.472***	-0.269***	-0.266
	(0.0262)	(0.0478)	(0.411)
Montgomery	-0.0241	-0.290***	0.934***
	(0.0181)	(0.0368)	(0.177)
Moore	-0.103***	-0.248***	0.453***
	(0.0125)	(0.0244)	(0.138)
Nash	0.0576***	0.162***	0.825***
	(0.0122)	(0.0230)	(0.127)
New Hanover	0.0733***	-0.0382**	-0.204
	(0.00997)	(0.0188)	(0.127)
Northampton	-0.00716	-0.0168	1.186***
	(0.0212)	(0.0424)	(0.177)
Onslow	-0.181***	-0.268***	-0.0291
	(0.0104)	(0.0201)	(0.128)
Orange	-0.220***	-0.358***	-0.309**
	(0.0117)	(0.0224)	(0.151)
Pamlico	-0.481***	-0.707***	0.333
	(0.0291)	(0.0629)	(0.282)
Pasquotank	-0.160***	-0.285***	-0.278
	(0.0160)	(0.0331)	(0.231)
Pender	0.0730***	-0.0205	1.034***
	(0.0134)	(0.0294)	(0.134)
Perquimans	-0.398***	-0.550***	0.420
	(0.0281)	(0.0615)	(0.307)
Person	-0.0637***	-0.179***	0.240
	(0.0164)	(0.0320)	(0.191)
Pitt	0.277***	0.321***	0.112
	(0.0102)	(0.0191)	(0.127)
Polk	-0.196***	-0.337***	0.471*
	(0.0215)	(0.0435)	(0.241)
Randolph	-0.0530***	-0.113***	0.415***
	(0.0114)	(0.0208)	(0.123)
Richmond	0.0144	0.243***	0.690***
	(0.0153)	(0.0283)	(0.170)
Robeson	0.175***	0.429***	1.139***
	(0.0109)	(0.0200)	(0.114)
Rockingham	-0.0890***	-0.227***	0.263*
	(0.0122)	(0.0241)	(0.142)
Rowan	-0.0321***	-0.0312	0.269**
	(0.0110)	(0.0205)	(0.133)
Rutherford	-0.206***	-0.202***	0.287*
	(0.0139)	(0.0263)	(0.156)
Sampson	0.117***	0.154***	0.915***
	(0.0132)	(0.0250)	(0.137)
Scotland	-0.121***	0.242***	0.715***
	(0.0167)	(0.0310)	(0.172)

Stanly	-0.119***	-0.262***	0.341**
	(0.0138)	(0.0286)	(0.165)
Stokes	-0.229***	-0.390***	0.412**
	(0.0164)	(0.0317)	(0.176)
Surry	-0.135***	-0.0438*	0.576***
	(0.0135)	(0.0253)	(0.142)
Swain	-0.534***	-0.596***	0.346
	(0.0274)	(0.0554)	(0.266)
Transylvania	-0.397***	-0.518***	0.183
	(0.0191)	(0.0376)	(0.225)
Tyrrell	0.239***	-0.469***	-0.446
	(0.0371)	(0.106)	(1.004)
Union	-0.0597***	-0.178***	-0.104
	(0.00986)	(0.0194)	(0.128)
Vance	0.230***	0.374***	0.666***
	(0.0142)	(0.0276)	(0.156)
Wake	0.144***	-0.0295*	-0.544***
	(0.00901)	(0.0162)	(0.105)
Warren	-0.0853***	-0.0470	0.871***
	(0.0218)	(0.0449)	(0.230)
Washington	-0.180***	-0.361***	0.334
	(0.0270)	(0.0558)	(0.292)
Watauga	-0.0161	-0.331***	-0.0930
	(0.0148)	(0.0292)	(0.208)
Wayne	0.00502	0.0997***	0.368***
	(0.0111)	(0.0213)	(0.131)
Wilkes	-0.253***	-0.178***	0.327**
	(0.0140)	(0.0259)	(0.155)
Wilson	0.110***	0.123***	0.465***
	(0.0127)	(0.0243)	(0.145)
Yadkin	-0.220***	-0.362***	0.481***
	(0.0183)	(0.0348)	(0.178)
Yancey	-0.595***	-0.591***	0.404*
	(0.0259)	(0.0521)	(0.246)
2014	0.00368	0.00541	-0.000477
	(0.00426)	(0.00806)	(0.0432)
2015	0.0973***	0.0949***	0.0669
	(0.00411)	(0.00801)	(0.0429)
2016	0.149***	0.136***	0.0926**
	(0.00413)	(0.00799)	(0.0423)
2017	0.172***	0.117***	0.0540
	(0.00398)	(0.00793)	(0.0425)
2018	0.180***	0.0786***	0.0932**
	(0.00404)	(0.00792)	(0.0425)
2019	0.189***	0.0716***	0.102**
	(0.00396)	(0.00793)	(0.0421)
February	-0.00378	0.0489***	-0.0389
	(0.00621)	(0.0112)	(0.0595)
March	-0.00286	0.0905***	0.00662
	(0.00588)	(0.0109)	(0.0603)
April	0.0254***	0.164***	0.0669
	(0.00567)	(0.0107)	(0.0587)
May	0.0742***	0.224***	0.151***
	(0.00562)	(0.0108)	(0.0580)
June	0.0521***	0.213***	0.202***
	(0.00576)	(0.0111)	(0.0592)
July	0.00299	0.158***	0.0634
	(0.00619)	(0.0119)	(0.0644)
August	0.0436***	0.205***	0.0920
	(0.00572)	(0.0110)	(0.0594)
September	0.0767***	0.213***	0.226***
	(0.00575)	(0.0108)	(0.0580)
October	0.232***	0.285***	0.248***
	(0.00552)	(0.0106)	(0.0567)
November	0.282***	0.216***	0.206***
	(0.00578)	(0.0110)	(0.0593)
December	0.181***	0.163***	0.0672
	(0.00583)	(0.0106)	(0.0576)
Monday	0.333***	0.201***	-0.208***
	(0.00422)	(0.00846)	(0.0425)

Tuesday	0.332***	0.191***	-0.180***
	(0.00420)	(0.00843)	(0.0419)
Wednesday	0.333***	0.191***	-0.155***
	(0.00421)	(0.00836)	(0.0418)
Thursday	0.345***	0.207***	-0.178***
	(0.00416)	(0.00827)	(0.0418)
Friday	0.506***	0.392***	0.00837
	(0.00417)	(0.00819)	(0.0400)
Saturday	0.219***	0.198***	0.102***
	(0.00428)	(0.00853)	(0.0390)
Rain After 3 or more Dry Days	0.0499***	0.0438***	-0.0454
	(0.00382)	(0.00716)	(0.0406)
Snow or Ice Conditions	0.0787***	-0.0141	-0.188**
	(0.00967)	(0.0141)	(0.0775)
Precipitation (inches)	0.0696***	0.0446***	-0.0118
	(0.00311)	(0.00585)	(0.0338)
Wind Event = 1	0.140***	0.0723	0.292
	(0.0221)	(0.0472)	(0.217)
Thunderstorm Wind Event = 1	0.100***	0.0949***	-0.153
	(0.00868)	(0.0187)	(0.106)
Storm Event (Tropical Cyclone) = 1	0.0765	-0.0213	-0.294
	(0.0503)	(0.0705)	(0.324)
	(0)	(0)	(0)
Precipitation Modifier, Wind Event	-0.0931***	-0.0905**	-0.194
	(0.0220)	(0.0457)	(0.158)
	(0)	(0)	(0)
Precipitation Modifier, Thunderstorm Wind Event	0.0196	-0.0395	0.280*
	(0.0185)	(0.0315)	(0.163)
	(0)	(0)	(0)
Precipitation Modifier, Storm Event	-0.0941***	-0.112***	0.177**
	(0.0204)	(0.0328)	(0.0773)
Flood Event	0.128***	0.0747***	0.121
	(0.0151)	(0.0268)	(0.139)
Winter Event	0.580***	0.361***	-0.00573
	(0.0191)	(0.0235)	(0.130)
Flood Event, 1-3 Day Lag	-0.0542***	-0.0625***	0.0710
	(0.00918)	(0.0183)	(0.0899)
Flood Event, 4-7 Day Lag	-0.0177**	0.00152	-0.344***
	(0.00712)	(0.0156)	(0.0903)
Wind Event, 1-3 Day Lag	-0.0339**	-0.0203	0.129
	(0.0132)	(0.0263)	(0.130)
Wind Event, 4-7 Day Lag	-0.0206*	-0.00832	-0.00146
	(0.0107)	(0.0222)	(0.121)
Thunderstorm Wind Event, 1-3 Day Lag	-0.0238***	-0.0137	-0.0430
	(0.00507)	(0.0109)	(0.0567)
Thunderstorm Wind Event, 4-7 Day Lag	-0.00814*	-0.0280***	0.0107
	(0.00448)	(0.00966)	(0.0508)
Storm Event (Tropical Cyclone), 1-3 Day Lag	-0.148***	-0.0681	-0.0902
	(0.0226)	(0.0422)	(0.185)
Storm Event (Tropical Cyclone), 4-7 Day Lag	-0.0342**	-0.0573*	-0.252
	(0.0143)	(0.0314)	(0.190)
Winter Event, 1-3 Day Lag	-0.0822***	-0.135***	-0.299***
	(0.0104)	(0.0166)	(0.107)
Winter Event, 4-7 Day Lag	0.0109	-0.0268**	0.0638
	(0.00725)	(0.0135)	(0.0694)
Holiday	-0.0900***	-0.0329***	0.0651
	(0.00522)	(0.00964)	(0.0455)
Daylight Savings Time week	0.0360***	0.0496***	-0.0654
	(0.00574)	(0.0125)	(0.0655)
Very Hot Day (95th percentile)	0.0219***	0.0265*	-0.150**
	(0.00665)	(0.0144)	(0.0751)
Sum of Very Hot Days (3 to 1 days ago)	-0.0135***	-0.0103**	0.0444*
	(0.00230)	(0.00494)	(0.0244)
lnalpha	-2.917***	-0.875***	0.866***
	(0.0165)	(0.00941)	(0.0538)
Constant	-10.14***	-10.80***	-15.06***
	(0.00972)	(0.0187)	(0.110)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Forecast Baseline Regression #1

nbreg Crashes i.CountyNum i.Year i.MoY i.DoW Ppt3day SnowIce c.Precip##(WindEv TStormEv) StormEv#CSP FloodEv WinterEv AnyEvLag123 AnyEvLag4567 Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store ForeB1C
outreg2 using ForeB1, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW Ppt3day SnowIce c.Precip##(WindEv TStormEv) StormEv#CSP FloodEv WinterEv AnyEvLag123 AnyEvLag4567 Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store ForeB1I
outreg2 using ForeB1, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW Ppt3day SnowIce c.Precip##(WindEv TStormEv) StormEv#CSP FloodEv WinterEv AnyEvLag123 AnyEvLag4567 Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store ForeB1K
outreg2 using ForeB1, word append ctitle(Fatalities, NB) label

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.533***	-0.619***	0.212
	(0.0185)	(0.0387)	(0.198)
Alleghany	-0.347***	-0.429***	0.412
	(0.0310)	(0.0615)	(0.292)
Anson	0.188***	0.310***	0.580***
	(0.0174)	(0.0344)	(0.199)
Ashe	-0.338***	-0.468***	0.333
	(0.0206)	(0.0415)	(0.212)
Avery	-0.328***	-0.442***	-0.137
	(0.0240)	(0.0483)	(0.303)
Beaufort	-0.116***	-0.166***	0.391**
	(0.0150)	(0.0325)	(0.170)
Bertie	-0.0744***	0.0661	1.235***
	(0.0213)	(0.0413)	(0.181)
Bladen	0.145***	0.209***	1.157***
	(0.0159)	(0.0337)	(0.165)
Brunswick	-0.150***	-0.277***	0.287**
	(0.0114)	(0.0227)	(0.135)
Buncombe	0.137***	-0.106***	0.0853
	(0.00986)	(0.0183)	(0.117)
Burke	-0.0825***	-0.0728***	0.390***
	(0.0129)	(0.0245)	(0.140)
Cabarrus	0.0818***	0.00927	-0.132
	(0.0101)	(0.0194)	(0.128)
Caldwell	-0.149***	-0.136***	0.0886
	(0.0128)	(0.0247)	(0.161)
Camden	-0.342***	-0.638***	0.402
	(0.0307)	(0.0653)	(0.365)
Carteret	-0.232***	-0.370***	-0.147
	(0.0141)	(0.0273)	(0.182)
Caswell	-0.272***	-0.328***	0.809***
	(0.0207)	(0.0406)	(0.187)
Catawba	0.170***	0.0373*	0.126
	(0.0104)	(0.0197)	(0.129)
Chatham	-0.188***	-0.494***	0.473***
	(0.0148)	(0.0279)	(0.152)

Cherokee	-0.418***	-0.467***	0.679***
	(0.0203)	(0.0396)	(0.187)
Chowan	-0.370***	-0.573***	0.413
	(0.0273)	(0.0591)	(0.272)
Clay	-0.356***	-0.568***	0.400
	(0.0315)	(0.0636)	(0.312)
Cleveland	0.0938***	0.00343	0.570***
	(0.0118)	(0.0227)	(0.133)
Columbus	0.254***	0.415***	1.203***
	(0.0128)	(0.0263)	(0.129)
Craven	-0.171***	-0.201***	0.172
	(0.0119)	(0.0232)	(0.142)
Cumberland	0.0159	0.0418**	0.201*
	(0.00993)	(0.0179)	(0.112)
Currituck	-0.472***	-0.556***	0.448**
	(0.0221)	(0.0461)	(0.218)
Dare	-0.0695***	-0.159***	-0.0167
	(0.0194)	(0.0346)	(0.216)
Davidson	-0.141***	-0.120***	0.406***
	(0.0107)	(0.0207)	(0.121)
Davie	-0.201***	-0.169***	0.371**
	(0.0181)	(0.0326)	(0.187)
Duplin	0.249***	0.0661**	0.897***
	(0.0134)	(0.0289)	(0.149)
Durham	0.272***	0.0693***	-0.193
	(0.00947)	(0.0177)	(0.118)
Edgecombe	-0.00127	0.0976***	0.561***
	(0.0143)	(0.0274)	(0.162)
Forsyth	0.0836***	-0.0339*	-0.109
	(0.00999)	(0.0179)	(0.115)
Franklin	-0.266***	-0.232***	0.441***
	(0.0141)	(0.0271)	(0.149)
Gaston	0.0876***	0.137***	0.158
	(0.0100)	(0.0186)	(0.119)
Gates	-0.229***	-0.175***	0.960***
	(0.0279)	(0.0579)	(0.244)
Graham	-0.203***	0.126**	1.447***
	(0.0319)	(0.0508)	(0.227)
Granville	-0.219***	-0.149***	0.702***
	(0.0148)	(0.0270)	(0.145)
Greene	-0.0612***	-0.173***	0.370
	(0.0203)	(0.0430)	(0.239)
Guilford	0.0968***	0.277***	0.00243
	(0.00923)	(0.0165)	(0.107)
Halifax	0.143***	0.216***	0.758***
	(0.0138)	(0.0295)	(0.152)
Harnett	-0.297***	-0.240***	0.633***
	(0.0117)	(0.0223)	(0.122)
Haywood	-0.277***	-0.213***	0.369**
	(0.0153)	(0.0273)	(0.161)
Henderson	-0.107***	-0.340***	-0.0431
	(0.0121)	(0.0236)	(0.146)
Hertford	-0.202***	0.0966**	0.494**
	(0.0201)	(0.0415)	(0.204)
Hoke	-0.369***	-0.120***	0.662***
	(0.0158)	(0.0299)	(0.159)
Hyde	-0.324***	-0.958***	-0.0204
	(0.0424)	(0.104)	(0.508)
Iredell	-0.0161	0.0321	0.188
	(0.0108)	(0.0197)	(0.122)
Jackson	-0.254***	-0.354***	0.446**
	(0.0177)	(0.0318)	(0.182)
Johnston	-0.0704***	-0.0539***	0.380***
	(0.0107)	(0.0198)	(0.120)
Jones	0.363***	0.129***	0.725***
	(0.0227)	(0.0500)	(0.281)
Lee	0.0272**	-0.0373	0.624***
	(0.0135)	(0.0284)	(0.152)
Lenoir	0.0559***	0.215***	0.533***
	(0.0138)	(0.0255)	(0.149)

Lincoln	-0.225***	-0.313***	0.328**
	(0.0141)	(0.0266)	(0.145)
Macon	-0.191***	-0.264***	0.556***
	(0.0169)	(0.0327)	(0.174)
Madison	-0.518***	-0.845***	0.489**
	(0.0238)	(0.0488)	(0.220)
Martin	0.111***	0.0502	0.526**
	(0.0195)	(0.0369)	(0.206)
McDowell	0.0151	-0.212***	0.371**
	(0.0150)	(0.0300)	(0.182)
Mecklenburg	0.308***	0.432***	-0.258**
	(0.00855)	(0.0158)	(0.102)
Mitchell	-0.472***	-0.273***	-0.270
	(0.0262)	(0.0478)	(0.411)
Montgomery	-0.0245	-0.290***	0.933***
	(0.0181)	(0.0368)	(0.177)
Moore	-0.103***	-0.246***	0.453***
	(0.0125)	(0.0244)	(0.138)
Nash	0.0573***	0.162***	0.825***
	(0.0122)	(0.0230)	(0.127)
New Hanover	0.0709***	-0.0378**	-0.212*
	(0.00997)	(0.0188)	(0.127)
Northampton	-0.00726	-0.0169	1.184***
	(0.0212)	(0.0424)	(0.177)
Onslow	-0.183***	-0.269***	-0.0364
	(0.0104)	(0.0201)	(0.128)
Orange	-0.220***	-0.358***	-0.309**
	(0.0117)	(0.0224)	(0.151)
Pamlico	-0.482***	-0.708***	0.327
	(0.0291)	(0.0629)	(0.282)
Pasquotank	-0.161***	-0.286***	-0.281
	(0.0160)	(0.0331)	(0.231)
Pender	0.0714***	-0.0204	1.028***
	(0.0134)	(0.0294)	(0.134)
Perquimans	-0.399***	-0.551***	0.417
	(0.0281)	(0.0615)	(0.307)
Person	-0.0636***	-0.179***	0.241
	(0.0164)	(0.0320)	(0.191)
Pitt	0.276***	0.321***	0.113
	(0.0103)	(0.0191)	(0.127)
Polk	-0.196***	-0.338***	0.468*
	(0.0215)	(0.0435)	(0.241)
Randolph	-0.0528***	-0.112***	0.416***
	(0.0114)	(0.0208)	(0.124)
Richmond	0.0142	0.244***	0.687***
	(0.0153)	(0.0283)	(0.170)
Robeson	0.174***	0.430***	1.138***
	(0.0109)	(0.0200)	(0.114)
Rockingham	-0.0883***	-0.225***	0.266*
	(0.0122)	(0.0241)	(0.142)
Rowan	-0.0313***	-0.0307	0.270**
	(0.0110)	(0.0205)	(0.133)
Rutherford	-0.206***	-0.201***	0.291*
	(0.0139)	(0.0263)	(0.156)
Sampson	0.116***	0.154***	0.914***
	(0.0132)	(0.0251)	(0.137)
Scotland	-0.122***	0.242***	0.710***
	(0.0167)	(0.0310)	(0.172)
Stanly	-0.120***	-0.262***	0.339**
	(0.0138)	(0.0286)	(0.165)
Stokes	-0.229***	-0.389***	0.416**
	(0.0164)	(0.0317)	(0.176)
Surry	-0.134***	-0.0423*	0.581***
	(0.0135)	(0.0254)	(0.143)
Swain	-0.534***	-0.597***	0.343
	(0.0274)	(0.0554)	(0.266)
Transylvania	-0.397***	-0.518***	0.176
	(0.0191)	(0.0376)	(0.225)
Tyrrell	0.238***	-0.469***	-0.450
	(0.0371)	(0.106)	(1.004)

Union	-0.0601***	-0.177***	-0.105
	(0.00986)	(0.0194)	(0.128)
Vance	0.230***	0.374***	0.666***
	(0.0142)	(0.0276)	(0.156)
Wake	0.144***	-0.0279*	-0.546***
	(0.00902)	(0.0162)	(0.105)
Warren	-0.0855***	-0.0471	0.870***
	(0.0218)	(0.0449)	(0.230)
Washington	-0.182***	-0.361***	0.331
	(0.0270)	(0.0558)	(0.292)
Watauga	-0.0163	-0.328***	-0.0880
	(0.0148)	(0.0292)	(0.207)
Wayne	0.00410	0.0997***	0.368***
	(0.0111)	(0.0214)	(0.131)
Wilkes	-0.253***	-0.177***	0.330**
	(0.0140)	(0.0259)	(0.155)
Wilson	0.109***	0.123***	0.464***
	(0.0127)	(0.0243)	(0.145)
Yadkin	-0.220***	-0.360***	0.483***
	(0.0183)	(0.0348)	(0.178)
Yancey	-0.595***	-0.595***	0.402
	(0.0259)	(0.0521)	(0.246)
2014	0.00407	0.00428	0.000554
	(0.00426)	(0.00806)	(0.0432)
2015	0.0975***	0.0944***	0.0672
	(0.00412)	(0.00801)	(0.0429)
2016	0.148***	0.136***	0.0945**
	(0.00414)	(0.00799)	(0.0424)
2017	0.173***	0.117***	0.0570
	(0.00399)	(0.00793)	(0.0425)
2018	0.179***	0.0775***	0.0902**
	(0.00404)	(0.00792)	(0.0425)
2019	0.189***	0.0721***	0.104**
	(0.00396)	(0.00793)	(0.0420)
February	-0.00367	0.0491***	-0.0360
	(0.00622)	(0.0112)	(0.0595)
March	-0.00339	0.0915***	0.00758
	(0.00585)	(0.0109)	(0.0602)
April	0.0254***	0.169***	0.0669
	(0.00557)	(0.0106)	(0.0581)
May	0.0741***	0.229***	0.150***
	(0.00552)	(0.0106)	(0.0573)
June	0.0533***	0.221***	0.205***
	(0.00559)	(0.0108)	(0.0579)
July	0.00362	0.165***	0.0628
	(0.00602)	(0.0116)	(0.0632)
August	0.0434***	0.211***	0.0886
	(0.00561)	(0.0108)	(0.0585)
September	0.0725***	0.216***	0.219***
	(0.00565)	(0.0107)	(0.0572)
October	0.228***	0.289***	0.242***
	(0.00544)	(0.0105)	(0.0560)
November	0.282***	0.220***	0.201***
	(0.00571)	(0.0110)	(0.0590)
December	0.181***	0.166***	0.0640
	(0.00581)	(0.0106)	(0.0574)
Monday	0.333***	0.201***	-0.210***
	(0.00422)	(0.00847)	(0.0425)
Tuesday	0.332***	0.191***	-0.183***
	(0.00420)	(0.00842)	(0.0419)
Wednesday	0.333***	0.191***	-0.158***
	(0.00421)	(0.00836)	(0.0418)
Thursday	0.345***	0.207***	-0.184***
	(0.00416)	(0.00826)	(0.0418)
Friday	0.506***	0.392***	0.00308
	(0.00417)	(0.00819)	(0.0400)
Saturday	0.219***	0.198***	0.0982**
	(0.00428)	(0.00853)	(0.0390)
Rain After 3 or more Dry Days	0.0516***	0.0456***	-0.0501
	(0.00382)	(0.00716)	(0.0405)

Snow or Ice Conditions	0.0707***	-0.0325**	-0.233***
	(0.00936)	(0.0137)	(0.0749)
Precipitation (inches)	0.0648***	0.0402***	0.0139
	(0.00311)	(0.00572)	(0.0317)
Wind Event = 1	0.153***	0.0849*	0.302
	(0.0223)	(0.0476)	(0.219)
Thunderstorm Wind Event = 1	0.101***	0.0954***	-0.150
	(0.00873)	(0.0187)	(0.106)
Precipitation Modifier, Wind Event	-0.111***	-0.103**	-0.171
	(0.0217)	(0.0475)	(0.171)
Precipitation Modifier, Thunderstorm Wind Event	0.0233	-0.0336	0.257
	(0.0191)	(0.0316)	(0.162)
No Storm, Cone or Spillover	0.0193**	0.00628	-0.0962
	(0.00940)	(0.0179)	(0.0981)
Storm, No Cone or Spillover	-0.285***	-0.402***	-0.0642
	(0.0599)	(0.0858)	(0.350)
Storm, Cone or Spillover	0.0298	-0.0384	0.193
	(0.0593)	(0.0779)	(0.320)
Flood Event	0.114***	0.0648**	0.138
	(0.0150)	(0.0263)	(0.134)
Winter Event	0.574***	0.344***	-0.0655
	(0.0188)	(0.0233)	(0.127)
Any Event, 1-3 Day Lag	-0.0517***	-0.0576***	-0.0716*
	(0.00435)	(0.00814)	(0.0434)
Any Event, 4-7 Day Lag	-0.00738**	-0.0241***	-0.0566
	(0.00344)	(0.00699)	(0.0372)
Holiday	-0.0900***	-0.0323***	0.0668
	(0.00524)	(0.00964)	(0.0455)
Daylight Savings Time week	0.0358***	0.0488***	-0.0656
	(0.00574)	(0.0125)	(0.0655)
Very Hot Day (95th percentile)	0.0198***	0.0232	-0.154**
	(0.00665)	(0.0144)	(0.0751)
Sum of Very Hot Days (3 to 1 days ago)	-0.0121***	-0.00870*	0.0473*
	(0.00230)	(0.00493)	(0.0243)
lnalpha	-2.914***	-0.874***	0.870***
	(0.0166)	(0.00940)	(0.0537)
Constant	-10.14***	-10.80***	-15.05***
	(0.00968)	(0.0186)	(0.109)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Forecast Baseline Regression#2

```
nbreg Crashes i.CountyNum i.Year i.MoY i.DoW Ppt3day SnowIce c.Precip##(WindEv
TStormEv) StormEv#CSP#Line FloodEv WinterEv AnyEvLag123 AnyEvLag4567 Holiday
DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store ForeB2C
outreg2 using ForeB2, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW Ppt3day SnowIce c.Precip##(WindEv
TStormEv) StormEv#CSP#Line FloodEv WinterEv AnyEvLag123 AnyEvLag4567 Holiday
DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store ForeB2I
outreg2 using ForeB2, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW Ppt3day SnowIce c.Precip##(WindEv
TStormEv) StormEv#CSP#Line FloodEv WinterEv AnyEvLag123 AnyEvLag4567 Holiday
DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store ForeB2K
outreg2 using ForeB2, word append ctitle(Fatalities, NB) label
```

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.533*** (0.0185)	-0.619*** (0.0387)	0.212 (0.198)
Alleghany	-0.347*** (0.0310)	-0.429*** (0.0615)	0.412 (0.292)
Anson	0.188*** (0.0174)	0.310*** (0.0343)	0.580*** (0.199)
Ashe	-0.338*** (0.0206)	-0.468*** (0.0415)	0.333 (0.212)
Avery	-0.328*** (0.0240)	-0.442*** (0.0483)	-0.137 (0.303)
Beaufort	-0.116*** (0.0150)	-0.166*** (0.0325)	0.391** (0.170)
Bertie	-0.0744*** (0.0213)	0.0661 (0.0413)	1.235*** (0.181)
Bladen	0.145*** (0.0159)	0.208*** (0.0337)	1.156*** (0.165)
Brunswick	-0.150*** (0.0114)	-0.277*** (0.0227)	0.287** (0.135)
Buncombe	0.137*** (0.00986)	-0.106*** (0.0183)	0.0852 (0.117)
Burke	-0.0825*** (0.0129)	-0.0728*** (0.0245)	0.390*** (0.140)
Cabarrus	0.0818*** (0.0101)	0.00924 (0.0194)	-0.133 (0.128)
Caldwell	-0.149*** (0.0128)	-0.136*** (0.0247)	0.0887 (0.161)
Camden	-0.342*** (0.0307)	-0.639*** (0.0653)	0.402 (0.365)
Carteret	-0.232*** (0.0141)	-0.370*** (0.0273)	-0.147 (0.182)
Caswell	-0.272*** (0.0207)	-0.328*** (0.0406)	0.809*** (0.187)
Catawba	0.170*** (0.0104)	0.0373* (0.0197)	0.126 (0.129)
Chatham	-0.188*** (0.0148)	-0.494*** (0.0279)	0.473*** (0.152)
Cherokee	-0.418*** (0.0203)	-0.467*** (0.0396)	0.679*** (0.187)
Chowan	-0.370*** (0.0273)	-0.573*** (0.0591)	0.413 (0.272)
Clay	-0.356*** (0.0315)	-0.568*** (0.0636)	0.400 (0.312)
Cleveland	0.0938*** (0.0118)	0.00344 (0.0227)	0.570*** (0.133)
Columbus	0.254*** (0.0128)	0.414*** (0.0263)	1.202*** (0.129)
Craven	-0.171*** (0.0119)	-0.201*** (0.0233)	0.172 (0.142)
Cumberland	0.0159 (0.00993)	0.0417** (0.0179)	0.201* (0.112)
Currituck	-0.472*** (0.0221)	-0.556*** (0.0461)	0.448** (0.218)
Dare	-0.0696*** (0.0194)	-0.160*** (0.0346)	-0.0167 (0.216)
Davidson	-0.141*** (0.0107)	-0.120*** (0.0207)	0.406*** (0.121)
Davie	-0.201*** (0.0181)	-0.169*** (0.0326)	0.371** (0.187)
Duplin	0.249*** (0.0134)	0.0659** (0.0289)	0.897*** (0.149)
Durham	0.272*** (0.00947)	0.0693*** (0.0177)	-0.193 (0.118)
Edgecombe	-0.00128 (0.0143)	0.0976*** (0.0274)	0.561*** (0.162)
Forsyth	0.0837*** (0.00999)	-0.0339* (0.0179)	-0.109 (0.115)

Franklin	-0.266***	-0.232***	0.441***
	(0.0141)	(0.0270)	(0.149)
Gaston	0.0876***	0.137***	0.158
	(0.0100)	(0.0186)	(0.119)
Gates	-0.229***	-0.175***	0.960***
	(0.0279)	(0.0579)	(0.244)
Graham	-0.203***	0.126**	1.447***
	(0.0319)	(0.0508)	(0.227)
Granville	-0.219***	-0.149***	0.702***
	(0.0148)	(0.0270)	(0.145)
Greene	-0.0613***	-0.174***	0.370
	(0.0203)	(0.0430)	(0.239)
Guilford	0.0968***	0.277***	0.00242
	(0.00923)	(0.0165)	(0.107)
Halifax	0.143***	0.216***	0.758***
	(0.0138)	(0.0295)	(0.152)
Harnett	-0.297***	-0.240***	0.633***
	(0.0117)	(0.0223)	(0.122)
Haywood	-0.277***	-0.213***	0.369**
	(0.0153)	(0.0273)	(0.161)
Henderson	-0.107***	-0.340***	-0.0432
	(0.0121)	(0.0236)	(0.146)
Hertford	-0.202***	0.0964**	0.494**
	(0.0201)	(0.0415)	(0.204)
Hoke	-0.369***	-0.121***	0.662***
	(0.0158)	(0.0299)	(0.159)
Hyde	-0.324***	-0.958***	-0.0208
	(0.0424)	(0.104)	(0.508)
Iredell	-0.0161	0.0321	0.188
	(0.0108)	(0.0197)	(0.122)
Jackson	-0.254***	-0.354***	0.446**
	(0.0177)	(0.0318)	(0.182)
Johnston	-0.0704***	-0.0540***	0.379***
	(0.0107)	(0.0198)	(0.120)
Jones	0.363***	0.129***	0.725***
	(0.0227)	(0.0500)	(0.281)
Lee	0.0272**	-0.0373	0.624***
	(0.0135)	(0.0284)	(0.152)
Lenoir	0.0558***	0.215***	0.533***
	(0.0138)	(0.0255)	(0.149)
Lincoln	-0.225***	-0.313***	0.328**
	(0.0141)	(0.0266)	(0.145)
Macon	-0.191***	-0.264***	0.556***
	(0.0169)	(0.0327)	(0.174)
Madison	-0.518***	-0.845***	0.489**
	(0.0238)	(0.0488)	(0.220)
Martin	0.111***	0.0500	0.526**
	(0.0195)	(0.0369)	(0.206)
McDowell	0.0151	-0.212***	0.371**
	(0.0150)	(0.0300)	(0.182)
Mecklenburg	0.308***	0.431***	-0.258**
	(0.00855)	(0.0157)	(0.102)
Mitchell	-0.472***	-0.273***	-0.270
	(0.0262)	(0.0478)	(0.411)
Montgomery	-0.0245	-0.290***	0.933***
	(0.0181)	(0.0368)	(0.177)
Moore	-0.103***	-0.246***	0.453***
	(0.0125)	(0.0244)	(0.138)
Nash	0.0573***	0.162***	0.825***
	(0.0122)	(0.0230)	(0.127)
New Hanover	0.0709***	-0.0379**	-0.212*
	(0.00998)	(0.0188)	(0.127)
Northampton	-0.00727	-0.0169	1.184***
	(0.0212)	(0.0424)	(0.177)
Onslow	-0.183***	-0.269***	-0.0364
	(0.0104)	(0.0201)	(0.128)
Orange	-0.220***	-0.358***	-0.309**
	(0.0117)	(0.0224)	(0.151)
Pamlico	-0.482***	-0.708***	0.327
	(0.0291)	(0.0629)	(0.282)

Pasquotank	-0.161***	-0.286***	-0.282
	(0.0160)	(0.0331)	(0.231)
Pender	0.0714***	-0.0206	1.028***
	(0.0134)	(0.0294)	(0.134)
Perquimans	-0.399***	-0.551***	0.417
	(0.0281)	(0.0615)	(0.307)
Person	-0.0636***	-0.179***	0.241
	(0.0164)	(0.0320)	(0.191)
Pitt	0.276***	0.321***	0.113
	(0.0103)	(0.0191)	(0.127)
Polk	-0.196***	-0.338***	0.468*
	(0.0215)	(0.0435)	(0.241)
Randolph	-0.0528***	-0.112***	0.416***
	(0.0114)	(0.0208)	(0.124)
Richmond	0.0141	0.243***	0.688***
	(0.0153)	(0.0283)	(0.170)
Robeson	0.174***	0.430***	1.138***
	(0.0109)	(0.0200)	(0.114)
Rockingham	-0.0883***	-0.225***	0.266*
	(0.0122)	(0.0241)	(0.142)
Rowan	-0.0313***	-0.0308	0.270**
	(0.0110)	(0.0205)	(0.133)
Rutherford	-0.206***	-0.201***	0.291*
	(0.0139)	(0.0263)	(0.156)
Sampson	0.116***	0.154***	0.913***
	(0.0132)	(0.0251)	(0.137)
Scotland	-0.122***	0.242***	0.710***
	(0.0167)	(0.0310)	(0.172)
Stanly	-0.120***	-0.262***	0.339**
	(0.0138)	(0.0286)	(0.165)
Stokes	-0.229***	-0.389***	0.416**
	(0.0164)	(0.0317)	(0.176)
Surry	-0.134***	-0.0423*	0.581***
	(0.0135)	(0.0254)	(0.143)
Swain	-0.534***	-0.597***	0.343
	(0.0274)	(0.0554)	(0.266)
Transylvania	-0.397***	-0.518***	0.176
	(0.0191)	(0.0377)	(0.225)
Tyrrell	0.238***	-0.469***	-0.450
	(0.0371)	(0.106)	(1.004)
Union	-0.0601***	-0.177***	-0.105
	(0.00986)	(0.0194)	(0.128)
Vance	0.230***	0.374***	0.666***
	(0.0142)	(0.0276)	(0.156)
Wake	0.144***	-0.0280*	-0.545***
	(0.00902)	(0.0162)	(0.105)
Warren	-0.0855***	-0.0470	0.871***
	(0.0218)	(0.0449)	(0.230)
Washington	-0.182***	-0.361***	0.331
	(0.0270)	(0.0558)	(0.292)
Watauga	-0.0163	-0.328***	-0.0879
	(0.0148)	(0.0292)	(0.207)
Wayne	0.00407	0.0995***	0.367***
	(0.0111)	(0.0214)	(0.131)
Wilkes	-0.253***	-0.177***	0.330**
	(0.0140)	(0.0259)	(0.155)
Wilson	0.109***	0.123***	0.464***
	(0.0127)	(0.0243)	(0.145)
Yadkin	-0.220***	-0.360***	0.483***
	(0.0183)	(0.0348)	(0.178)
Yancey	-0.595***	-0.595***	0.402
	(0.0259)	(0.0521)	(0.246)
2014	0.00410	0.00442	0.000715
	(0.00426)	(0.00806)	(0.0431)
2015	0.0976***	0.0944***	0.0673
	(0.00412)	(0.00801)	(0.0428)
2016	0.148***	0.136***	0.0948**
	(0.00414)	(0.00799)	(0.0423)
2017	0.173***	0.117***	0.0572
	(0.00399)	(0.00793)	(0.0425)

2018	0.179***	0.0775***	0.0903**
	(0.00404)	(0.00792)	(0.0425)
2019	0.189***	0.0723***	0.105**
	(0.00396)	(0.00793)	(0.0420)
February	-0.00367	0.0491***	-0.0360
	(0.00622)	(0.0112)	(0.0595)
March	-0.00339	0.0915***	0.00758
	(0.00585)	(0.0109)	(0.0602)
April	0.0254***	0.169***	0.0669
	(0.00557)	(0.0106)	(0.0581)
May	0.0741***	0.229***	0.150***
	(0.00552)	(0.0106)	(0.0573)
June	0.0533***	0.221***	0.205***
	(0.00559)	(0.0108)	(0.0579)
July	0.00365	0.165***	0.0629
	(0.00602)	(0.0116)	(0.0632)
August	0.0434***	0.211***	0.0887
	(0.00561)	(0.0108)	(0.0585)
September	0.0726***	0.217***	0.219***
	(0.00565)	(0.0107)	(0.0572)
October	0.228***	0.288***	0.241***
	(0.00544)	(0.0105)	(0.0560)
November	0.282***	0.220***	0.201***
	(0.00571)	(0.0110)	(0.0590)
December	0.181***	0.166***	0.0639
	(0.00581)	(0.0106)	(0.0574)
Monday	0.333***	0.201***	-0.210***
	(0.00422)	(0.00847)	(0.0425)
Tuesday	0.332***	0.191***	-0.183***
	(0.00420)	(0.00842)	(0.0419)
Wednesday	0.333***	0.191***	-0.158***
	(0.00421)	(0.00836)	(0.0418)
Thursday	0.345***	0.207***	-0.184***
	(0.00416)	(0.00826)	(0.0418)
Friday	0.506***	0.391***	0.00302
	(0.00417)	(0.00818)	(0.0400)
Saturday	0.219***	0.198***	0.0982**
	(0.00428)	(0.00853)	(0.0390)
Rain After 3 or more Dry Days	0.0516***	0.0456***	-0.0501
	(0.00382)	(0.00716)	(0.0405)
Snow or Ice Conditions	0.0707***	-0.0325**	-0.233***
	(0.00936)	(0.0137)	(0.0749)
Precipitation (inches)	0.0648***	0.0401***	0.0139
	(0.00311)	(0.00572)	(0.0317)
Wind Event = 1	0.153***	0.0855*	0.301
	(0.0223)	(0.0476)	(0.218)
Thunderstorm Wind Event = 1	0.100***	0.0953***	-0.150
	(0.00873)	(0.0187)	(0.106)
Precipitation Modifier, Wind Event	-0.111***	-0.103**	-0.170
	(0.0216)	(0.0475)	(0.169)
Precipitation Modifier, Thunderstorm Wind Event	0.0233	-0.0335	0.257
	(0.0191)	(0.0316)	(0.162)
No Storm, Cone or Spillover	0.0180*	-0.00379	-0.108
	(0.00963)	(0.0186)	(0.101)
No Storm, Cone or Spillover, Line Effect	0.0378	0.139**	0.0529
	(0.0400)	(0.0613)	(0.382)
Storm, No Cone or Spillover	-0.285***	-0.401***	-0.0645
	(0.0599)	(0.0858)	(0.350)
Storm, Cone or Spillover	0.00804	-0.0751	0.223
	(0.0651)	(0.0777)	(0.331)
Storm, Cone or Spillover, Line Effect	0.158	0.185	-0.0681
	(0.150)	(0.271)	(1.147)
Flood Event	0.114***	0.0647**	0.138
	(0.0150)	(0.0263)	(0.134)
Winter Event	0.574***	0.344***	-0.0655
	(0.0188)	(0.0233)	(0.127)
Any Event, 1-3 Day Lag	-0.0517***	-0.0575***	-0.0716*
	(0.00435)	(0.00814)	(0.0434)
Any Event, 4-7 Day Lag	-0.00737**	-0.0240***	-0.0565
	(0.00344)	(0.00699)	(0.0372)

Holiday	-0.0900***	-0.0322***	0.0669
	(0.00524)	(0.00964)	(0.0455)
Daylight Savings Time week	0.0358***	0.0488***	-0.0656
	(0.00574)	(0.0125)	(0.0655)
Very Hot Day (95th percentile)	0.0199***	0.0233	-0.154**
	(0.00665)	(0.0144)	(0.0751)
Sum of Very Hot Days (3 to 1 days ago)	-0.0121***	-0.00872*	0.0473*
	(0.00230)	(0.00493)	(0.0243)
lnalpha	-2.913***	-0.874***	0.870***
	(0.0166)	(0.00940)	(0.0537)
Constant	-10.14***	-10.80***	-15.05***
	(0.00968)	(0.0186)	(0.109)
Observations	255,600	255,600	255,600

Stata Prompt and Results for All Factor Forecast Regression #1

```
nbreg Crashes i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce Cone Line SpOver
FloodEv WindEv TStormEv StormEv WinterEv FlEvLag123 FlEvLag4567 WiEvLag123
WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567 WntEvLag123
WntEvLag4567 Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Fore1C
outreg2 using Fore1, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce Cone Line SpOver
FloodEv WindEv TStormEv StormEv WinterEv FlEvLag123 FlEvLag4567 WiEvLag123
WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567 WntEvLag123
WntEvLag4567 Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Fore1I
outreg2 using Fore1, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce Cone Line SpOver
FloodEv WindEv TStormEv StormEv WinterEv FlEvLag123 FlEvLag4567 WiEvLag123
WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567 WntEvLag123
WntEvLag4567 Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Fore1K
outreg2 using Fore1, word append ctitle(Fatalities, NB) label
```

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.533***	-0.617***	0.212
	(0.0185)	(0.0387)	(0.198)
Alleghany	-0.346***	-0.429***	0.409
	(0.0310)	(0.0615)	(0.291)
Anson	0.189***	0.310***	0.582***
	(0.0174)	(0.0344)	(0.199)
Ashe	-0.337***	-0.469***	0.326
	(0.0207)	(0.0416)	(0.213)
Avery	-0.327***	-0.438***	-0.134
	(0.0240)	(0.0483)	(0.303)
Beaufort	-0.115***	-0.165***	0.395**
	(0.0150)	(0.0325)	(0.170)
Bertie	-0.0739***	0.0666	1.238***
	(0.0213)	(0.0413)	(0.181)
Bladen	0.145***	0.207***	1.158***
	(0.0159)	(0.0337)	(0.165)
Brunswick	-0.148***	-0.278***	0.292**

	(0.0114)	(0.0227)	(0.135)
Buncombe	0.137***	-0.103***	0.0877
	(0.00985)	(0.0183)	(0.117)
Burke	-0.0828***	-0.0725***	0.392***
	(0.0129)	(0.0245)	(0.141)
Cabarrus	0.0820***	0.00862	-0.130
	(0.0101)	(0.0193)	(0.128)
Caldwell	-0.149***	-0.134***	0.0924
	(0.0128)	(0.0247)	(0.161)
Camden	-0.341***	-0.638***	0.404
	(0.0307)	(0.0653)	(0.365)
Carteret	-0.230***	-0.369***	-0.141
	(0.0141)	(0.0273)	(0.182)
Caswell	-0.273***	-0.330***	0.806***
	(0.0207)	(0.0406)	(0.187)
Catawba	0.170***	0.0376*	0.126
	(0.0104)	(0.0197)	(0.129)
Chatham	-0.188***	-0.494***	0.473***
	(0.0148)	(0.0279)	(0.152)
Cherokee	-0.418***	-0.468***	0.680***
	(0.0203)	(0.0396)	(0.187)
Chowan	-0.370***	-0.572***	0.415
	(0.0273)	(0.0591)	(0.272)
Clay	-0.356***	-0.568***	0.401
	(0.0315)	(0.0636)	(0.312)
Cleveland	0.0936***	0.00298	0.569***
	(0.0118)	(0.0227)	(0.133)
Columbus	0.254***	0.413***	1.204***
	(0.0128)	(0.0263)	(0.129)
Craven	-0.169***	-0.201***	0.177
	(0.0119)	(0.0232)	(0.142)
Cumberland	0.0168*	0.0412**	0.206*
	(0.00991)	(0.0179)	(0.112)
Currituck	-0.471***	-0.556***	0.451**
	(0.0221)	(0.0461)	(0.218)
Dare	-0.0675***	-0.159***	-0.0123
	(0.0194)	(0.0347)	(0.216)
Davidson	-0.141***	-0.120***	0.406***
	(0.0107)	(0.0207)	(0.121)
Davie	-0.201***	-0.168***	0.372**
	(0.0181)	(0.0326)	(0.187)
Duplin	0.250***	0.0657**	0.900***
	(0.0134)	(0.0289)	(0.149)
Durham	0.273***	0.0693***	-0.190
	(0.00947)	(0.0177)	(0.118)
Edgecombe	-0.000558	0.0977***	0.564***
	(0.0143)	(0.0274)	(0.162)
Forsyth	0.0835***	-0.0340*	-0.110
	(0.00998)	(0.0179)	(0.115)
Franklin	-0.266***	-0.232***	0.440***
	(0.0141)	(0.0270)	(0.148)
Gaston	0.0874***	0.136***	0.156
	(0.0100)	(0.0186)	(0.119)
Gates	-0.229***	-0.174***	0.962***
	(0.0279)	(0.0579)	(0.244)
Graham	-0.202***	0.129**	1.449***
	(0.0319)	(0.0508)	(0.227)
Granville	-0.219***	-0.148***	0.703***
	(0.0148)	(0.0270)	(0.145)
Greene	-0.0603***	-0.173***	0.374
	(0.0203)	(0.0430)	(0.239)
Guilford	0.0973***	0.277***	0.00661
	(0.00923)	(0.0165)	(0.107)
Halifax	0.143***	0.216***	0.757***
	(0.0138)	(0.0295)	(0.152)
Harnett	-0.297***	-0.241***	0.636***
	(0.0117)	(0.0223)	(0.122)
Haywood	-0.276***	-0.210***	0.370**
	(0.0153)	(0.0273)	(0.161)
Henderson	-0.107***	-0.339***	-0.0388

	(0.0121)	(0.0236)	(0.146)
Hertford	-0.202***	0.0965**	0.497**
	(0.0201)	(0.0415)	(0.204)
Hoke	-0.368***	-0.121***	0.667***
	(0.0158)	(0.0299)	(0.159)
Hyde	-0.322***	-0.958***	-0.0163
	(0.0424)	(0.104)	(0.507)
Iredell	-0.0167	0.0321	0.186
	(0.0108)	(0.0197)	(0.122)
Jackson	-0.254***	-0.352***	0.448**
	(0.0176)	(0.0318)	(0.182)
Johnston	-0.0704***	-0.0553***	0.379***
	(0.0107)	(0.0198)	(0.120)
Jones	0.364***	0.130***	0.729***
	(0.0227)	(0.0500)	(0.281)
Lee	0.0279**	-0.0368	0.626***
	(0.0135)	(0.0284)	(0.152)
Lenoir	0.0567***	0.215***	0.537***
	(0.0138)	(0.0255)	(0.149)
Lincoln	-0.225***	-0.313***	0.327**
	(0.0141)	(0.0266)	(0.145)
Macon	-0.191***	-0.262***	0.559***
	(0.0169)	(0.0327)	(0.174)
Madison	-0.518***	-0.842***	0.489**
	(0.0238)	(0.0488)	(0.220)
Martin	0.111***	0.0500	0.529**
	(0.0195)	(0.0369)	(0.207)
McDowell	0.0150	-0.212***	0.370**
	(0.0150)	(0.0300)	(0.182)
Mecklenburg	0.307***	0.430***	-0.259**
	(0.00855)	(0.0157)	(0.102)
Mitchell	-0.472***	-0.268***	-0.266
	(0.0262)	(0.0478)	(0.411)
Montgomery	-0.0242	-0.290***	0.935***
	(0.0181)	(0.0368)	(0.177)
Moore	-0.103***	-0.248***	0.453***
	(0.0125)	(0.0244)	(0.138)
Nash	0.0577***	0.162***	0.825***
	(0.0122)	(0.0230)	(0.127)
New Hanover	0.0730***	-0.0383**	-0.205
	(0.00998)	(0.0188)	(0.127)
Northampton	-0.00710	-0.0167	1.186***
	(0.0212)	(0.0424)	(0.177)
Onslow	-0.181***	-0.268***	-0.0293
	(0.0104)	(0.0201)	(0.128)
Orange	-0.219***	-0.358***	-0.309**
	(0.0117)	(0.0224)	(0.151)
Pamlico	-0.481***	-0.707***	0.333
	(0.0291)	(0.0629)	(0.282)
Pasquotank	-0.160***	-0.286***	-0.279
	(0.0160)	(0.0331)	(0.231)
Pender	0.0727***	-0.0209	1.034***
	(0.0134)	(0.0294)	(0.134)
Perquimans	-0.398***	-0.551***	0.420
	(0.0281)	(0.0614)	(0.307)
Person	-0.0636***	-0.179***	0.240
	(0.0164)	(0.0320)	(0.191)
Pitt	0.276***	0.321***	0.114
	(0.0102)	(0.0191)	(0.127)
Polk	-0.196***	-0.337***	0.470*
	(0.0215)	(0.0435)	(0.241)
Randolph	-0.0530***	-0.114***	0.415***
	(0.0114)	(0.0208)	(0.123)
Richmond	0.0145	0.243***	0.690***
	(0.0153)	(0.0283)	(0.170)
Robeson	0.174***	0.428***	1.139***
	(0.0109)	(0.0200)	(0.114)
Rockingham	-0.0888***	-0.227***	0.263*
	(0.0122)	(0.0241)	(0.142)
Rowan	-0.0322***	-0.0313	0.268**

	(0.0110)	(0.0205)	(0.133)
Rutherford	-0.206***	-0.202***	0.288*
	(0.0139)	(0.0263)	(0.156)
Sampson	0.116***	0.153***	0.916***
	(0.0132)	(0.0251)	(0.137)
Scotland	-0.121***	0.242***	0.716***
	(0.0167)	(0.0310)	(0.172)
Stanly	-0.119***	-0.262***	0.341**
	(0.0138)	(0.0286)	(0.165)
Stokes	-0.229***	-0.390***	0.413**
	(0.0164)	(0.0317)	(0.176)
Surry	-0.135***	-0.0438*	0.576***
	(0.0135)	(0.0254)	(0.142)
Swain	-0.534***	-0.595***	0.345
	(0.0274)	(0.0554)	(0.266)
Transylvania	-0.396***	-0.517***	0.182
	(0.0191)	(0.0376)	(0.225)
Tyrrell	0.239***	-0.468***	-0.446
	(0.0371)	(0.106)	(1.004)
Union	-0.0600***	-0.178***	-0.105
	(0.00986)	(0.0194)	(0.128)
Vance	0.230***	0.374***	0.666***
	(0.0142)	(0.0276)	(0.156)
Wake	0.144***	-0.0292*	-0.544***
	(0.00901)	(0.0162)	(0.105)
Warren	-0.0853***	-0.0469	0.872***
	(0.0218)	(0.0449)	(0.230)
Washington	-0.181***	-0.361***	0.335
	(0.0270)	(0.0558)	(0.292)
Watauga	-0.0152	-0.330***	-0.0926
	(0.0148)	(0.0292)	(0.208)
Wayne	0.00455	0.0992***	0.369***
	(0.0111)	(0.0213)	(0.131)
Wilkes	-0.253***	-0.178***	0.327**
	(0.0140)	(0.0259)	(0.155)
Wilson	0.110***	0.123***	0.465***
	(0.0127)	(0.0243)	(0.145)
Yadkin	-0.220***	-0.362***	0.481***
	(0.0183)	(0.0348)	(0.178)
Yancey	-0.595***	-0.590***	0.404
	(0.0259)	(0.0521)	(0.246)
2014	0.00384	0.00555	-0.000743
	(0.00426)	(0.00807)	(0.0432)
2015	0.0974***	0.0950***	0.0667
	(0.00411)	(0.00801)	(0.0429)
2016	0.149***	0.136***	0.0949**
	(0.00413)	(0.00799)	(0.0423)
2017	0.172***	0.117***	0.0550
	(0.00398)	(0.00793)	(0.0425)
2018	0.180***	0.0785***	0.0936**
	(0.00404)	(0.00793)	(0.0426)
2019	0.189***	0.0715***	0.104**
	(0.00396)	(0.00793)	(0.0421)
February	-0.00375	0.0490***	-0.0392
	(0.00621)	(0.0112)	(0.0595)
March	-0.00296	0.0905***	0.00665
	(0.00588)	(0.0109)	(0.0603)
April	0.0258***	0.164***	0.0664
	(0.00567)	(0.0107)	(0.0587)
May	0.0739***	0.223***	0.151***
	(0.00562)	(0.0108)	(0.0580)
June	0.0520***	0.213***	0.201***
	(0.00576)	(0.0111)	(0.0592)
July	0.00308	0.159***	0.0624
	(0.00620)	(0.0119)	(0.0644)
August	0.0435***	0.206***	0.0928
	(0.00573)	(0.0110)	(0.0594)
September	0.0750***	0.212***	0.229***
	(0.00577)	(0.0108)	(0.0582)
October	0.231***	0.284***	0.251***

	(0.00555)	(0.0106)	(0.0568)
November	0.282***	0.216***	0.205***
	(0.00578)	(0.0110)	(0.0593)
December	0.181***	0.164***	0.0660
	(0.00583)	(0.0106)	(0.0576)
Monday	0.333***	0.201***	-0.208***
	(0.00422)	(0.00846)	(0.0425)
Tuesday	0.332***	0.192***	-0.181***
	(0.00420)	(0.00842)	(0.0419)
Wednesday	0.333***	0.192***	-0.154***
	(0.00421)	(0.00836)	(0.0418)
Thursday	0.345***	0.208***	-0.178***
	(0.00416)	(0.00827)	(0.0418)
Friday	0.506***	0.392***	0.00861
	(0.00417)	(0.00819)	(0.0400)
Saturday	0.219***	0.198***	0.102***
	(0.00428)	(0.00853)	(0.0390)
Precipitation (inches)	0.0631***	0.0365***	0.00370
	(0.00315)	(0.00568)	(0.0308)
Rain After 3 or more Dry Days	0.0514***	0.0455***	-0.0470
	(0.00383)	(0.00716)	(0.0405)
Snow or Ice Conditions	0.0782***	-0.0147	-0.187**
	(0.00967)	(0.0141)	(0.0775)
Cone, Any Arrival Timing	0.0180*	0.00305	-0.0558
	(0.0109)	(0.0204)	(0.111)
Forecast Line over County	0.0456	0.165**	0.0779
	(0.0414)	(0.0659)	(0.378)
Spillover, Any Arrival Time	0.0367*	0.0107	-0.224
	(0.0217)	(0.0394)	(0.196)
Flood Event	0.119***	0.0659**	0.126
	(0.0152)	(0.0267)	(0.138)
Wind Event	0.0805***	0.0189	0.172
	(0.0206)	(0.0418)	(0.203)
Thunderstorm Wind Event	0.106***	0.0873***	-0.0810
	(0.00789)	(0.0170)	(0.0978)
Storm Event (Tropical Cyclone)	-0.0810*	-0.192***	0.118
	(0.0446)	(0.0612)	(0.247)
Winter Event	0.581***	0.362***	-0.00838
	(0.0191)	(0.0235)	(0.130)
Flood Event, 1-3 Day Lag	-0.0544***	-0.0629***	0.0715
	(0.00919)	(0.0183)	(0.0895)
Flood Event, 4-7 Day Lag	-0.0172**	0.00244	-0.346***
	(0.00712)	(0.0156)	(0.0903)
Wind Event, 1-3 Day Lag	-0.0347***	-0.0199	0.124
	(0.0133)	(0.0263)	(0.130)
Wind Event, 4-7 Day Lag	-0.0201*	-0.00818	-0.00104
	(0.0107)	(0.0222)	(0.121)
Thunderstorm Wind Event, 1-3 Day Lag	-0.0224***	-0.0126	-0.0439
	(0.00507)	(0.0109)	(0.0567)
Thunderstorm Wind Event, 4-7 Day Lag	-0.00830*	-0.0281***	0.0107
	(0.00448)	(0.00966)	(0.0508)
Storm Event (Tropical Cyclone), 1-3 Day Lag	-0.176***	-0.0983**	-0.0556
	(0.0232)	(0.0423)	(0.176)
Storm Event (Tropical Cyclone), 4-7 Day Lag	-0.0250*	-0.0474	-0.265
	(0.0143)	(0.0313)	(0.190)
Winter Event, 1-3 Day Lag	-0.0817***	-0.135***	-0.300***
	(0.0104)	(0.0166)	(0.107)
Winter Event, 4-7 Day Lag	0.0106	-0.0270**	0.0646
	(0.00725)	(0.0135)	(0.0694)
Holiday	-0.0896***	-0.0327***	0.0670
	(0.00523)	(0.00964)	(0.0455)
Daylight Savings Time week	0.0358***	0.0495***	-0.0652
	(0.00575)	(0.0125)	(0.0655)
Very Hot Day (95th percentile)	0.0213***	0.0263*	-0.151**
	(0.00664)	(0.0144)	(0.0751)
Sum of Very Hot Days (3 to 1 days ago)	-0.0135***	-0.0103**	0.0438*
	(0.00230)	(0.00495)	(0.0244)
lnalpha	-2.915***	-0.874***	0.868***
	(0.0165)	(0.00940)	(0.0537)
Constant	-10.14***	-10.80***	-15.06***

	(0.00972)	(0.0187)	(0.110)
Observations	255,600	255,600	255,600

Stata Prompt and Results for All Factor Forecast Regression #2

```
nbreg Crashes i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce Cone01 Cone234
Line SpOver01 SpOver234 FloodEv WindEv TStormEv StormEv WinterEv FlEvLag123
FlEvLag4567 WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123
StEvLag4567 WntEvLag123 WntEvLag4567 Holiday DST Vhot c.VhotSum,
exposure(YearPop) vce(robust)
estimates store Fore2C
outreg2 using Fore2, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce Cone01 Cone234
Line SpOver01 SpOver234 FloodEv WindEv TStormEv StormEv WinterEv FlEvLag123
FlEvLag4567 WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123
StEvLag4567 WntEvLag123 WntEvLag4567 Holiday DST Vhot c.VhotSum,
exposure(YearPop) vce(robust)
estimates store Fore2I
outreg2 using Fore2, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW c.Precip Ppt3day SnowIce Cone01 Cone234
Line SpOver01 SpOver234 FloodEv WindEv TStormEv StormEv WinterEv FlEvLag123
FlEvLag4567 WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123
StEvLag4567 WntEvLag123 WntEvLag4567 Holiday DST Vhot c.VhotSum,
exposure(YearPop) vce(robust)
estimates store Fore2K
outreg2 using Fore2, word append ctitle(Fatalities, NB) label
```

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.533***	-0.617***	0.211
	(0.0185)	(0.0387)	(0.198)
Alleghany	-0.346***	-0.429***	0.409
	(0.0310)	(0.0615)	(0.291)
Anson	0.189***	0.309***	0.582***
	(0.0174)	(0.0344)	(0.199)
Ashe	-0.337***	-0.469***	0.326
	(0.0207)	(0.0416)	(0.213)
Avery	-0.327***	-0.438***	-0.134
	(0.0240)	(0.0483)	(0.303)
Beaufort	-0.115***	-0.166***	0.394**
	(0.0150)	(0.0325)	(0.170)
Bertie	-0.0740***	0.0667	1.237***
	(0.0213)	(0.0413)	(0.181)
Bladen	0.144***	0.207***	1.157***
	(0.0159)	(0.0337)	(0.165)
Brunswick	-0.149***	-0.278***	0.293**
	(0.0114)	(0.0227)	(0.135)
Buncombe	0.137***	-0.104***	0.0879
	(0.00986)	(0.0183)	(0.117)
Burke	-0.0826***	-0.0724***	0.392***
	(0.0128)	(0.0245)	(0.141)
Cabarrus	0.0819***	0.00854	-0.130
	(0.0101)	(0.0193)	(0.128)

Caldwell	-0.149***	-0.134***	0.0923
	(0.0128)	(0.0247)	(0.161)
Camden	-0.342***	-0.638***	0.405
	(0.0307)	(0.0653)	(0.365)
Carteret	-0.230***	-0.369***	-0.142
	(0.0141)	(0.0273)	(0.182)
Caswell	-0.273***	-0.330***	0.806***
	(0.0207)	(0.0406)	(0.187)
Catawba	0.170***	0.0378*	0.126
	(0.0104)	(0.0197)	(0.129)
Chatham	-0.188***	-0.494***	0.473***
	(0.0148)	(0.0279)	(0.152)
Cherokee	-0.418***	-0.468***	0.679***
	(0.0203)	(0.0396)	(0.187)
Chowan	-0.370***	-0.573***	0.415
	(0.0273)	(0.0591)	(0.272)
Clay	-0.356***	-0.568***	0.401
	(0.0315)	(0.0636)	(0.312)
Cleveland	0.0937***	0.00308	0.569***
	(0.0118)	(0.0227)	(0.133)
Columbus	0.253***	0.412***	1.205***
	(0.0128)	(0.0263)	(0.129)
Craven	-0.169***	-0.201***	0.177
	(0.0119)	(0.0232)	(0.142)
Cumberland	0.0164*	0.0410**	0.207*
	(0.00991)	(0.0179)	(0.112)
Currituck	-0.471***	-0.556***	0.451**
	(0.0221)	(0.0461)	(0.218)
Dare	-0.0678***	-0.159***	-0.0117
	(0.0194)	(0.0347)	(0.216)
Davidson	-0.141***	-0.120***	0.406***
	(0.0107)	(0.0207)	(0.121)
Davie	-0.201***	-0.168***	0.372**
	(0.0181)	(0.0326)	(0.187)
Duplin	0.250***	0.0658**	0.899***
	(0.0134)	(0.0289)	(0.149)
Durham	0.273***	0.0693***	-0.190
	(0.00947)	(0.0177)	(0.118)
Edgecombe	-0.000532	0.0978***	0.563***
	(0.0143)	(0.0274)	(0.162)
Forsyth	0.0836***	-0.0338*	-0.111
	(0.00998)	(0.0179)	(0.115)
Franklin	-0.266***	-0.232***	0.439***
	(0.0141)	(0.0270)	(0.148)
Gaston	0.0873***	0.136***	0.156
	(0.01000)	(0.0186)	(0.119)
Gates	-0.229***	-0.174***	0.962***
	(0.0279)	(0.0579)	(0.244)
Graham	-0.203***	0.129**	1.449***
	(0.0319)	(0.0508)	(0.227)
Granville	-0.219***	-0.148***	0.703***
	(0.0148)	(0.0270)	(0.145)
Greene	-0.0603***	-0.173***	0.373
	(0.0203)	(0.0430)	(0.239)
Guilford	0.0971***	0.277***	0.00659
	(0.00922)	(0.0165)	(0.107)
Halifax	0.143***	0.216***	0.757***
	(0.0138)	(0.0295)	(0.152)
Harnett	-0.297***	-0.241***	0.636***
	(0.0117)	(0.0223)	(0.122)
Haywood	-0.276***	-0.210***	0.370**
	(0.0153)	(0.0273)	(0.161)
Henderson	-0.107***	-0.339***	-0.0390
	(0.0121)	(0.0236)	(0.146)
Hertford	-0.202***	0.0966**	0.496**
	(0.0201)	(0.0415)	(0.204)
Hoke	-0.368***	-0.121***	0.667***
	(0.0158)	(0.0299)	(0.159)
Hyde	-0.322***	-0.958***	-0.0164
	(0.0424)	(0.104)	(0.507)

Iredell	-0.0167	0.0323	0.185
	(0.0108)	(0.0197)	(0.122)
Jackson	-0.254***	-0.352***	0.448**
	(0.0176)	(0.0318)	(0.182)
Johnston	-0.0705***	-0.0553***	0.379***
	(0.0107)	(0.0198)	(0.120)
Jones	0.363***	0.129***	0.729***
	(0.0227)	(0.0500)	(0.281)
Lee	0.0279**	-0.0367	0.626***
	(0.0135)	(0.0284)	(0.152)
Lenoir	0.0564***	0.215***	0.537***
	(0.0138)	(0.0255)	(0.149)
Lincoln	-0.225***	-0.313***	0.327**
	(0.0141)	(0.0266)	(0.145)
Macon	-0.191***	-0.262***	0.559***
	(0.0169)	(0.0327)	(0.174)
Madison	-0.519***	-0.842***	0.489**
	(0.0238)	(0.0488)	(0.220)
Martin	0.111***	0.0500	0.528**
	(0.0195)	(0.0369)	(0.207)
McDowell	0.0149	-0.212***	0.369**
	(0.0150)	(0.0300)	(0.182)
Mecklenburg	0.307***	0.430***	-0.259**
	(0.00854)	(0.0157)	(0.102)
Mitchell	-0.472***	-0.268***	-0.266
	(0.0262)	(0.0478)	(0.411)
Montgomery	-0.0242	-0.290***	0.934***
	(0.0181)	(0.0368)	(0.177)
Moore	-0.103***	-0.247***	0.452***
	(0.0125)	(0.0244)	(0.138)
Nash	0.0577***	0.162***	0.825***
	(0.0121)	(0.0230)	(0.127)
New Hanover	0.0725***	-0.0386**	-0.205
	(0.00998)	(0.0188)	(0.127)
Northampton	-0.00716	-0.0167	1.186***
	(0.0212)	(0.0424)	(0.177)
Onslow	-0.181***	-0.268***	-0.0290
	(0.0104)	(0.0201)	(0.128)
Orange	-0.220***	-0.358***	-0.309**
	(0.0117)	(0.0224)	(0.151)
Pamlico	-0.481***	-0.707***	0.332
	(0.0291)	(0.0629)	(0.282)
Pasquotank	-0.160***	-0.286***	-0.279
	(0.0160)	(0.0330)	(0.231)
Pender	0.0722***	-0.0211	1.034***
	(0.0134)	(0.0294)	(0.134)
Perquimans	-0.399***	-0.551***	0.420
	(0.0281)	(0.0614)	(0.307)
Person	-0.0636***	-0.179***	0.239
	(0.0164)	(0.0320)	(0.191)
Pitt	0.276***	0.321***	0.114
	(0.0102)	(0.0191)	(0.127)
Polk	-0.196***	-0.337***	0.470*
	(0.0215)	(0.0435)	(0.241)
Randolph	-0.0531***	-0.114***	0.415***
	(0.0114)	(0.0208)	(0.123)
Richmond	0.0144	0.243***	0.689***
	(0.0153)	(0.0283)	(0.170)
Robeson	0.174***	0.428***	1.138***
	(0.0109)	(0.0200)	(0.114)
Rockingham	-0.0889***	-0.227***	0.264*
	(0.0122)	(0.0241)	(0.142)
Rowan	-0.0322***	-0.0312	0.268**
	(0.0110)	(0.0205)	(0.133)
Rutherford	-0.206***	-0.202***	0.288*
	(0.0139)	(0.0263)	(0.156)
Sampson	0.116***	0.153***	0.915***
	(0.0132)	(0.0251)	(0.137)
Scotland	-0.121***	0.242***	0.716***
	(0.0167)	(0.0310)	(0.172)

Stanly	-0.119***	-0.262***	0.341**
	(0.0138)	(0.0286)	(0.165)
Stokes	-0.229***	-0.390***	0.412**
	(0.0164)	(0.0317)	(0.176)
Surry	-0.134***	-0.0435*	0.576***
	(0.0135)	(0.0254)	(0.142)
Swain	-0.534***	-0.595***	0.345
	(0.0274)	(0.0554)	(0.266)
Transylvania	-0.396***	-0.517***	0.182
	(0.0191)	(0.0376)	(0.225)
Tyrrell	0.239***	-0.469***	-0.445
	(0.0371)	(0.106)	(1.004)
Union	-0.0600***	-0.178***	-0.105
	(0.00986)	(0.0194)	(0.128)
Vance	0.230***	0.374***	0.666***
	(0.0142)	(0.0276)	(0.156)
Wake	0.145***	-0.0291*	-0.545***
	(0.00901)	(0.0162)	(0.105)
Warren	-0.0852***	-0.0468	0.871***
	(0.0218)	(0.0449)	(0.230)
Washington	-0.181***	-0.361***	0.334
	(0.0270)	(0.0558)	(0.292)
Watauga	-0.0151	-0.330***	-0.0925
	(0.0148)	(0.0292)	(0.208)
Wayne	0.00443	0.0992***	0.368***
	(0.0111)	(0.0213)	(0.131)
Wilkes	-0.253***	-0.178***	0.327**
	(0.0140)	(0.0259)	(0.155)
Wilson	0.110***	0.123***	0.465***
	(0.0127)	(0.0243)	(0.145)
Yadkin	-0.220***	-0.362***	0.480***
	(0.0183)	(0.0348)	(0.178)
Yancey	-0.595***	-0.590***	0.404
	(0.0259)	(0.0521)	(0.246)
2014	0.00385	0.00557	-0.000539
	(0.00426)	(0.00807)	(0.0432)
2015	0.0974***	0.0950***	0.0671
	(0.00411)	(0.00801)	(0.0429)
2016	0.149***	0.136***	0.0944**
	(0.00413)	(0.00799)	(0.0424)
2017	0.172***	0.117***	0.0547
	(0.00398)	(0.00793)	(0.0425)
2018	0.180***	0.0787***	0.0931**
	(0.00404)	(0.00793)	(0.0426)
2019	0.189***	0.0718***	0.103**
	(0.00396)	(0.00793)	(0.0421)
February	-0.00376	0.0490***	-0.0392
	(0.00621)	(0.0112)	(0.0595)
March	-0.00294	0.0905***	0.00661
	(0.00588)	(0.0109)	(0.0603)
April	0.0258***	0.164***	0.0664
	(0.00567)	(0.0107)	(0.0587)
May	0.0736***	0.223***	0.151***
	(0.00562)	(0.0108)	(0.0580)
June	0.0511***	0.213***	0.201***
	(0.00575)	(0.0111)	(0.0592)
July	0.00303	0.159***	0.0620
	(0.00620)	(0.0119)	(0.0644)
August	0.0436***	0.206***	0.0921
	(0.00573)	(0.0110)	(0.0594)
September	0.0764***	0.214***	0.227***
	(0.00577)	(0.0108)	(0.0582)
October	0.232***	0.285***	0.249***
	(0.00555)	(0.0106)	(0.0568)
November	0.282***	0.216***	0.205***
	(0.00578)	(0.0110)	(0.0593)
December	0.181***	0.164***	0.0660
	(0.00583)	(0.0106)	(0.0576)
Monday	0.333***	0.202***	-0.209***
	(0.00422)	(0.00846)	(0.0425)

Tuesday	0.333***	0.192***	-0.181***
	(0.00420)	(0.00843)	(0.0419)
Wednesday	0.333***	0.192***	-0.154***
	(0.00421)	(0.00836)	(0.0418)
Thursday	0.345***	0.208***	-0.179***
	(0.00415)	(0.00827)	(0.0418)
Friday	0.507***	0.392***	0.00811
	(0.00417)	(0.00819)	(0.0400)
Saturday	0.218***	0.198***	0.102***
	(0.00428)	(0.00853)	(0.0390)
Precipitation (inches)	0.0630***	0.0365***	0.00348
	(0.00315)	(0.00568)	(0.0308)
Rain After 3 or more Dry Days	0.0510***	0.0453***	-0.0468
	(0.00383)	(0.00717)	(0.0405)
Snow or Ice Conditions	0.0782***	-0.0147	-0.187**
	(0.00967)	(0.0141)	(0.0775)
Cone, Arrival <48 hours	0.155***	0.111**	-0.224
	(0.0284)	(0.0451)	(0.222)
Cone, Arrival >48 hours	-0.0150	-0.0216	-0.0143
	(0.0111)	(0.0221)	(0.123)
Forecast Line over County	0.0120	0.134**	0.136
	(0.0414)	(0.0649)	(0.370)
Spillover, Arrival <48 hours	0.121***	-0.00732	0.0703
	(0.0382)	(0.0607)	(0.257)
Spillover, Arrival >48 hours	-0.0452**	-0.0282	-0.153
	(0.0218)	(0.0457)	(0.213)
Flood Event	0.118***	0.0654**	0.121
	(0.0151)	(0.0267)	(0.137)
Wind Event	0.0773***	0.0180	0.170
	(0.0208)	(0.0419)	(0.204)
Thunderstorm Wind Event	0.107***	0.0873***	-0.0806
	(0.00788)	(0.0170)	(0.0978)
Storm Event (Tropical Cyclone)	-0.145***	-0.230***	0.122
	(0.0446)	(0.0628)	(0.254)
Winter Event	0.581***	0.362***	-0.00833
	(0.0191)	(0.0235)	(0.130)
Flood Event, 1-3 Day Lag	-0.0539***	-0.0625***	0.0726
	(0.00918)	(0.0183)	(0.0894)
Flood Event, 4-7 Day Lag	-0.0170**	0.00267	-0.346***
	(0.00711)	(0.0156)	(0.0903)
Wind Event, 1-3 Day Lag	-0.0349***	-0.0201	0.124
	(0.0133)	(0.0263)	(0.130)
Wind Event, 4-7 Day Lag	-0.0206*	-0.00864	-0.000153
	(0.0107)	(0.0222)	(0.121)
Thunderstorm Wind Event, 1-3 Day Lag	-0.0223***	-0.0126	-0.0437
	(0.00506)	(0.0109)	(0.0567)
Thunderstorm Wind Event, 4-7 Day Lag	-0.00805*	-0.0280***	0.0107
	(0.00448)	(0.00966)	(0.0508)
Storm Event (Tropical Cyclone), 1-3 Day Lag	-0.168***	-0.0939**	-0.0537
	(0.0230)	(0.0422)	(0.176)
Storm Event (Tropical Cyclone), 4-7 Day Lag	-0.0247*	-0.0474	-0.265
	(0.0143)	(0.0313)	(0.190)
Winter Event, 1-3 Day Lag	-0.0817***	-0.135***	-0.300***
	(0.0104)	(0.0166)	(0.107)
Winter Event, 4-7 Day Lag	0.0106	-0.0270**	0.0646
	(0.00725)	(0.0135)	(0.0694)
Holiday	-0.0897***	-0.0326***	0.0664
	(0.00523)	(0.00964)	(0.0455)
Daylight Savings Time week	0.0358***	0.0494***	-0.0652
	(0.00575)	(0.0125)	(0.0655)
Very Hot Day (95th percentile)	0.0211***	0.0262*	-0.151**
	(0.00664)	(0.0144)	(0.0751)
Sum of Very Hot Days (3 to 1 days ago)	-0.0134***	-0.0103**	0.0439*
	(0.00230)	(0.00495)	(0.0244)
lnalpha	-2.917***	-0.875***	0.868***
	(0.0166)	(0.00940)	(0.0537)
Constant	-10.14***	-10.80***	-15.06***
	(0.00972)	(0.0187)	(0.110)
Observations	255,600	255,600	255,600

Stata Prompt and Results for All Factor Forecast Regression #3

```
nbreg Crashes i.CountyNum i.Year i.MoY i.DoW c.Precip##(WindEv TStormEv)
StormEv#Cone#Line#SpOver Ppt3day SnowIce FloodEv WinterEv FlEvLag123 FlEvLag4567
WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567
WntEvLag123 WntEvLag4567 Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Fore3C
outreg2 using Fore3, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW c.Precip##(WindEv TStormEv)
StormEv#Cone#Line#SpOver Ppt3day SnowIce FloodEv WinterEv FlEvLag123 FlEvLag4567
WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567
WntEvLag123 WntEvLag4567 Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Fore3I
outreg2 using Fore3, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW c.Precip##(WindEv TStormEv)
StormEv#Cone#Line#SpOver Ppt3day SnowIce FloodEv WinterEv FlEvLag123 FlEvLag4567
WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123 StEvLag4567
WntEvLag123 WntEvLag4567 Holiday DST Vhot c.VhotSum, exposure(YearPop) vce(robust)
estimates store Fore3K
outreg2 using Fore3, word append ctitle(Fatalities, NB) label
```

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.533***	-0.617***	0.212
	(0.0185)	(0.0387)	(0.198)
Alleghany	-0.347***	-0.429***	0.408
	(0.0310)	(0.0615)	(0.291)
Anson	0.189***	0.310***	0.582***
	(0.0174)	(0.0343)	(0.199)
Ashe	-0.338***	-0.470***	0.324
	(0.0207)	(0.0416)	(0.213)
Avery	-0.328***	-0.438***	-0.134
	(0.0240)	(0.0483)	(0.303)
Beaufort	-0.115***	-0.166***	0.394**
	(0.0150)	(0.0324)	(0.170)
Bertie	-0.0735***	0.0669	1.237***
	(0.0213)	(0.0413)	(0.181)
Bladen	0.146***	0.208***	1.155***
	(0.0159)	(0.0337)	(0.165)
Brunswick	-0.148***	-0.278***	0.293**
	(0.0114)	(0.0227)	(0.135)
Buncombe	0.137***	-0.103***	0.0866
	(0.00985)	(0.0183)	(0.117)
Burke	-0.0830***	-0.0726***	0.390***
	(0.0128)	(0.0245)	(0.140)
Cabarrus	0.0819***	0.00865	-0.131
	(0.0101)	(0.0193)	(0.128)
Caldwell	-0.149***	-0.134***	0.0921
	(0.0128)	(0.0247)	(0.161)
Camden	-0.341***	-0.638***	0.405
	(0.0307)	(0.0653)	(0.365)
Carteret	-0.230***	-0.369***	-0.143
	(0.0141)	(0.0273)	(0.182)
Caswell	-0.273***	-0.330***	0.806***

	(0.0207)	(0.0406)	(0.187)
Catawba	0.170***	0.0377*	0.127
	(0.0104)	(0.0197)	(0.129)
Chatham	-0.188***	-0.494***	0.473***
	(0.0148)	(0.0279)	(0.152)
Cherokee	-0.418***	-0.468***	0.679***
	(0.0203)	(0.0396)	(0.187)
Chowan	-0.369***	-0.572***	0.415
	(0.0273)	(0.0591)	(0.272)
Clay	-0.356***	-0.568***	0.401
	(0.0315)	(0.0636)	(0.312)
Cleveland	0.0936***	0.00319	0.568***
	(0.0118)	(0.0227)	(0.133)
Columbus	0.255***	0.414***	1.205***
	(0.0128)	(0.0263)	(0.129)
Craven	-0.169***	-0.201***	0.175
	(0.0119)	(0.0232)	(0.142)
Cumberland	0.0167*	0.0412**	0.206*
	(0.00991)	(0.0179)	(0.112)
Currituck	-0.471***	-0.556***	0.450**
	(0.0221)	(0.0461)	(0.218)
Dare	-0.0677***	-0.159***	-0.0121
	(0.0194)	(0.0346)	(0.216)
Davidson	-0.141***	-0.120***	0.405***
	(0.0107)	(0.0207)	(0.121)
Davie	-0.201***	-0.168***	0.371**
	(0.0181)	(0.0326)	(0.187)
Duplin	0.250***	0.0656**	0.900***
	(0.0134)	(0.0289)	(0.149)
Durham	0.273***	0.0694***	-0.190
	(0.00947)	(0.0177)	(0.118)
Edgecombe	-0.000549	0.0976***	0.564***
	(0.0143)	(0.0274)	(0.162)
Forsyth	0.0834***	-0.0337*	-0.110
	(0.00998)	(0.0179)	(0.115)
Franklin	-0.266***	-0.232***	0.440***
	(0.0141)	(0.0270)	(0.148)
Gaston	0.0874***	0.136***	0.155
	(0.0100)	(0.0186)	(0.119)
Gates	-0.229***	-0.174***	0.961***
	(0.0279)	(0.0579)	(0.244)
Graham	-0.202***	0.129**	1.449***
	(0.0319)	(0.0508)	(0.227)
Granville	-0.219***	-0.148***	0.703***
	(0.0148)	(0.0270)	(0.145)
Greene	-0.0603***	-0.173***	0.374
	(0.0203)	(0.0430)	(0.239)
Guilford	0.0972***	0.277***	0.00524
	(0.00923)	(0.0165)	(0.107)
Halifax	0.143***	0.216***	0.757***
	(0.0138)	(0.0295)	(0.152)
Harnett	-0.297***	-0.240***	0.637***
	(0.0117)	(0.0223)	(0.122)
Haywood	-0.276***	-0.210***	0.369**
	(0.0153)	(0.0273)	(0.161)
Henderson	-0.107***	-0.339***	-0.0395
	(0.0121)	(0.0236)	(0.146)
Hertford	-0.202***	0.0968**	0.496**
	(0.0201)	(0.0415)	(0.204)
Hoke	-0.368***	-0.120***	0.666***
	(0.0158)	(0.0299)	(0.159)
Hyde	-0.322***	-0.958***	-0.0168
	(0.0424)	(0.104)	(0.508)
Iredell	-0.0167	0.0323	0.184
	(0.0108)	(0.0197)	(0.122)
Jackson	-0.254***	-0.352***	0.447**
	(0.0176)	(0.0318)	(0.182)
Johnston	-0.0703***	-0.0550***	0.380***
	(0.0107)	(0.0198)	(0.120)
Jones	0.364***	0.130***	0.729***

	(0.0227)	(0.0500)	(0.281)
Lee	0.0279**	-0.0366	0.626***
	(0.0135)	(0.0284)	(0.152)
Lenoir	0.0568***	0.215***	0.538***
	(0.0138)	(0.0254)	(0.149)
Lincoln	-0.225***	-0.313***	0.327**
	(0.0141)	(0.0266)	(0.145)
Macon	-0.191***	-0.262***	0.558***
	(0.0169)	(0.0327)	(0.174)
Madison	-0.518***	-0.842***	0.489**
	(0.0238)	(0.0488)	(0.220)
Martin	0.111***	0.0501	0.529**
	(0.0195)	(0.0369)	(0.207)
McDowell	0.0146	-0.213***	0.369**
	(0.0150)	(0.0300)	(0.182)
Mecklenburg	0.307***	0.430***	-0.258**
	(0.00854)	(0.0157)	(0.102)
Mitchell	-0.472***	-0.268***	-0.267
	(0.0262)	(0.0478)	(0.411)
Montgomery	-0.0242	-0.290***	0.934***
	(0.0181)	(0.0368)	(0.177)
Moore	-0.103***	-0.247***	0.453***
	(0.0125)	(0.0244)	(0.138)
Nash	0.0576***	0.162***	0.824***
	(0.0121)	(0.0230)	(0.127)
New Hanover	0.0731***	-0.0384**	-0.204
	(0.00997)	(0.0188)	(0.127)
Northampton	-0.00712	-0.0165	1.185***
	(0.0212)	(0.0424)	(0.177)
Onslow	-0.181***	-0.269***	-0.0281
	(0.0104)	(0.0201)	(0.128)
Orange	-0.219***	-0.358***	-0.309**
	(0.0117)	(0.0224)	(0.151)
Pamlico	-0.481***	-0.707***	0.332
	(0.0291)	(0.0629)	(0.282)
Pasquotank	-0.160***	-0.285***	-0.279
	(0.0160)	(0.0330)	(0.231)
Pender	0.0726***	-0.0211	1.035***
	(0.0134)	(0.0294)	(0.134)
Perquimans	-0.398***	-0.550***	0.420
	(0.0281)	(0.0615)	(0.307)
Person	-0.0637***	-0.179***	0.239
	(0.0164)	(0.0320)	(0.191)
Pitt	0.276***	0.321***	0.115
	(0.0102)	(0.0191)	(0.127)
Polk	-0.196***	-0.337***	0.470*
	(0.0215)	(0.0435)	(0.241)
Randolph	-0.0530***	-0.113***	0.415***
	(0.0114)	(0.0208)	(0.123)
Richmond	0.0144	0.243***	0.690***
	(0.0153)	(0.0283)	(0.170)
Robeson	0.175***	0.429***	1.140***
	(0.0109)	(0.0200)	(0.114)
Rockingham	-0.0889***	-0.227***	0.263*
	(0.0122)	(0.0241)	(0.142)
Rowan	-0.0321***	-0.0311	0.267**
	(0.0110)	(0.0205)	(0.133)
Rutherford	-0.206***	-0.202***	0.288*
	(0.0139)	(0.0263)	(0.156)
Sampson	0.116***	0.153***	0.915***
	(0.0132)	(0.0250)	(0.137)
Scotland	-0.121***	0.242***	0.715***
	(0.0167)	(0.0310)	(0.172)
Stanly	-0.119***	-0.262***	0.341**
	(0.0138)	(0.0286)	(0.165)
Stokes	-0.229***	-0.390***	0.413**
	(0.0164)	(0.0317)	(0.176)
Surry	-0.135***	-0.0437*	0.576***
	(0.0135)	(0.0253)	(0.142)
Swain	-0.534***	-0.595***	0.345

	(0.0274)	(0.0554)	(0.266)
Transylvania	-0.397***	-0.517***	0.181
	(0.0191)	(0.0376)	(0.225)
Tyrrell	0.239***	-0.468***	-0.445
	(0.0371)	(0.106)	(1.004)
Union	-0.0598***	-0.178***	-0.104
	(0.00986)	(0.0194)	(0.128)
Vance	0.230***	0.374***	0.666***
	(0.0142)	(0.0276)	(0.156)
Wake	0.144***	-0.0292*	-0.544***
	(0.00901)	(0.0162)	(0.105)
Warren	-0.0853***	-0.0468	0.872***
	(0.0218)	(0.0449)	(0.230)
Washington	-0.181***	-0.361***	0.334
	(0.0270)	(0.0558)	(0.292)
Watauga	-0.0159	-0.330***	-0.0941
	(0.0148)	(0.0292)	(0.208)
Wayne	0.00473	0.0995***	0.369***
	(0.0111)	(0.0213)	(0.131)
Wilkes	-0.253***	-0.178***	0.327**
	(0.0140)	(0.0259)	(0.155)
Wilson	0.110***	0.123***	0.465***
	(0.0127)	(0.0243)	(0.145)
Yadkin	-0.220***	-0.361***	0.481***
	(0.0183)	(0.0348)	(0.178)
Yancey	-0.595***	-0.590***	0.404
	(0.0259)	(0.0521)	(0.246)
2014	0.00392	0.00566	-0.000810
	(0.00426)	(0.00807)	(0.0432)
2015	0.0975***	0.0951***	0.0666
	(0.00411)	(0.00801)	(0.0429)
2016	0.149***	0.136***	0.0945**
	(0.00413)	(0.00799)	(0.0423)
2017	0.172***	0.117***	0.0549
	(0.00399)	(0.00793)	(0.0425)
2018	0.180***	0.0787***	0.0928**
	(0.00404)	(0.00793)	(0.0426)
2019	0.189***	0.0718***	0.103**
	(0.00396)	(0.00793)	(0.0421)
February	-0.00376	0.0489***	-0.0388
	(0.00621)	(0.0112)	(0.0595)
March	-0.00290	0.0905***	0.00696
	(0.00588)	(0.0109)	(0.0603)
April	0.0255***	0.164***	0.0666
	(0.00567)	(0.0107)	(0.0587)
May	0.0740***	0.223***	0.152***
	(0.00562)	(0.0108)	(0.0580)
June	0.0519***	0.213***	0.203***
	(0.00576)	(0.0111)	(0.0592)
July	0.00301	0.158***	0.0639
	(0.00620)	(0.0119)	(0.0644)
August	0.0435***	0.206***	0.0933
	(0.00573)	(0.0110)	(0.0594)
September	0.0757***	0.213***	0.230***
	(0.00577)	(0.0108)	(0.0582)
October	0.231***	0.285***	0.251***
	(0.00555)	(0.0106)	(0.0568)
November	0.282***	0.216***	0.206***
	(0.00578)	(0.0110)	(0.0593)
December	0.181***	0.164***	0.0666
	(0.00583)	(0.0106)	(0.0576)
Monday	0.333***	0.201***	-0.209***
	(0.00422)	(0.00846)	(0.0425)
Tuesday	0.332***	0.192***	-0.181***
	(0.00420)	(0.00842)	(0.0419)
Wednesday	0.333***	0.192***	-0.155***
	(0.00421)	(0.00836)	(0.0418)
Thursday	0.345***	0.208***	-0.179***
	(0.00416)	(0.00827)	(0.0418)
Friday	0.506***	0.392***	0.00805

	(0.00417)	(0.00819)	(0.0400)
Saturday	0.219***	0.198***	0.101***
	(0.00428)	(0.00853)	(0.0390)
Precipitation (inches)	0.0661***	0.0405***	0.00390
	(0.00311)	(0.00576)	(0.0320)
Wind Event = 1	0.146***	0.0781	0.283
	(0.0221)	(0.0476)	(0.217)
Thunderstorm Wind Event = 1	0.0995***	0.0942***	-0.151
	(0.00868)	(0.0187)	(0.106)
	(0)	(0)	(0)
Precipitation Modifier, Wind Event	-0.105***	-0.0987**	-0.169
	(0.0215)	(0.0479)	(0.162)
	(0)	(0)	(0)
Precipitation Modifier, Thunderstorm Wind Event	0.0234	-0.0354	0.262
	(0.0185)	(0.0315)	(0.162)
	(0)	(0)	(0)
No Storm Event, Next to Cone (Spillover)	0.0333	0.0198	-0.374*
	(0.0208)	(0.0406)	(0.222)
No Storm Event, In Cone	0.0122	-0.00918	-0.0426
	(0.0108)	(0.0207)	(0.112)
No Storm Event, In Cone, Line Effect	0.0353	0.140**	0.0490
	(0.0400)	(0.0613)	(0.382)
Storm Event, Not in Cone, No Spillover	-0.204***	-0.371***	-0.0681
	(0.0606)	(0.0901)	(0.353)
Storm Event, Next to Cone (Spillover)	-0.0225	-0.308**	0.702
	(0.119)	(0.142)	(0.451)
Storm Event, In Cone	0.0395	0.0296	-0.221
	(0.0767)	(0.0915)	(0.488)
Storm Event, In Cone, Line Effect	0.169	0.185	-0.0646
	(0.153)	(0.271)	(1.142)
Rain After 3 or more Dry Days	0.0506***	0.0448***	-0.0482
	(0.00382)	(0.00716)	(0.0405)
Snow or Ice Conditions	0.0785***	-0.0144	-0.187**
	(0.00967)	(0.0141)	(0.0775)
Flood Event	0.125***	0.0729***	0.121
	(0.0151)	(0.0267)	(0.137)
Winter Event	0.581***	0.361***	-0.00790
	(0.0191)	(0.0235)	(0.130)
Flood Event, 1-3 Day Lag	-0.0536***	-0.0618***	0.0746
	(0.00919)	(0.0183)	(0.0891)
Flood Event, 4-7 Day Lag	-0.0171**	0.00244	-0.345***
	(0.00712)	(0.0156)	(0.0903)
Wind Event, 1-3 Day Lag	-0.0341**	-0.0207	0.126
	(0.0132)	(0.0263)	(0.130)
Wind Event, 4-7 Day Lag	-0.0206*	-0.00884	-0.00200
	(0.0107)	(0.0222)	(0.121)
Thunderstorm Wind Event, 1-3 Day Lag	-0.0231***	-0.0130	-0.0462
	(0.00507)	(0.0109)	(0.0567)
Thunderstorm Wind Event, 4-7 Day Lag	-0.00817*	-0.0279***	0.0109
	(0.00449)	(0.00966)	(0.0508)
Storm Event (Tropical Cyclone), 1-3 Day Lag	-0.152***	-0.0698*	-0.0183
	(0.0226)	(0.0424)	(0.172)
Storm Event (Tropical Cyclone), 4-7 Day Lag	-0.0266*	-0.0486	-0.271
	(0.0143)	(0.0312)	(0.191)
Winter Event, 1-3 Day Lag	-0.0819***	-0.135***	-0.300***
	(0.0104)	(0.0166)	(0.107)
Winter Event, 4-7 Day Lag	0.0107	-0.0270**	0.0647
	(0.00725)	(0.0135)	(0.0694)
Holiday	-0.0901***	-0.0327***	0.0660
	(0.00523)	(0.00964)	(0.0455)
Daylight Savings Time week	0.0359***	0.0495***	-0.0650
	(0.00575)	(0.0125)	(0.0655)
Very Hot Day (95th percentile)	0.0217***	0.0261*	-0.149**
	(0.00665)	(0.0145)	(0.0751)
Sum of Very Hot Days (3 to 1 days ago)	-0.0134***	-0.0102**	0.0440*
	(0.00230)	(0.00495)	(0.0244)
lnalpha	-2.917***	-0.875***	0.866***
	(0.0165)	(0.00940)	(0.0538)
Constant	-10.14***	-10.80***	-15.06***
	(0.00972)	(0.0187)	(0.110)

Observations	255,600	255,600	255,600

Stata Prompt and Results for All Factor Forecast Regression #4

```
nbreg Crashes i.CountyNum i.Year i.MoY i.DoW c.Precip##(WindEv TStormEv)
StormEv#Cone01#Cone234#Line#SpOver Ppt3day SnowIce FloodEv WinterEv FlEvLag123
FlEvLag4567 WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123
StEvLag4567 WntEvLag123 WntEvLag4567 Holiday DST Vhot c.VhotSum,
exposure(YearPop) vce(robust)
estimates store Fore4C
outreg2 using Fore4, word replace ctitle(Collisions, NB) label
nbreg Injured i.CountyNum i.Year i.MoY i.DoW c.Precip##(WindEv TStormEv)
StormEv#Cone01#Cone234#Line#SpOver Ppt3day SnowIce FloodEv WinterEv FlEvLag123
FlEvLag4567 WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123
StEvLag4567 WntEvLag123 WntEvLag4567 Holiday DST Vhot c.VhotSum,
exposure(YearPop) vce(robust)
estimates store Fore4I
outreg2 using Fore4, word append ctitle(Injuries, NB) label
nbreg Killed i.CountyNum i.Year i.MoY i.DoW c.Precip##(WindEv TStormEv)
StormEv#Cone01#Cone234#Line#SpOver Ppt3day SnowIce FloodEv WinterEv FlEvLag123
FlEvLag4567 WiEvLag123 WiEvLag4567 TStEvLag123 TStEvLag4567 StEvLag123
StEvLag4567 WntEvLag123 WntEvLag4567 Holiday DST Vhot c.VhotSum,
exposure(YearPop) vce(robust)
estimates store Fore4K
outreg2 using Fore4, word append ctitle(Fatalities, NB) label
```

VARIABLES	(1) Collisions NB	(2) Injuries NB	(3) Fatalities NB
Alexander	-0.533***	-0.617***	0.212
	(0.0185)	(0.0387)	(0.198)
Alleghany	-0.347***	-0.429***	0.408
	(0.0310)	(0.0615)	(0.291)
Anson	0.189***	0.310***	0.582***
	(0.0174)	(0.0343)	(0.199)
Ashe	-0.337***	-0.470***	0.323
	(0.0207)	(0.0416)	(0.213)
Avery	-0.328***	-0.438***	-0.135
	(0.0240)	(0.0483)	(0.303)
Beaufort	-0.115***	-0.166***	0.394**
	(0.0150)	(0.0324)	(0.170)
Bertie	-0.0736***	0.0668	1.238***
	(0.0213)	(0.0413)	(0.181)
Bladen	0.145***	0.207***	1.155***
	(0.0159)	(0.0337)	(0.165)
Brunswick	-0.149***	-0.278***	0.293**
	(0.0114)	(0.0227)	(0.135)
Buncombe	0.137***	-0.103***	0.0864
	(0.00985)	(0.0183)	(0.117)
Burke	-0.0829***	-0.0726***	0.390***
	(0.0128)	(0.0245)	(0.140)
Cabarrus	0.0819***	0.00865	-0.131
	(0.0101)	(0.0193)	(0.128)
Caldwell	-0.149***	-0.134***	0.0917

	(0.0128)	(0.0247)	(0.161)
Camden	-0.341***	-0.638***	0.406
	(0.0307)	(0.0653)	(0.365)
Carteret	-0.229***	-0.369***	-0.143
	(0.0141)	(0.0273)	(0.182)
Caswell	-0.273***	-0.330***	0.806***
	(0.0207)	(0.0406)	(0.187)
Catawba	0.170***	0.0378*	0.126
	(0.0104)	(0.0197)	(0.129)
Chatham	-0.188***	-0.494***	0.474***
	(0.0148)	(0.0279)	(0.152)
Cherokee	-0.418***	-0.468***	0.679***
	(0.0203)	(0.0396)	(0.187)
Chowan	-0.369***	-0.572***	0.415
	(0.0273)	(0.0591)	(0.272)
Clay	-0.356***	-0.568***	0.400
	(0.0315)	(0.0636)	(0.312)
Cleveland	0.0938***	0.00324	0.567***
	(0.0118)	(0.0227)	(0.133)
Columbus	0.254***	0.413***	1.204***
	(0.0128)	(0.0263)	(0.129)
Craven	-0.169***	-0.201***	0.175
	(0.0119)	(0.0232)	(0.142)
Cumberland	0.0165*	0.0411**	0.205*
	(0.00991)	(0.0179)	(0.112)
Currituck	-0.471***	-0.556***	0.451**
	(0.0221)	(0.0461)	(0.218)
Dare	-0.0675***	-0.159***	-0.0122
	(0.0194)	(0.0346)	(0.216)
Davidson	-0.141***	-0.120***	0.405***
	(0.0107)	(0.0207)	(0.121)
Davie	-0.201***	-0.168***	0.371**
	(0.0181)	(0.0326)	(0.187)
Duplin	0.250***	0.0656**	0.900***
	(0.0134)	(0.0289)	(0.149)
Durham	0.273***	0.0694***	-0.191
	(0.00947)	(0.0177)	(0.118)
Edgecombe	-0.000496	0.0976***	0.563***
	(0.0143)	(0.0274)	(0.162)
Forsyth	0.0836***	-0.0337*	-0.111
	(0.00997)	(0.0179)	(0.115)
Franklin	-0.266***	-0.232***	0.439***
	(0.0141)	(0.0270)	(0.148)
Gaston	0.0875***	0.137***	0.155
	(0.01000)	(0.0186)	(0.119)
Gates	-0.229***	-0.174***	0.960***
	(0.0279)	(0.0579)	(0.244)
Graham	-0.202***	0.129**	1.449***
	(0.0319)	(0.0508)	(0.227)
Granville	-0.219***	-0.148***	0.702***
	(0.0148)	(0.0270)	(0.145)
Greene	-0.0603***	-0.173***	0.374
	(0.0203)	(0.0430)	(0.239)
Guilford	0.0972***	0.277***	0.00513
	(0.00922)	(0.0165)	(0.107)
Halifax	0.143***	0.216***	0.757***
	(0.0138)	(0.0295)	(0.152)
Harnett	-0.297***	-0.241***	0.636***
	(0.0117)	(0.0223)	(0.122)
Haywood	-0.276***	-0.210***	0.369**
	(0.0153)	(0.0273)	(0.161)
Henderson	-0.107***	-0.339***	-0.0401
	(0.0121)	(0.0236)	(0.146)
Hertford	-0.202***	0.0968**	0.495**
	(0.0201)	(0.0415)	(0.204)
Hoke	-0.368***	-0.121***	0.666***
	(0.0158)	(0.0299)	(0.159)
Hyde	-0.322***	-0.957***	-0.0167
	(0.0424)	(0.104)	(0.508)
Iredell	-0.0166	0.0324*	0.184

	(0.0108)	(0.0197)	(0.122)
Jackson	-0.254***	-0.352***	0.447**
	(0.0176)	(0.0318)	(0.182)
Johnston	-0.0704***	-0.0551***	0.380***
	(0.0107)	(0.0198)	(0.120)
Jones	0.364***	0.130***	0.728***
	(0.0227)	(0.0500)	(0.281)
Lee	0.0279**	-0.0366	0.626***
	(0.0135)	(0.0284)	(0.152)
Lenoir	0.0567***	0.215***	0.538***
	(0.0138)	(0.0254)	(0.149)
Lincoln	-0.225***	-0.313***	0.327**
	(0.0141)	(0.0266)	(0.145)
Macon	-0.191***	-0.262***	0.558***
	(0.0169)	(0.0327)	(0.174)
Madison	-0.518***	-0.842***	0.489**
	(0.0238)	(0.0488)	(0.220)
Martin	0.111***	0.0501	0.530**
	(0.0195)	(0.0368)	(0.207)
McDowell	0.0147	-0.212***	0.369**
	(0.0150)	(0.0300)	(0.182)
Mecklenburg	0.308***	0.430***	-0.258**
	(0.00854)	(0.0157)	(0.102)
Mitchell	-0.472***	-0.268***	-0.267
	(0.0262)	(0.0478)	(0.411)
Montgomery	-0.0241	-0.290***	0.934***
	(0.0181)	(0.0368)	(0.177)
Moore	-0.103***	-0.247***	0.453***
	(0.0125)	(0.0244)	(0.138)
Nash	0.0576***	0.162***	0.824***
	(0.0121)	(0.0230)	(0.127)
New Hanover	0.0729***	-0.0385**	-0.204
	(0.00997)	(0.0188)	(0.127)
Northampton	-0.00718	-0.0166	1.185***
	(0.0211)	(0.0424)	(0.177)
Onslow	-0.181***	-0.269***	-0.0273
	(0.0104)	(0.0201)	(0.128)
Orange	-0.219***	-0.358***	-0.309**
	(0.0117)	(0.0224)	(0.151)
Pamlico	-0.481***	-0.707***	0.333
	(0.0291)	(0.0629)	(0.282)
Pasquotank	-0.160***	-0.286***	-0.280
	(0.0160)	(0.0330)	(0.231)
Pender	0.0723***	-0.0212	1.035***
	(0.0134)	(0.0294)	(0.134)
Perquimans	-0.398***	-0.550***	0.420
	(0.0281)	(0.0615)	(0.307)
Person	-0.0636***	-0.179***	0.239
	(0.0164)	(0.0320)	(0.191)
Pitt	0.276***	0.321***	0.115
	(0.0102)	(0.0191)	(0.127)
Polk	-0.196***	-0.337***	0.470*
	(0.0215)	(0.0435)	(0.241)
Randolph	-0.0530***	-0.113***	0.416***
	(0.0114)	(0.0208)	(0.123)
Richmond	0.0146	0.243***	0.690***
	(0.0153)	(0.0283)	(0.170)
Robeson	0.174***	0.429***	1.141***
	(0.0109)	(0.0200)	(0.114)
Rockingham	-0.0888***	-0.227***	0.263*
	(0.0122)	(0.0241)	(0.142)
Rowan	-0.0320***	-0.0311	0.267**
	(0.0110)	(0.0205)	(0.133)
Rutherford	-0.206***	-0.202***	0.288*
	(0.0139)	(0.0263)	(0.156)
Sampson	0.116***	0.153***	0.915***
	(0.0132)	(0.0251)	(0.137)
Scotland	-0.121***	0.242***	0.715***
	(0.0167)	(0.0310)	(0.172)
Stanly	-0.119***	-0.262***	0.341**

	(0.0138)	(0.0286)	(0.165)
Stokes	-0.229***	-0.390***	0.412**
	(0.0164)	(0.0317)	(0.176)
Surry	-0.135***	-0.0436*	0.576***
	(0.0135)	(0.0253)	(0.142)
Swain	-0.534***	-0.595***	0.345
	(0.0274)	(0.0554)	(0.266)
Transylvania	-0.397***	-0.517***	0.181
	(0.0191)	(0.0376)	(0.225)
Tyrrell	0.239***	-0.468***	-0.445
	(0.0371)	(0.106)	(1.004)
Union	-0.0598***	-0.178***	-0.104
	(0.00985)	(0.0194)	(0.128)
Vance	0.230***	0.374***	0.666***
	(0.0142)	(0.0276)	(0.156)
Wake	0.144***	-0.0292*	-0.544***
	(0.00901)	(0.0162)	(0.105)
Warren	-0.0853***	-0.0468	0.872***
	(0.0218)	(0.0449)	(0.230)
Washington	-0.181***	-0.361***	0.334
	(0.0270)	(0.0558)	(0.292)
Watauga	-0.0158	-0.330***	-0.0945
	(0.0148)	(0.0292)	(0.208)
Wayne	0.00460	0.0994***	0.369***
	(0.0110)	(0.0213)	(0.131)
Wilkes	-0.253***	-0.178***	0.327**
	(0.0140)	(0.0259)	(0.155)
Wilson	0.110***	0.123***	0.465***
	(0.0127)	(0.0243)	(0.145)
Yadkin	-0.220***	-0.361***	0.480***
	(0.0183)	(0.0348)	(0.178)
Yancey	-0.595***	-0.590***	0.404
	(0.0259)	(0.0521)	(0.246)
2014	0.00397	0.00569	-0.000599
	(0.00426)	(0.00807)	(0.0432)
2015	0.0975***	0.0951***	0.0673
	(0.00411)	(0.00801)	(0.0429)
2016	0.149***	0.136***	0.0946**
	(0.00413)	(0.00799)	(0.0423)
2017	0.172***	0.117***	0.0547
	(0.00398)	(0.00793)	(0.0425)
2018	0.180***	0.0788***	0.0931**
	(0.00404)	(0.00793)	(0.0425)
2019	0.189***	0.0718***	0.103**
	(0.00396)	(0.00793)	(0.0420)
February	-0.00377	0.0489***	-0.0388
	(0.00621)	(0.0112)	(0.0595)
March	-0.00289	0.0905***	0.00691
	(0.00588)	(0.0109)	(0.0603)
April	0.0255***	0.164***	0.0665
	(0.00567)	(0.0107)	(0.0587)
May	0.0738***	0.223***	0.153***
	(0.00562)	(0.0108)	(0.0580)
June	0.0513***	0.213***	0.203***
	(0.00576)	(0.0111)	(0.0592)
July	0.00289	0.158***	0.0640
	(0.00620)	(0.0119)	(0.0644)
August	0.0435***	0.206***	0.0932
	(0.00573)	(0.0110)	(0.0594)
September	0.0762***	0.213***	0.229***
	(0.00577)	(0.0108)	(0.0582)
October	0.231***	0.285***	0.251***
	(0.00555)	(0.0106)	(0.0568)
November	0.282***	0.216***	0.206***
	(0.00578)	(0.0110)	(0.0593)
December	0.181***	0.164***	0.0666
	(0.00583)	(0.0106)	(0.0576)
Monday	0.333***	0.201***	-0.209***
	(0.00422)	(0.00846)	(0.0425)
Tuesday	0.332***	0.192***	-0.182***

	(0.00420)	(0.00843)	(0.0419)
Wednesday	0.333***	0.191***	-0.154***
	(0.00421)	(0.00836)	(0.0418)
Thursday	0.345***	0.207***	-0.180***
	(0.00415)	(0.00827)	(0.0418)
Friday	0.506***	0.392***	0.00797
	(0.00417)	(0.00819)	(0.0400)
Saturday	0.218***	0.198***	0.101***
	(0.00428)	(0.00853)	(0.0390)
Precipitation (inches)	0.0659***	0.0403***	0.00391
	(0.00311)	(0.00576)	(0.0320)
Wind Event = 1	0.145***	0.0773	0.290
	(0.0222)	(0.0476)	(0.218)
Thunderstorm Wind Event = 1	0.0997***	0.0942***	-0.151
	(0.00867)	(0.0187)	(0.106)
0b.WindEv#co.Precip	0	0	0
	(0)	(0)	(0)
1.WindEv#c.Precip	-0.104***	-0.0984**	-0.169
	(0.0217)	(0.0479)	(0.162)
0b.TStormEv#co.Precip	0	0	0
	(0)	(0)	(0)
1.TStormEv#c.Precip	0.0237	-0.0352	0.262
	(0.0185)	(0.0315)	(0.163)
No Storm, Next to Cone (Spillover)	0.0332	0.0198	-0.374*
	(0.0208)	(0.0406)	(0.222)
No Storm, Projected Arrival > 48 hours	-0.00935	-0.0178	0.0209
	(0.0112)	(0.0223)	(0.121)
No Storm, Projected Arrival > 48 hours, Line Effect	-0.00765	0.0782	-0.399
	(0.0450)	(0.0695)	(0.529)
No Storm, Projected Arrival < 48 hours	0.134***	0.0431	-0.442
	(0.0306)	(0.0530)	(0.292)
No Storm, Projected Arrival < 48 hours, Line Effect	0.117	0.240**	0.505
	(0.0770)	(0.111)	(0.490)
No Storm, Projected Arrival Two Storms (2016)	-0.318	-0.411	-15.42***
	(0.256)	(0.421)	(0.421)
Storm, Not in Cone, Not Spillover	-0.203***	-0.370***	-0.0681
	(0.0605)	(0.0900)	(0.353)
Storm, Next to Forecast Cone (Spillover)	-0.0219	-0.308**	0.702
	(0.120)	(0.142)	(0.451)
Storm, Projected Arrival > 48 hours	-0.437***	-0.365*	-16.82***
	(0.158)	(0.221)	(0.455)
Storm, Projected Arrival < 48 hours	0.0590	0.0489	-0.178
	(0.0786)	(0.0946)	(0.489)
Storm, Projected Arrival < 48 hours, Line Effect	0.170	0.186	-0.0650
	(0.153)	(0.271)	(1.142)
Rain After 3 or more Dry Days	0.0505***	0.0448***	-0.0478
	(0.00382)	(0.00716)	(0.0405)
Snow or Ice Conditions	0.0785***	-0.0144	-0.187**
	(0.00967)	(0.0141)	(0.0775)
Flood Event	0.124***	0.0723***	0.122
	(0.0151)	(0.0267)	(0.137)
Winter Event	0.581***	0.361***	-0.00797
	(0.0191)	(0.0235)	(0.130)
Flood Event, 1-3 Day Lag	-0.0534***	-0.0616***	0.0746
	(0.00919)	(0.0183)	(0.0891)
Flood Event, 4-7 Day Lag	-0.0169**	0.00252	-0.345***
	(0.00712)	(0.0156)	(0.0903)
Wind Event, 1-3 Day Lag	-0.0341**	-0.0207	0.126
	(0.0132)	(0.0263)	(0.130)
Wind Event, 4-7 Day Lag	-0.0208*	-0.00895	-0.00165
	(0.0107)	(0.0222)	(0.121)
Thunderstorm Wind Event, 1-3 Day Lag	-0.0230***	-0.0129	-0.0464
	(0.00507)	(0.0109)	(0.0567)
Thunderstorm Wind Event, 4-7 Day Lag	-0.00799*	-0.0278***	0.0108
	(0.00449)	(0.00966)	(0.0508)
Storm Event (Tropical Cyclone), 1-3 Day Lag	-0.152***	-0.0698*	-0.0185
	(0.0226)	(0.0424)	(0.172)
Storm Event (Tropical Cyclone), 4-7 Day Lag	-0.0264*	-0.0486	-0.272
	(0.0143)	(0.0312)	(0.191)
Winter Event, 1-3 Day Lag	-0.0819***	-0.135***	-0.300***

	(0.0104)	(0.0166)	(0.107)
Winter Event, 4-7 Day Lag	0.0107	-0.0270**	0.0647
	(0.00725)	(0.0135)	(0.0694)
Holiday	-0.0902***	-0.0329***	0.0655
	(0.00523)	(0.00964)	(0.0455)
Daylight Savings Time week	0.0359***	0.0495***	-0.0650
	(0.00575)	(0.0125)	(0.0655)
Very Hot Day (95th percentile)	0.0215***	0.0260*	-0.150**
	(0.00665)	(0.0145)	(0.0751)
Sum of Very Hot Days (3 to 1 days ago)	-0.0133***	-0.0101**	0.0441*
	(0.00230)	(0.00495)	(0.0244)
lnalpha	-2.917***	-0.875***	0.865***
	(0.0166)	(0.00940)	(0.0538)
Constant	-10.14***	-10.80***	-15.06***
	(0.00972)	(0.0187)	(0.110)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Discovery Regression #1

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nbreg Crashes i.CountyNum#(AnyEv c.Precip) i.Year i.MoY i.DoW, vce(robust)
exposure(YearPop)
estimates store Discover1Coll
outreg2 using Discover1, word replace ctitle(Crashes, NB)
nbreg Injured i.CountyNum#(AnyEv c.Precip) i.Year i.MoY i.DoW, vce(robust)
exposure(YearPop)
estimates store Discover1Inj
outreg2 using Discover1, word append ctitle(Injuries, NB)
nbreg Killed i.CountyNum#(AnyEv c.Precip) i.Year i.MoY i.DoW, vce(robust)
exposure(YearPop)
estimates store Discover1Kil
outreg2 using Discover1, word append ctitle(Fatalities, NB)
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VARIABLES	(1) Crashes NB	(2) Injuries NB	(3) Fatalities NB
1b.CountyNum#0b.AnyEv	0	0	0
	(0)	(0)	(0)
1b.CountyNum#1.AnyEv	0.430***	0.264***	-0.712
	(0.0653)	(0.0754)	(0.714)
2.CountyNum#0b.AnyEv	-0.530***	-0.626***	0.298
	(0.0198)	(0.0419)	(0.206)
2.CountyNum#1.AnyEv	-0.0210	-0.237	-18.45***
	(0.107)	(0.179)	(0.203)
3.CountyNum#0b.AnyEv	-0.348***	-0.435***	0.229
	(0.0335)	(0.0675)	(0.311)
3.CountyNum#1.AnyEv	0.323**	-0.0718	1.211
	(0.155)	(0.352)	(1.086)
4.CountyNum#0b.AnyEv	0.198***	0.315***	0.670***
	(0.0183)	(0.0367)	(0.210)
4.CountyNum#1.AnyEv	0.444***	0.409**	-17.78***
	(0.117)	(0.196)	(0.220)
5.CountyNum#0b.AnyEv	-0.320***	-0.480***	0.177
	(0.0216)	(0.0448)	(0.231)
5.CountyNum#1.AnyEv	0.0786	-0.126	0.490
	(0.122)	(0.176)	(0.786)
6.CountyNum#0b.AnyEv	-0.329***	-0.482***	-0.508
	(0.0257)	(0.0547)	(0.331)
6.CountyNum#1.AnyEv	0.336***	0.0503	0.479

	(0.0988)	(0.156)	(0.997)
7.CountyNum#0b.AnyEv	-0.0907***	-0.157***	0.358*
	(0.0158)	(0.0350)	(0.186)
7.CountyNum#1.AnyEv	0.214	-0.194	1.046*
	(0.151)	(0.179)	(0.636)
8.CountyNum#0b.AnyEv	-0.0774***	0.0751*	1.169***
	(0.0228)	(0.0438)	(0.189)
8.CountyNum#1.AnyEv	0.542***	0.621***	1.070
	(0.147)	(0.205)	(1.189)
9.CountyNum#0b.AnyEv	0.161***	0.217***	1.072***
	(0.0165)	(0.0358)	(0.175)
9.CountyNum#1.AnyEv	0.377***	0.422**	2.099***
	(0.135)	(0.185)	(0.687)
10.CountyNum#0b.AnyEv	-0.125***	-0.255***	0.247*
	(0.0120)	(0.0246)	(0.144)
10.CountyNum#1.AnyEv	0.101	-0.193	-0.882
	(0.0720)	(0.118)	(1.064)
11.CountyNum#0b.AnyEv	0.154***	-0.0982***	0.0270
	(0.0104)	(0.0200)	(0.128)
11.CountyNum#1.AnyEv	0.297***	-0.00160	-0.289
	(0.0432)	(0.0666)	(0.388)
12.CountyNum#0b.AnyEv	-0.0815***	-0.0724***	0.251
	(0.0132)	(0.0266)	(0.153)
12.CountyNum#1.AnyEv	0.196***	0.0928	0.664
	(0.0750)	(0.0931)	(0.473)
13.CountyNum#0b.AnyEv	0.0936***	0.0191	-0.220
	(0.0106)	(0.0211)	(0.138)
13.CountyNum#1.AnyEv	0.311***	0.171**	-0.929
	(0.0654)	(0.0742)	(0.722)
14.CountyNum#0b.AnyEv	-0.131***	-0.117***	0.103
	(0.0132)	(0.0270)	(0.176)
14.CountyNum#1.AnyEv	0.132*	-0.0756	-1.033
	(0.0789)	(0.0867)	(0.991)
15.CountyNum#0b.AnyEv	-0.343***	-0.587***	0.617*
	(0.0327)	(0.0712)	(0.368)
15.CountyNum#1.AnyEv	0.0749	-0.138	-16.24***
	(0.208)	(0.374)	(0.244)
16.CountyNum#0b.AnyEv	-0.205***	-0.336***	-0.188
	(0.0149)	(0.0290)	(0.195)
16.CountyNum#1.AnyEv	0.000558	-0.170	0.489
	(0.0864)	(0.139)	(0.710)
17.CountyNum#0b.AnyEv	-0.259***	-0.323***	0.828***
	(0.0222)	(0.0435)	(0.198)
17.CountyNum#1.AnyEv	-0.0886	-0.189	-18.13***
	(0.131)	(0.189)	(0.232)
18.CountyNum#0b.AnyEv	0.170***	0.0428**	0.129
	(0.0107)	(0.0214)	(0.139)
18.CountyNum#1.AnyEv	0.594***	0.272***	0.299
	(0.0859)	(0.0918)	(0.537)
19.CountyNum#0b.AnyEv	-0.180***	-0.472***	0.474***
	(0.0161)	(0.0303)	(0.164)
19.CountyNum#1.AnyEv	0.209**	-0.217*	1.059*
	(0.0915)	(0.129)	(0.619)
20.CountyNum#0b.AnyEv	-0.411***	-0.488***	0.585***
	(0.0223)	(0.0439)	(0.200)
20.CountyNum#1.AnyEv	-0.162	-0.225	1.121
	(0.178)	(0.273)	(1.023)
21.CountyNum#0b.AnyEv	-0.361***	-0.561***	0.279
	(0.0279)	(0.0616)	(0.281)
21.CountyNum#1.AnyEv	0.317	0.132	-19.32***
	(0.228)	(0.321)	(5.277)
22.CountyNum#0b.AnyEv	-0.362***	-0.580***	0.198
	(0.0348)	(0.0663)	(0.342)
22.CountyNum#1.AnyEv	-0.0724	-0.280	-17.75***
	(0.215)	(0.673)	(0.388)
23.CountyNum#0b.AnyEv	0.0990***	0.00995	0.500***
	(0.0122)	(0.0245)	(0.148)
23.CountyNum#1.AnyEv	0.389***	0.249*	0.588
	(0.132)	(0.150)	(0.564)
24.CountyNum#0b.AnyEv	0.262***	0.439***	1.158***

	(0.0133)	(0.0283)	(0.138)
24.CountyNum#1.AnyEv	0.462***	0.467***	0.624
	(0.0872)	(0.150)	(0.740)
25.CountyNum#0b.AnyEv	-0.146***	-0.165***	0.123
	(0.0125)	(0.0251)	(0.156)
25.CountyNum#1.AnyEv	0.00456	-0.318***	-0.808
	(0.0976)	(0.115)	(0.764)
26.CountyNum#0b.AnyEv	0.0280***	0.0585***	0.162
	(0.0104)	(0.0194)	(0.121)
26.CountyNum#1.AnyEv	0.0895	-0.00607	-0.0713
	(0.0586)	(0.0727)	(0.404)
27.CountyNum#0b.AnyEv	-0.456***	-0.550***	0.396*
	(0.0231)	(0.0490)	(0.239)
27.CountyNum#1.AnyEv	-0.293**	-0.465*	0.708
	(0.147)	(0.270)	(1.085)
28.CountyNum#0b.AnyEv	-0.0758***	-0.178***	-0.183
	(0.0206)	(0.0373)	(0.234)
28.CountyNum#1.AnyEv	-0.0891	-0.622**	0.698
	(0.153)	(0.279)	(0.847)
29.CountyNum#0b.AnyEv	-0.139***	-0.111***	0.386***
	(0.0114)	(0.0225)	(0.132)
29.CountyNum#1.AnyEv	0.259***	0.182*	0.388
	(0.0687)	(0.102)	(0.405)
30.CountyNum#0b.AnyEv	-0.218***	-0.166***	0.467**
	(0.0182)	(0.0358)	(0.201)
30.CountyNum#1.AnyEv	0.587***	0.137	-18.36***
	(0.154)	(0.186)	(0.228)
31.CountyNum#0b.AnyEv	0.264***	0.0822***	0.785***
	(0.0136)	(0.0310)	(0.159)
31.CountyNum#1.AnyEv	0.785***	0.518***	0.465
	(0.172)	(0.150)	(0.712)
32.CountyNum#0b.AnyEv	0.284***	0.0847***	-0.266**
	(0.00994)	(0.0193)	(0.129)
32.CountyNum#1.AnyEv	0.425***	0.0841	-0.695
	(0.0419)	(0.0582)	(0.477)
33.CountyNum#0b.AnyEv	0.0141	0.109***	0.551***
	(0.0149)	(0.0296)	(0.181)
33.CountyNum#1.AnyEv	0.266**	0.340**	1.317**
	(0.115)	(0.168)	(0.557)
34.CountyNum#0b.AnyEv	0.0804***	-0.0358*	-0.173
	(0.0105)	(0.0197)	(0.127)
34.CountyNum#1.AnyEv	0.473***	0.201***	-0.556
	(0.0695)	(0.0714)	(0.399)
35.CountyNum#0b.AnyEv	-0.247***	-0.216***	0.329**
	(0.0149)	(0.0293)	(0.163)
35.CountyNum#1.AnyEv	0.132	-0.128	0.0920
	(0.0889)	(0.148)	(0.661)
36.CountyNum#0b.AnyEv	0.0838***	0.137***	0.0988
	(0.0105)	(0.0204)	(0.130)
36.CountyNum#1.AnyEv	0.402***	0.267***	-0.627
	(0.0661)	(0.0704)	(0.589)
37.CountyNum#0b.AnyEv	-0.204***	-0.130**	0.788***
	(0.0293)	(0.0625)	(0.261)
37.CountyNum#1.AnyEv	0.222	0.0643	1.690*
	(0.267)	(0.370)	(0.991)
38.CountyNum#0b.AnyEv	-0.184***	0.183***	1.435***
	(0.0355)	(0.0552)	(0.245)
38.CountyNum#1.AnyEv	0.0257	-0.205	-17.21***
	(0.148)	(0.351)	(0.198)
39.CountyNum#0b.AnyEv	-0.229***	-0.167***	0.640***
	(0.0157)	(0.0296)	(0.155)
39.CountyNum#1.AnyEv	0.260**	0.375***	-0.224
	(0.113)	(0.130)	(1.030)
40.CountyNum#0b.AnyEv	-0.0604***	-0.151***	0.311
	(0.0209)	(0.0451)	(0.254)
40.CountyNum#1.AnyEv	0.297	-0.00214	1.528
	(0.182)	(0.298)	(1.014)
41.CountyNum#0b.AnyEv	0.0970***	0.278***	-0.0903
	(0.00973)	(0.0181)	(0.116)
41.CountyNum#1.AnyEv	0.397***	0.406***	0.350

	(0.0534)	(0.0506)	(0.260)
42.CountyNum#0b.AnyEv	0.142***	0.226***	0.694***
	(0.0149)	(0.0331)	(0.160)
42.CountyNum#1.AnyEv	0.512***	0.448***	-0.229
	(0.0864)	(0.129)	(1.052)
43.CountyNum#0b.AnyEv	-0.280***	-0.224***	0.579***
	(0.0123)	(0.0243)	(0.131)
43.CountyNum#1.AnyEv	-0.104	-0.200*	0.135
	(0.0807)	(0.112)	(0.537)
44.CountyNum#0b.AnyEv	-0.273***	-0.224***	0.413**
	(0.0163)	(0.0300)	(0.177)
44.CountyNum#1.AnyEv	0.0698	0.0798	0.199
	(0.0788)	(0.109)	(0.717)
45.CountyNum#0b.AnyEv	-0.0957***	-0.335***	-0.0832
	(0.0125)	(0.0258)	(0.157)
45.CountyNum#1.AnyEv	0.261***	-0.0495	-0.609
	(0.0944)	(0.104)	(0.756)
46.CountyNum#0b.AnyEv	-0.189***	0.119***	0.390*
	(0.0209)	(0.0434)	(0.211)
46.CountyNum#1.AnyEv	0.196	0.378	0.871
	(0.194)	(0.282)	(1.279)
47.CountyNum#0b.AnyEv	-0.372***	-0.129***	0.690***
	(0.0168)	(0.0322)	(0.171)
47.CountyNum#1.AnyEv	-0.0271	-0.0947	-18.72***
	(0.117)	(0.179)	(0.227)
48.CountyNum#0b.AnyEv	-0.331***	-0.926***	-0.358
	(0.0450)	(0.112)	(0.561)
48.CountyNum#1.AnyEv	0.389	-0.533	2.418*
	(0.256)	(0.611)	(1.389)
49.CountyNum#0b.AnyEv	-0.0148	0.0318	0.149
	(0.0110)	(0.0214)	(0.134)
49.CountyNum#1.AnyEv	0.369***	0.233***	0.397
	(0.0861)	(0.0811)	(0.361)
50.CountyNum#0b.AnyEv	-0.259***	-0.359***	0.467**
	(0.0191)	(0.0353)	(0.202)
50.CountyNum#1.AnyEv	0.255**	-0.0187	-0.0141
	(0.107)	(0.133)	(1.009)
51.CountyNum#0b.AnyEv	-0.0654***	-0.0407*	0.318**
	(0.0114)	(0.0217)	(0.133)
51.CountyNum#1.AnyEv	0.209***	0.0431	0.630**
	(0.0671)	(0.0736)	(0.294)
52.CountyNum#0b.AnyEv	0.390***	0.149***	0.675**
	(0.0239)	(0.0522)	(0.292)
52.CountyNum#1.AnyEv	0.719**	0.566	-17.58***
	(0.287)	(0.454)	(1.124)
53.CountyNum#0b.AnyEv	0.0266*	-0.0377	0.494***
	(0.0143)	(0.0309)	(0.165)
53.CountyNum#1.AnyEv	0.403***	0.0713	0.399
	(0.0932)	(0.129)	(0.679)
54.CountyNum#0b.AnyEv	0.0685***	0.236***	0.448***
	(0.0144)	(0.0272)	(0.162)
54.CountyNum#1.AnyEv	0.613***	0.431**	1.719***
	(0.170)	(0.203)	(0.476)
55.CountyNum#0b.AnyEv	-0.228***	-0.310***	0.160
	(0.0143)	(0.0289)	(0.162)
55.CountyNum#1.AnyEv	0.211	0.0237	0.970**
	(0.159)	(0.182)	(0.460)
56.CountyNum#0b.AnyEv	-0.180***	-0.226***	0.389**
	(0.0181)	(0.0358)	(0.196)
56.CountyNum#1.AnyEv	0.112	-0.198	-0.140
	(0.113)	(0.155)	(0.770)
57.CountyNum#0b.AnyEv	-0.512***	-0.851***	0.209
	(0.0265)	(0.0544)	(0.248)
57.CountyNum#1.AnyEv	-0.0610	-0.394*	0.707
	(0.0962)	(0.214)	(1.062)
58.CountyNum#0b.AnyEv	0.102***	0.0371	0.530**
	(0.0208)	(0.0394)	(0.221)
58.CountyNum#1.AnyEv	0.758***	0.778***	-18.10***
	(0.171)	(0.217)	(0.275)
59.CountyNum#0b.AnyEv	0.000197	-0.220***	0.187

	(0.0156)	(0.0332)	(0.210)
59.CountyNum#1.AnyEv	0.349***	-0.0385	0.645
	(0.0768)	(0.117)	(0.408)
60.CountyNum#0b.AnyEv	0.311***	0.436***	-0.306***
	(0.00902)	(0.0173)	(0.112)
60.CountyNum#1.AnyEv	0.496***	0.521***	-0.662***
	(0.0279)	(0.0333)	(0.256)
61.CountyNum#0b.AnyEv	-0.424***	-0.258***	-0.0918
	(0.0293)	(0.0530)	(0.439)
61.CountyNum#1.AnyEv	-0.129	-0.188	-17.26***
	(0.100)	(0.198)	(0.235)
62.CountyNum#0b.AnyEv	-0.0212	-0.282***	0.831***
	(0.0196)	(0.0394)	(0.194)
62.CountyNum#1.AnyEv	0.357***	-0.00783	0.543
	(0.128)	(0.185)	(1.045)
63.CountyNum#0b.AnyEv	-0.0889***	-0.236***	0.408***
	(0.0132)	(0.0266)	(0.149)
63.CountyNum#1.AnyEv	0.0510	-0.100	0.736
	(0.0972)	(0.112)	(0.579)
64.CountyNum#0b.AnyEv	0.0608***	0.181***	0.727***
	(0.0128)	(0.0250)	(0.137)
64.CountyNum#1.AnyEv	0.466***	0.256**	0.393
	(0.0920)	(0.122)	(0.838)
65.CountyNum#0b.AnyEv	0.0914***	-0.0117	-0.263*
	(0.0107)	(0.0206)	(0.137)
65.CountyNum#1.AnyEv	0.223***	0.0348	-0.913
	(0.0501)	(0.0692)	(0.794)
66.CountyNum#0b.AnyEv	-0.0165	-0.00843	1.132***
	(0.0221)	(0.0460)	(0.189)
66.CountyNum#1.AnyEv	0.792***	0.600***	1.801**
	(0.145)	(0.175)	(0.716)
67.CountyNum#0b.AnyEv	-0.161***	-0.255***	-0.0840
	(0.0113)	(0.0221)	(0.139)
67.CountyNum#1.AnyEv	0.0920	-0.0263	0.818**
	(0.109)	(0.137)	(0.383)
68.CountyNum#0b.AnyEv	-0.210***	-0.346***	-0.304*
	(0.0124)	(0.0243)	(0.161)
68.CountyNum#1.AnyEv	0.0850	-0.302***	-1.392
	(0.0610)	(0.0825)	(1.028)
69.CountyNum#0b.AnyEv	-0.461***	-0.698***	0.376
	(0.0309)	(0.0675)	(0.298)
69.CountyNum#1.AnyEv	0.171	-0.0470	-17.25***
	(0.258)	(0.487)	(0.342)
70.CountyNum#0b.AnyEv	-0.141***	-0.256***	-0.210
	(0.0173)	(0.0353)	(0.249)
70.CountyNum#1.AnyEv	0.0605	-0.515**	-18.28***
	(0.133)	(0.218)	(0.286)
71.CountyNum#0b.AnyEv	0.0973***	0.0138	1.022***
	(0.0140)	(0.0315)	(0.142)
71.CountyNum#1.AnyEv	0.340***	0.0699	1.549**
	(0.105)	(0.146)	(0.614)
72.CountyNum#0b.AnyEv	-0.385***	-0.529***	0.220
	(0.0297)	(0.0689)	(0.294)
72.CountyNum#1.AnyEv	0.117	-0.0289	-20.72***
	(0.209)	(0.383)	(4.361)
73.CountyNum#0b.AnyEv	-0.0595***	-0.176***	0.353*
	(0.0172)	(0.0347)	(0.202)
73.CountyNum#1.AnyEv	0.357***	0.00245	-18.27***
	(0.118)	(0.144)	(0.190)
74.CountyNum#0b.AnyEv	0.292***	0.343***	0.0372
	(0.0108)	(0.0208)	(0.138)
74.CountyNum#1.AnyEv	0.555***	0.409***	-0.450
	(0.0925)	(0.0853)	(0.659)
75.CountyNum#0b.AnyEv	-0.206***	-0.366***	0.407
	(0.0231)	(0.0477)	(0.258)
75.CountyNum#1.AnyEv	0.156	-0.00604	0.760
	(0.119)	(0.195)	(1.067)
76.CountyNum#0b.AnyEv	-0.0514***	-0.117***	0.395***
	(0.0122)	(0.0226)	(0.134)
76.CountyNum#1.AnyEv	0.198***	0.0379	0.424

	(0.0604)	(0.0692)	(0.417)
77.CountyNum#0b.AnyEv	0.0101	0.247***	0.599***
	(0.0160)	(0.0304)	(0.178)
77.CountyNum#1.AnyEv	0.529***	0.609***	0.653
	(0.116)	(0.140)	(0.803)
78.CountyNum#0b.AnyEv	0.175***	0.435***	1.080***
	(0.0114)	(0.0214)	(0.123)
78.CountyNum#1.AnyEv	0.461***	0.598***	0.942**
	(0.0756)	(0.101)	(0.388)
79.CountyNum#0b.AnyEv	-0.0874***	-0.217***	0.222
	(0.0129)	(0.0262)	(0.154)
79.CountyNum#1.AnyEv	0.196***	0.00607	-19.87***
	(0.0667)	(0.0924)	(0.269)
80.CountyNum#0b.AnyEv	-0.0343***	-0.0255	0.105
	(0.0117)	(0.0223)	(0.143)
80.CountyNum#1.AnyEv	0.321***	0.148*	-0.347
	(0.0733)	(0.0832)	(0.538)
81.CountyNum#0b.AnyEv	-0.215***	-0.213***	0.268
	(0.0145)	(0.0285)	(0.169)
81.CountyNum#1.AnyEv	0.107	-0.0298	-0.111
	(0.0807)	(0.117)	(0.735)
82.CountyNum#0b.AnyEv	0.125***	0.171***	0.863***
	(0.0139)	(0.0268)	(0.147)
82.CountyNum#1.AnyEv	0.271***	0.167	1.066**
	(0.0833)	(0.129)	(0.505)
83.CountyNum#0b.AnyEv	-0.126***	0.242***	0.617***
	(0.0173)	(0.0330)	(0.181)
83.CountyNum#1.AnyEv	0.348**	0.487***	0.295
	(0.143)	(0.184)	(1.336)
84.CountyNum#0b.AnyEv	-0.106***	-0.253***	0.310*
	(0.0147)	(0.0313)	(0.171)
84.CountyNum#1.AnyEv	0.0874	-0.266**	-19.35***
	(0.110)	(0.122)	(0.294)
85.CountyNum#0b.AnyEv	-0.215***	-0.372***	0.420**
	(0.0174)	(0.0338)	(0.185)
85.CountyNum#1.AnyEv	0.134	-0.112	0.608
	(0.111)	(0.208)	(1.058)
86.CountyNum#0b.AnyEv	-0.127***	-0.0356	0.512***
	(0.0140)	(0.0281)	(0.159)
86.CountyNum#1.AnyEv	0.280***	0.0954	1.142**
	(0.105)	(0.113)	(0.481)
87.CountyNum#0b.AnyEv	-0.528***	-0.582***	0.0909
	(0.0301)	(0.0624)	(0.317)
87.CountyNum#1.AnyEv	-0.476***	-1.155***	0.212
	(0.130)	(0.276)	(0.631)
88.CountyNum#0b.AnyEv	-0.386***	-0.522***	0.0775
	(0.0205)	(0.0412)	(0.259)
88.CountyNum#1.AnyEv	-0.0407	-0.620***	-18.86***
	(0.108)	(0.165)	(0.527)
89.CountyNum#0b.AnyEv	0.247***	-0.486***	-0.255
	(0.0392)	(0.109)	(1.005)
89.CountyNum#1.AnyEv	0.315	0.520	-15.20***
	(0.469)	(0.728)	(0.301)
90.CountyNum#0b.AnyEv	-0.0490***	-0.167***	-0.132
	(0.0105)	(0.0210)	(0.138)
90.CountyNum#1.AnyEv	0.0980	-0.0723	-1.499
	(0.0656)	(0.0879)	(1.017)
91.CountyNum#0b.AnyEv	0.237***	0.390***	0.506***
	(0.0148)	(0.0302)	(0.170)
91.CountyNum#1.AnyEv	0.663***	0.540***	-0.104
	(0.112)	(0.139)	(1.103)
92.CountyNum#0b.AnyEv	0.153***	-0.0186	-0.639***
	(0.00942)	(0.0177)	(0.115)
92.CountyNum#1.AnyEv	0.301***	-0.00331	-0.322
	(0.0366)	(0.0348)	(0.213)
93.CountyNum#0b.AnyEv	-0.0965***	-0.0430	0.919***
	(0.0226)	(0.0483)	(0.254)
93.CountyNum#1.AnyEv	0.469***	-0.239	1.222
	(0.123)	(0.241)	(1.006)
94.CountyNum#0b.AnyEv	-0.160***	-0.338***	0.317

	(0.0287)	(0.0595)	(0.320)
94.CountyNum#1.AnyEv	0.229	0.793**	2.474**
	(0.268)	(0.350)	(1.007)
95.CountyNum#0b.AnyEv	0.00975	-0.300***	0.00434
	(0.0158)	(0.0319)	(0.224)
95.CountyNum#1.AnyEv	0.321***	-0.194	-18.49***
	(0.0841)	(0.126)	(0.260)
96.CountyNum#0b.AnyEv	0.0176	0.119***	0.314**
	(0.0115)	(0.0232)	(0.141)
96.CountyNum#1.AnyEv	0.278***	0.204**	0.603
	(0.0921)	(0.103)	(0.461)
97.CountyNum#0b.AnyEv	-0.265***	-0.184***	0.286*
	(0.0148)	(0.0278)	(0.167)
97.CountyNum#1.AnyEv	0.0932	0.0857	0.0477
	(0.0932)	(0.135)	(0.744)
98.CountyNum#0b.AnyEv	0.115***	0.142***	0.442***
	(0.0133)	(0.0262)	(0.159)
98.CountyNum#1.AnyEv	0.260***	0.0558	0.262
	(0.0827)	(0.110)	(0.667)
99.CountyNum#0b.AnyEv	-0.214***	-0.343***	0.441**
	(0.0195)	(0.0373)	(0.194)
99.CountyNum#1.AnyEv	0.256*	-0.186	0.171
	(0.134)	(0.162)	(1.059)
100.CountyNum#0b.AnyEv	-0.553***	-0.552***	0.547**
	(0.0285)	(0.0584)	(0.262)
100.CountyNum#1.AnyEv	-0.346***	-0.823***	0.696
	(0.0991)	(0.227)	(1.029)
1b.CountyNum#c.Precip	0.0860***	0.0739*	-0.437
	(0.0217)	(0.0389)	(0.475)
2.CountyNum#c.Precip	0.0636*	0.102	-1.260
	(0.0374)	(0.0724)	(0.891)
3.CountyNum#c.Precip	0.0631	0.0853	0.295
	(0.0580)	(0.118)	(0.315)
4.CountyNum#c.Precip	0.0404	0.0719	-1.579
	(0.0318)	(0.0573)	(1.103)
5.CountyNum#c.Precip	-0.00893	0.0737	0.323
	(0.0489)	(0.0960)	(0.309)
6.CountyNum#c.Precip	0.0543	0.150	0.633*
	(0.0495)	(0.131)	(0.359)
7.CountyNum#c.Precip	-0.0671*	0.0709	-0.316
	(0.0405)	(0.0727)	(0.436)
8.CountyNum#c.Precip	0.0736	-0.0122	0.0772
	(0.0610)	(0.0764)	(0.242)
9.CountyNum#c.Precip	-0.000754	0.0233	-0.0845
	(0.0291)	(0.0506)	(0.184)
10.CountyNum#c.Precip	-0.0464**	-0.0246	0.0127
	(0.0199)	(0.0348)	(0.180)
11.CountyNum#c.Precip	0.0737***	0.0613*	0.000922
	(0.0203)	(0.0336)	(0.228)
12.CountyNum#c.Precip	0.0873***	0.0543	0.202
	(0.0283)	(0.0457)	(0.242)
13.CountyNum#c.Precip	0.0321	0.0228	0.283*
	(0.0198)	(0.0347)	(0.156)
14.CountyNum#c.Precip	0.0296	0.00468	-0.385
	(0.0274)	(0.0432)	(0.499)
15.CountyNum#c.Precip	0.101	-0.321*	-5.608*
	(0.0797)	(0.194)	(3.114)
16.CountyNum#c.Precip	-0.0518**	-0.106**	-0.186
	(0.0256)	(0.0495)	(0.217)
17.CountyNum#c.Precip	0.0544	0.0611	-0.503
	(0.0513)	(0.105)	(0.616)
18.CountyNum#c.Precip	0.0741***	0.0376	-0.625*
	(0.0220)	(0.0367)	(0.328)
19.CountyNum#c.Precip	0.0341	-0.0820	-0.824*
	(0.0422)	(0.0653)	(0.458)
20.CountyNum#c.Precip	0.0879**	0.198**	0.151
	(0.0425)	(0.0897)	(0.283)
21.CountyNum#c.Precip	0.00321	-0.0448	0.558
	(0.0488)	(0.113)	(0.613)
22.CountyNum#c.Precip	0.159**	0.169	0.699*

	(0.0653)	(0.145)	(0.361)
23.CountyNum#c.Precip	0.0805***	0.0500	0.0626
	(0.0237)	(0.0447)	(0.318)
24.CountyNum#c.Precip	0.0382	-0.0462	-0.00679
	(0.0281)	(0.0493)	(0.150)
25.CountyNum#c.Precip	-0.0402*	-0.0869**	0.0624
	(0.0229)	(0.0402)	(0.239)
26.CountyNum#c.Precip	0.0558***	0.0232	-0.0900
	(0.0171)	(0.0200)	(0.142)
27.CountyNum#c.Precip	0.0329	0.0782	-0.0910
	(0.0507)	(0.111)	(0.582)
28.CountyNum#c.Precip	0.159***	0.235***	0.315
	(0.0390)	(0.0626)	(0.223)
29.CountyNum#c.Precip	0.0791**	-0.00659	-0.422
	(0.0317)	(0.0523)	(0.296)
30.CountyNum#c.Precip	0.104**	0.0720	-1.649
	(0.0408)	(0.0774)	(1.080)
31.CountyNum#c.Precip	-0.0289	-0.0430	0.276***
	(0.0313)	(0.0432)	(0.107)
32.CountyNum#c.Precip	0.0663***	0.0210	0.150
	(0.0140)	(0.0270)	(0.160)
33.CountyNum#c.Precip	0.0245	0.0193	-0.663
	(0.0296)	(0.0558)	(0.555)
34.CountyNum#c.Precip	0.104***	0.0809***	0.0713
	(0.0234)	(0.0300)	(0.183)
35.CountyNum#c.Precip	-0.0378	0.00419	0.327
	(0.0363)	(0.0626)	(0.210)
36.CountyNum#c.Precip	0.121***	0.109***	0.116
	(0.0204)	(0.0317)	(0.216)
37.CountyNum#c.Precip	-0.0566	-0.200	0.269**
	(0.0631)	(0.148)	(0.108)
38.CountyNum#c.Precip	0.0822	-0.136	-0.141
	(0.0750)	(0.144)	(0.499)
39.CountyNum#c.Precip	0.157***	0.145**	0.113
	(0.0319)	(0.0581)	(0.250)
40.CountyNum#c.Precip	0.0950***	-0.0291	-0.166
	(0.0323)	(0.0786)	(0.343)
41.CountyNum#c.Precip	0.0945***	0.0883***	0.000956
	(0.0257)	(0.0289)	(0.139)
42.CountyNum#c.Precip	0.103***	0.0279	0.117
	(0.0370)	(0.0611)	(0.411)
43.CountyNum#c.Precip	0.0178	0.0158	0.0303
	(0.0200)	(0.0395)	(0.180)
44.CountyNum#c.Precip	0.161***	0.141**	-0.992
	(0.0375)	(0.0648)	(0.854)
45.CountyNum#c.Precip	0.0371	0.0219	-0.0581
	(0.0241)	(0.0396)	(0.230)
46.CountyNum#c.Precip	0.0404	-0.0427	0.187
	(0.0350)	(0.0870)	(0.244)
47.CountyNum#c.Precip	0.111***	0.162**	-0.568
	(0.0310)	(0.0630)	(0.406)
48.CountyNum#c.Precip	0.0599	-0.129	0.0915
	(0.0857)	(0.294)	(0.491)
49.CountyNum#c.Precip	0.0753***	0.0780***	-0.309
	(0.0175)	(0.0288)	(0.262)
50.CountyNum#c.Precip	0.126***	0.0963	-0.567
	(0.0414)	(0.0691)	(0.561)
51.CountyNum#c.Precip	0.0545**	0.00576	-0.130
	(0.0238)	(0.0371)	(0.245)
52.CountyNum#c.Precip	-0.0512	-0.0219	0.0596
	(0.0542)	(0.0987)	(0.474)
53.CountyNum#c.Precip	0.103***	0.120***	0.386**
	(0.0273)	(0.0451)	(0.158)
54.CountyNum#c.Precip	-0.00297	-0.0234	-0.0461
	(0.0334)	(0.0444)	(0.212)
55.CountyNum#c.Precip	0.113***	0.0555	0.437
	(0.0301)	(0.0604)	(0.311)
56.CountyNum#c.Precip	0.0878**	-0.0991	0.575**
	(0.0395)	(0.0760)	(0.255)
57.CountyNum#c.Precip	0.101	0.0430	0.887**

	(0.0687)	(0.144)	(0.347)
58.CountyNum#c.Precip	0.113**	0.108	-0.343
	(0.0539)	(0.0870)	(0.543)
59.CountyNum#c.Precip	0.140***	0.0941*	0.339
	(0.0272)	(0.0532)	(0.230)
60.CountyNum#c.Precip	0.0763***	0.0587***	-0.0391
	(0.0126)	(0.0155)	(0.138)
61.CountyNum#c.Precip	-0.0945	0.0562	-2.782
	(0.0832)	(0.133)	(2.224)
62.CountyNum#c.Precip	0.0786	0.0388	0.291
	(0.0504)	(0.0893)	(0.300)
63.CountyNum#c.Precip	0.0386	0.0233	-0.235
	(0.0259)	(0.0493)	(0.378)
64.CountyNum#c.Precip	0.0733***	-0.000836	0.269
	(0.0251)	(0.0420)	(0.198)
65.CountyNum#c.Precip	-0.00913	-0.0479*	0.0507
	(0.0188)	(0.0264)	(0.147)
66.CountyNum#c.Precip	0.0611	-0.0330	-0.199
	(0.0504)	(0.0826)	(0.304)
67.CountyNum#c.Precip	-0.0268	0.00246	-0.215
	(0.0256)	(0.0366)	(0.157)
68.CountyNum#c.Precip	0.0469*	0.0356	-0.392
	(0.0249)	(0.0470)	(0.451)
69.CountyNum#c.Precip	-0.0507	0.00659	-0.702
	(0.0586)	(0.105)	(0.957)
70.CountyNum#c.Precip	0.00368	-0.0411	-1.198
	(0.0390)	(0.0763)	(1.245)
71.CountyNum#c.Precip	-0.0492**	-0.0989**	-0.421
	(0.0237)	(0.0497)	(0.328)
72.CountyNum#c.Precip	-0.00258	-0.0946	0.837*
	(0.0700)	(0.206)	(0.442)
73.CountyNum#c.Precip	0.0654*	0.0732	-1.832*
	(0.0378)	(0.0657)	(1.000)
74.CountyNum#c.Precip	0.0188	-0.0207	0.145
	(0.0215)	(0.0356)	(0.154)
75.CountyNum#c.Precip	0.144***	0.187***	-0.0492
	(0.0344)	(0.0705)	(0.410)
76.CountyNum#c.Precip	0.103***	0.111***	-0.401
	(0.0284)	(0.0409)	(0.260)
77.CountyNum#c.Precip	0.0760**	0.0408	0.177
	(0.0370)	(0.0550)	(0.225)
78.CountyNum#c.Precip	0.0704***	0.0453*	0.0335
	(0.0195)	(0.0242)	(0.109)
79.CountyNum#c.Precip	0.0731***	-0.0121	0.186
	(0.0271)	(0.0492)	(0.298)
80.CountyNum#c.Precip	0.109***	0.0514	0.618**
	(0.0257)	(0.0402)	(0.290)
81.CountyNum#c.Precip	0.144***	0.147***	-0.197
	(0.0327)	(0.0547)	(0.409)
82.CountyNum#c.Precip	0.0660**	0.0207	-0.0824
	(0.0267)	(0.0487)	(0.189)
83.CountyNum#c.Precip	0.105***	0.0943*	0.263
	(0.0335)	(0.0511)	(0.246)
84.CountyNum#c.Precip	0.0287	0.0750	-0.0147
	(0.0341)	(0.0684)	(0.391)
85.CountyNum#c.Precip	-6.12e-05	-0.0552	-0.671
	(0.0409)	(0.0878)	(0.742)
86.CountyNum#c.Precip	0.0359	0.0450	-0.197
	(0.0305)	(0.0606)	(0.386)
87.CountyNum#c.Precip	0.194***	0.146	0.639**
	(0.0503)	(0.122)	(0.325)
88.CountyNum#c.Precip	0.0491	0.130**	0.315
	(0.0362)	(0.0598)	(0.344)
89.CountyNum#c.Precip	0.0803	0.102	-3.540***
	(0.0712)	(0.191)	(0.133)
90.CountyNum#c.Precip	0.0434**	0.0366	-0.106
	(0.0218)	(0.0356)	(0.242)
91.CountyNum#c.Precip	0.0752**	-0.00104	0.559**
	(0.0351)	(0.0721)	(0.242)
92.CountyNum#c.Precip	0.0529***	0.0359**	-0.00648

	(0.0152)	(0.0174)	(0.108)
93.CountyNum#c.Precip	0.128***	0.137*	-1.276
	(0.0322)	(0.0810)	(1.138)
94.CountyNum#c.Precip	-0.0286	-0.184	-1.027
	(0.0619)	(0.123)	(1.057)
95.CountyNum#c.Precip	-0.0239	-0.101	-1.227
	(0.0337)	(0.0673)	(0.925)
96.CountyNum#c.Precip	0.0244	-0.00595	-0.0870
	(0.0236)	(0.0396)	(0.166)
97.CountyNum#c.Precip	0.149***	0.0940*	-0.0855
	(0.0249)	(0.0497)	(0.273)
98.CountyNum#c.Precip	0.101***	0.0198	-0.253
	(0.0247)	(0.0415)	(0.344)
99.CountyNum#c.Precip	0.0306	-0.0238	-0.102
	(0.0428)	(0.0959)	(0.471)
100.CountyNum#c.Precip	-0.00323	-0.0271	-3.230
	(0.0779)	(0.153)	(2.386)
2014	0.00959**	0.00608	-0.00266
	(0.00433)	(0.00805)	(0.0430)
2015	0.0997***	0.0952***	0.0704*
	(0.00416)	(0.00797)	(0.0424)
2016	0.145***	0.134***	0.0967**
	(0.00417)	(0.00792)	(0.0418)
2017	0.171***	0.118***	0.0617
	(0.00403)	(0.00792)	(0.0423)
2018	0.175***	0.0737***	0.0892**
	(0.00409)	(0.00788)	(0.0420)
2019	0.184***	0.0707***	0.109***
	(0.00398)	(0.00787)	(0.0415)
February	-0.00776	0.0505***	-0.0218
	(0.00648)	(0.0112)	(0.0589)
March	-0.0105*	0.107***	0.0290
	(0.00588)	(0.0106)	(0.0576)
April	-0.00260	0.171***	0.113**
	(0.00570)	(0.0104)	(0.0566)
May	0.0280***	0.223***	0.208***
	(0.00561)	(0.0104)	(0.0550)
June	0.00780	0.212***	0.246***
	(0.00567)	(0.0104)	(0.0552)
July	-0.0525***	0.152***	0.116**
	(0.00570)	(0.0106)	(0.0567)
August	0.00508	0.208***	0.143**
	(0.00561)	(0.0104)	(0.0557)
September	0.0325***	0.212***	0.271***
	(0.00578)	(0.0104)	(0.0552)
October	0.192***	0.286***	0.288***
	(0.00551)	(0.0102)	(0.0543)
November	0.267***	0.236***	0.234***
	(0.00558)	(0.0104)	(0.0556)
December	0.157***	0.169***	0.113**
	(0.00593)	(0.0105)	(0.0563)
Monday	0.336***	0.205***	-0.212***
	(0.00430)	(0.00846)	(0.0424)
Tuesday	0.342***	0.198***	-0.188***
	(0.00424)	(0.00837)	(0.0416)
Wednesday	0.341***	0.195***	-0.165***
	(0.00423)	(0.00832)	(0.0416)
Thursday	0.345***	0.208***	-0.192***
	(0.00416)	(0.00823)	(0.0416)
Friday	0.508***	0.394***	-0.00258
	(0.00420)	(0.00817)	(0.0397)
Saturday	0.221***	0.199***	0.0963**
	(0.00429)	(0.00850)	(0.0389)
lnalpha	-2.863***	-0.873***	0.852***
	(0.0173)	(0.00939)	(0.0535)
Constant	-10.12***	-10.81***	-15.05***
	(0.0100)	(0.0196)	(0.116)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Discovery Regression #2

```
nbreg Crashes i.CountyNum#(Holiday) i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store Discover2Coll
outreg2 using Discover2, word replace ctitle(Crashes, NB)
nbreg Injured i.CountyNum#(Holiday) i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store Discover2Inj
outreg2 using Discover2, word append ctitle(Injuries, NB)
nbreg Killed i.CountyNum#(Holiday) i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store Discover2Kil
outreg2 using Discover2, word append ctitle(Fatalities, NB)
```

VARIABLES	(1) Crashes NB	(2) Injuries NB	(3) Fatalities NB
1b.CountyNum#0b.Holiday	0	0	0
	(0)	(0)	(0)
1b.CountyNum#1.Holiday	-0.150***	-0.0523	-0.0489
	(0.0348)	(0.0630)	(0.358)
2.CountyNum#0b.Holiday	-0.530***	-0.607***	0.251
	(0.0194)	(0.0399)	(0.202)
2.CountyNum#1.Holiday	-0.734***	-0.843***	-0.634
	(0.0821)	(0.151)	(1.003)
3.CountyNum#0b.Holiday	-0.357***	-0.440***	0.472
	(0.0326)	(0.0639)	(0.292)
3.CountyNum#1.Holiday	-0.254**	-0.311	-16.66***
	(0.108)	(0.221)	(0.126)
4.CountyNum#0b.Holiday	0.165***	0.305***	0.526**
	(0.0183)	(0.0351)	(0.211)
4.CountyNum#1.Holiday	0.255***	0.298**	1.181**
	(0.0616)	(0.150)	(0.505)
5.CountyNum#0b.Holiday	-0.345***	-0.484***	0.279
	(0.0218)	(0.0416)	(0.224)
5.CountyNum#1.Holiday	-0.259***	-0.317	0.789
	(0.0796)	(0.209)	(0.581)
6.CountyNum#0b.Holiday	-0.316***	-0.458***	-0.0919
	(0.0255)	(0.0501)	(0.304)
6.CountyNum#1.Holiday	-0.184**	-0.175	-17.14***
	(0.0885)	(0.177)	(0.126)
7.CountyNum#0b.Holiday	-0.131***	-0.160***	0.366**
	(0.0160)	(0.0336)	(0.178)
7.CountyNum#1.Holiday	-0.175***	-0.346***	0.755*
	(0.0526)	(0.110)	(0.452)
8.CountyNum#0b.Holiday	-0.0927***	0.0759*	1.269***
	(0.0225)	(0.0429)	(0.186)
8.CountyNum#1.Holiday	-0.0172	-0.145	0.719
	(0.0741)	(0.138)	(0.712)
9.CountyNum#0b.Holiday	0.120***	0.189***	1.177***
	(0.0167)	(0.0350)	(0.170)
9.CountyNum#1.Holiday	0.217***	0.383***	0.896
	(0.0572)	(0.112)	(0.610)
10.CountyNum#0b.Holiday	-0.169***	-0.283***	0.248*
	(0.0121)	(0.0235)	(0.142)
10.CountyNum#1.Holiday	-0.147***	-0.268***	0.813***
	(0.0397)	(0.0710)	(0.294)
11.CountyNum#0b.Holiday	0.142***	-0.0986***	0.0906
	(0.0106)	(0.0190)	(0.120)
11.CountyNum#1.Holiday	-0.0500	-0.287***	-0.176
	(0.0351)	(0.0506)	(0.410)
12.CountyNum#0b.Holiday	-0.0860***	-0.0704***	0.313**

	(0.0139)	(0.0255)	(0.148)
12.CountyNum#1.Holiday	-0.107**	-0.177**	1.062***
	(0.0462)	(0.0730)	(0.324)
13.CountyNum#0b.Holiday	0.0733***	0.00798	-0.122
	(0.0110)	(0.0200)	(0.133)
13.CountyNum#1.Holiday	-0.0325	-0.0559	-0.289
	(0.0336)	(0.0558)	(0.352)
14.CountyNum#0b.Holiday	-0.149***	-0.134***	0.0935
	(0.0138)	(0.0255)	(0.167)
14.CountyNum#1.Holiday	-0.196***	-0.200**	-0.0452
	(0.0411)	(0.0793)	(0.500)
15.CountyNum#0b.Holiday	-0.363***	-0.637***	0.388
	(0.0320)	(0.0672)	(0.386)
15.CountyNum#1.Holiday	-0.267**	-0.726***	0.662
	(0.115)	(0.274)	(1.004)
16.CountyNum#0b.Holiday	-0.254***	-0.382***	-0.136
	(0.0147)	(0.0281)	(0.189)
16.CountyNum#1.Holiday	-0.176***	-0.274***	-0.151
	(0.0580)	(0.102)	(0.581)
17.CountyNum#0b.Holiday	-0.292***	-0.342***	0.848***
	(0.0217)	(0.0419)	(0.191)
17.CountyNum#1.Holiday	-0.202***	-0.226	-0.174
	(0.0768)	(0.152)	(0.999)
18.CountyNum#0b.Holiday	0.168***	0.0391*	0.119
	(0.0117)	(0.0205)	(0.133)
18.CountyNum#1.Holiday	0.0150	-0.0645	0.212
	(0.0352)	(0.0617)	(0.379)
19.CountyNum#0b.Holiday	-0.195***	-0.495***	0.470***
	(0.0160)	(0.0289)	(0.158)
19.CountyNum#1.Holiday	-0.299***	-0.544***	0.511
	(0.0451)	(0.0998)	(0.417)
20.CountyNum#0b.Holiday	-0.434***	-0.472***	0.728***
	(0.0212)	(0.0408)	(0.191)
20.CountyNum#1.Holiday	-0.401***	-0.452***	-0.363
	(0.0786)	(0.154)	(1.002)
21.CountyNum#0b.Holiday	-0.385***	-0.563***	0.426
	(0.0286)	(0.0608)	(0.281)
21.CountyNum#1.Holiday	-0.381***	-0.788***	0.321
	(0.102)	(0.248)	(1.000)
22.CountyNum#0b.Holiday	-0.376***	-0.570***	0.305
	(0.0327)	(0.0661)	(0.341)
22.CountyNum#1.Holiday	-0.313***	-0.595***	1.269*
	(0.120)	(0.219)	(0.708)
23.CountyNum#0b.Holiday	0.0842***	0.0106	0.572***
	(0.0129)	(0.0235)	(0.139)
23.CountyNum#1.Holiday	-0.00365	-0.184**	0.584*
	(0.0374)	(0.0785)	(0.337)
24.CountyNum#0b.Holiday	0.231***	0.402***	1.195***
	(0.0136)	(0.0273)	(0.134)
24.CountyNum#1.Holiday	0.270***	0.487***	1.389***
	(0.0439)	(0.0813)	(0.336)
25.CountyNum#0b.Holiday	-0.183***	-0.204***	0.173
	(0.0127)	(0.0239)	(0.148)
25.CountyNum#1.Holiday	-0.282***	-0.251***	0.286
	(0.0462)	(0.0844)	(0.381)
26.CountyNum#0b.Holiday	0.00616	0.0413**	0.207*
	(0.0107)	(0.0185)	(0.116)
26.CountyNum#1.Holiday	-0.133***	-0.0537	0.161
	(0.0339)	(0.0466)	(0.252)
27.CountyNum#0b.Holiday	-0.495***	-0.572***	0.455**
	(0.0232)	(0.0484)	(0.226)
27.CountyNum#1.Holiday	-0.362***	-0.389***	0.422
	(0.0767)	(0.140)	(0.714)
28.CountyNum#0b.Holiday	-0.111***	-0.186***	-0.0154
	(0.0200)	(0.0358)	(0.225)
28.CountyNum#1.Holiday	0.238***	0.115	0.0855
	(0.0799)	(0.124)	(0.706)
29.CountyNum#0b.Holiday	-0.147***	-0.120***	0.397***
	(0.0119)	(0.0214)	(0.125)
29.CountyNum#1.Holiday	-0.234***	-0.189***	0.507

	(0.0366)	(0.0716)	(0.357)
30.CountyNum#0b.Holiday	-0.199***	-0.160***	0.396**
	(0.0198)	(0.0337)	(0.192)
30.CountyNum#1.Holiday	-0.389***	-0.349***	-0.0662
	(0.0664)	(0.132)	(0.711)
31.CountyNum#0b.Holiday	0.231***	0.0536*	0.909***
	(0.0147)	(0.0301)	(0.153)
31.CountyNum#1.Holiday	0.268***	0.178**	0.807
	(0.0432)	(0.0902)	(0.535)
32.CountyNum#0b.Holiday	0.271***	0.0703***	-0.184
	(0.0102)	(0.0183)	(0.122)
32.CountyNum#1.Holiday	0.0582	-0.0494	-0.355
	(0.0357)	(0.0553)	(0.334)
33.CountyNum#0b.Holiday	-0.0178	0.0841***	0.497***
	(0.0152)	(0.0281)	(0.172)
33.CountyNum#1.Holiday	0.0258	0.234**	1.225***
	(0.0499)	(0.108)	(0.374)
34.CountyNum#0b.Holiday	0.0863***	-0.0299	-0.0933
	(0.0113)	(0.0187)	(0.119)
34.CountyNum#1.Holiday	-0.121***	-0.166***	-0.455
	(0.0325)	(0.0456)	(0.318)
35.CountyNum#0b.Holiday	-0.272***	-0.233***	0.414***
	(0.0150)	(0.0280)	(0.154)
35.CountyNum#1.Holiday	-0.385***	-0.299***	0.763*
	(0.0480)	(0.0911)	(0.436)
36.CountyNum#0b.Holiday	0.0792***	0.138***	0.125
	(0.0110)	(0.0194)	(0.125)
36.CountyNum#1.Holiday	-0.0618**	0.0343	0.577**
	(0.0310)	(0.0500)	(0.229)
37.CountyNum#0b.Holiday	-0.247***	-0.203***	0.986***
	(0.0291)	(0.0606)	(0.250)
37.CountyNum#1.Holiday	-0.160	0.138	0.563
	(0.108)	(0.187)	(1.002)
38.CountyNum#0b.Holiday	-0.240***	0.0769	1.399***
	(0.0333)	(0.0536)	(0.241)
38.CountyNum#1.Holiday	0.252**	0.682***	1.948***
	(0.105)	(0.148)	(0.580)
39.CountyNum#0b.Holiday	-0.229***	-0.146***	0.683***
	(0.0160)	(0.0280)	(0.150)
39.CountyNum#1.Holiday	-0.227***	-0.237**	0.968**
	(0.0502)	(0.0965)	(0.435)
40.CountyNum#0b.Holiday	-0.0805***	-0.198***	0.312
	(0.0213)	(0.0446)	(0.256)
40.CountyNum#1.Holiday	-0.0366	0.0920	1.037*
	(0.0722)	(0.152)	(0.582)
41.CountyNum#0b.Holiday	0.0972***	0.280***	0.0101
	(0.0105)	(0.0172)	(0.110)
41.CountyNum#1.Holiday	-0.0946***	0.134***	-0.204
	(0.0294)	(0.0386)	(0.238)
42.CountyNum#0b.Holiday	0.123***	0.205***	0.700***
	(0.0148)	(0.0310)	(0.162)
42.CountyNum#1.Holiday	0.247***	0.320***	1.342***
	(0.0490)	(0.0866)	(0.321)
43.CountyNum#0b.Holiday	-0.305***	-0.241***	0.646***
	(0.0125)	(0.0231)	(0.126)
43.CountyNum#1.Holiday	-0.411***	-0.297***	0.435
	(0.0425)	(0.0706)	(0.326)
44.CountyNum#0b.Holiday	-0.271***	-0.216***	0.382**
	(0.0162)	(0.0284)	(0.165)
44.CountyNum#1.Holiday	-0.248***	-0.143	-0.0380
	(0.0576)	(0.0909)	(0.745)
45.CountyNum#0b.Holiday	-0.107***	-0.336***	-0.0175
	(0.0133)	(0.0246)	(0.149)
45.CountyNum#1.Holiday	-0.171***	-0.441***	-0.649
	(0.0423)	(0.0704)	(0.753)
46.CountyNum#0b.Holiday	-0.208***	0.0930**	0.530**
	(0.0211)	(0.0430)	(0.208)
46.CountyNum#1.Holiday	-0.315***	0.0959	-0.169
	(0.0791)	(0.149)	(1.000)
47.CountyNum#0b.Holiday	-0.381***	-0.123***	0.644***

	(0.0168)	(0.0310)	(0.166)
47.CountyNum#1.Holiday	-0.457***	-0.151	0.980**
	(0.0584)	(0.106)	(0.432)
48.CountyNum#0b.Holiday	-0.340***	-0.936***	-0.233
	(0.0440)	(0.107)	(0.585)
48.CountyNum#1.Holiday	-0.345**	-1.478***	1.332
	(0.168)	(0.399)	(0.997)
49.CountyNum#0b.Holiday	-0.0163	0.0398*	0.169
	(0.0121)	(0.0204)	(0.128)
49.CountyNum#1.Holiday	-0.168***	-0.168***	0.367
	(0.0410)	(0.0639)	(0.282)
50.CountyNum#0b.Holiday	-0.251***	-0.348***	0.408**
	(0.0188)	(0.0330)	(0.190)
50.CountyNum#1.Holiday	-0.296***	-0.438***	0.838
	(0.0695)	(0.112)	(0.533)
51.CountyNum#0b.Holiday	-0.0757***	-0.0571***	0.392***
	(0.0119)	(0.0205)	(0.124)
51.CountyNum#1.Holiday	-0.194***	-0.109*	0.113
	(0.0332)	(0.0593)	(0.310)
52.CountyNum#0b.Holiday	0.334***	0.111**	0.738**
	(0.0238)	(0.0518)	(0.291)
52.CountyNum#1.Holiday	0.515***	0.333*	0.697
	(0.0803)	(0.185)	(1.000)
53.CountyNum#0b.Holiday	0.0163	-0.0334	0.614***
	(0.0144)	(0.0294)	(0.159)
53.CountyNum#1.Holiday	-0.0305	-0.160*	0.809**
	(0.0518)	(0.0860)	(0.381)
54.CountyNum#0b.Holiday	0.0370**	0.209***	0.567***
	(0.0149)	(0.0264)	(0.153)
54.CountyNum#1.Holiday	0.0743	0.243***	0.0335
	(0.0491)	(0.0816)	(0.581)
55.CountyNum#0b.Holiday	-0.224***	-0.304***	0.351**
	(0.0153)	(0.0276)	(0.149)
55.CountyNum#1.Holiday	-0.480***	-0.530***	-0.0493
	(0.0456)	(0.0887)	(0.501)
56.CountyNum#0b.Holiday	-0.194***	-0.276***	0.516***
	(0.0177)	(0.0340)	(0.181)
56.CountyNum#1.Holiday	-0.228***	-0.0982	1.012*
	(0.0675)	(0.109)	(0.531)
57.CountyNum#0b.Holiday	-0.513***	-0.844***	0.504**
	(0.0247)	(0.0503)	(0.225)
57.CountyNum#1.Holiday	-0.478***	-0.840***	-0.0825
	(0.0986)	(0.206)	(1.007)
58.CountyNum#0b.Holiday	0.0925***	0.0377	0.599***
	(0.0207)	(0.0378)	(0.208)
58.CountyNum#1.Holiday	0.150**	0.187	-17.40***
	(0.0690)	(0.154)	(0.126)
59.CountyNum#0b.Holiday	0.0107	-0.210***	0.372**
	(0.0161)	(0.0309)	(0.189)
59.CountyNum#1.Holiday	0.0268	-0.296**	0.270
	(0.0539)	(0.117)	(0.581)
60.CountyNum#0b.Holiday	0.304***	0.436***	-0.270**
	(0.00937)	(0.0163)	(0.106)
60.CountyNum#1.Holiday	0.0577**	0.227***	-0.172
	(0.0287)	(0.0344)	(0.199)
61.CountyNum#0b.Holiday	-0.459***	-0.263***	-0.215
	(0.0272)	(0.0492)	(0.411)
61.CountyNum#1.Holiday	-0.458***	-0.381**	-16.98***
	(0.100)	(0.191)	(0.126)
62.CountyNum#0b.Holiday	-0.0383**	-0.301***	0.925***
	(0.0191)	(0.0382)	(0.183)
62.CountyNum#1.Holiday	-0.0586	-0.201	1.085*
	(0.0661)	(0.128)	(0.613)
63.CountyNum#0b.Holiday	-0.106***	-0.240***	0.411***
	(0.0134)	(0.0253)	(0.143)
63.CountyNum#1.Holiday	-0.333***	-0.459***	0.906**
	(0.0446)	(0.0802)	(0.359)
64.CountyNum#0b.Holiday	0.0494***	0.163***	0.802***
	(0.0134)	(0.0239)	(0.133)
64.CountyNum#1.Holiday	-0.00330	0.0864	1.129***

	(0.0376)	(0.0683)	(0.307)
65.CountyNum#0b.Holiday	0.0581***	-0.0435**	-0.225*
	(0.0107)	(0.0194)	(0.132)
65.CountyNum#1.Holiday	-0.0289	-0.0496	0.0758
	(0.0386)	(0.0547)	(0.298)
66.CountyNum#0b.Holiday	-0.0300	-0.0258	1.148***
	(0.0226)	(0.0442)	(0.184)
66.CountyNum#1.Holiday	0.142**	0.0787	1.624***
	(0.0721)	(0.143)	(0.536)
67.CountyNum#0b.Holiday	-0.193***	-0.266***	-0.00260
	(0.0113)	(0.0209)	(0.132)
67.CountyNum#1.Holiday	-0.311***	-0.397***	-0.521
	(0.0348)	(0.0613)	(0.471)
68.CountyNum#0b.Holiday	-0.222***	-0.362***	-0.322**
	(0.0126)	(0.0232)	(0.158)
68.CountyNum#1.Holiday	-0.353***	-0.379***	-0.199
	(0.0461)	(0.0659)	(0.415)
69.CountyNum#0b.Holiday	-0.515***	-0.713***	0.333
	(0.0303)	(0.0659)	(0.293)
69.CountyNum#1.Holiday	-0.288***	-0.668***	0.434
	(0.109)	(0.194)	(0.998)
70.CountyNum#0b.Holiday	-0.172***	-0.295***	-0.251
	(0.0169)	(0.0341)	(0.237)
70.CountyNum#1.Holiday	-0.238***	-0.221*	-0.717
	(0.0567)	(0.123)	(1.001)
71.CountyNum#0b.Holiday	0.0412***	-0.0472	1.014***
	(0.0141)	(0.0306)	(0.140)
71.CountyNum#1.Holiday	0.242***	0.247***	1.314***
	(0.0444)	(0.0865)	(0.330)
72.CountyNum#0b.Holiday	-0.416***	-0.574***	0.357
	(0.0293)	(0.0636)	(0.333)
72.CountyNum#1.Holiday	-0.377***	-0.299	1.080
	(0.109)	(0.227)	(0.708)
73.CountyNum#0b.Holiday	-0.0698***	-0.181***	0.166
	(0.0177)	(0.0332)	(0.200)
73.CountyNum#1.Holiday	-0.0921*	-0.208*	0.921*
	(0.0532)	(0.111)	(0.535)
74.CountyNum#0b.Holiday	0.272***	0.327***	0.137
	(0.0111)	(0.0198)	(0.131)
74.CountyNum#1.Holiday	0.0510	0.150***	-0.214
	(0.0366)	(0.0554)	(0.384)
75.CountyNum#0b.Holiday	-0.204***	-0.340***	0.365
	(0.0225)	(0.0452)	(0.256)
75.CountyNum#1.Holiday	-0.191**	-0.307**	1.376**
	(0.0837)	(0.152)	(0.617)
76.CountyNum#0b.Holiday	-0.0588***	-0.112***	0.398***
	(0.0124)	(0.0215)	(0.128)
76.CountyNum#1.Holiday	-0.162***	-0.207***	0.561*
	(0.0340)	(0.0682)	(0.320)
77.CountyNum#0b.Holiday	0.00260	0.238***	0.636***
	(0.0164)	(0.0292)	(0.176)
77.CountyNum#1.Holiday	-0.0728	0.247**	1.262**
	(0.0529)	(0.104)	(0.506)
78.CountyNum#0b.Holiday	0.152***	0.422***	1.119***
	(0.0118)	(0.0206)	(0.119)
78.CountyNum#1.Holiday	0.198***	0.419***	1.449***
	(0.0354)	(0.0616)	(0.231)
79.CountyNum#0b.Holiday	-0.0981***	-0.223***	0.250*
	(0.0132)	(0.0249)	(0.147)
79.CountyNum#1.Holiday	-0.150***	-0.377***	0.406
	(0.0417)	(0.0819)	(0.434)
80.CountyNum#0b.Holiday	-0.0377***	-0.0366*	0.283**
	(0.0122)	(0.0211)	(0.138)
80.CountyNum#1.Holiday	-0.142***	-0.0247	-0.0383
	(0.0379)	(0.0725)	(0.385)
81.CountyNum#0b.Holiday	-0.212***	-0.198***	0.297*
	(0.0149)	(0.0272)	(0.162)
81.CountyNum#1.Holiday	-0.278***	-0.320***	0.178
	(0.0525)	(0.0965)	(0.504)
82.CountyNum#0b.Holiday	0.0999***	0.150***	0.873***

	(0.0141)	(0.0260)	(0.145)
82.CountyNum#1.Holiday	0.0863**	0.138*	1.423***
	(0.0440)	(0.0821)	(0.302)
83.CountyNum#0b.Holiday	-0.148***	0.230***	0.714***
	(0.0177)	(0.0323)	(0.179)
83.CountyNum#1.Holiday	-0.00714	0.350***	0.798
	(0.0592)	(0.102)	(0.504)
84.CountyNum#0b.Holiday	-0.126***	-0.252***	0.349**
	(0.0147)	(0.0295)	(0.172)
84.CountyNum#1.Holiday	-0.301***	-0.520***	0.247
	(0.0500)	(0.102)	(0.505)
85.CountyNum#0b.Holiday	-0.235***	-0.397***	0.422**
	(0.0175)	(0.0328)	(0.182)
85.CountyNum#1.Holiday	-0.333***	-0.350***	0.261
	(0.0596)	(0.120)	(0.583)
86.CountyNum#0b.Holiday	-0.138***	-0.0433*	0.572***
	(0.0147)	(0.0263)	(0.148)
86.CountyNum#1.Holiday	-0.243***	-0.124	0.635*
	(0.0457)	(0.0849)	(0.378)
87.CountyNum#0b.Holiday	-0.529***	-0.603***	0.267
	(0.0284)	(0.0575)	(0.283)
87.CountyNum#1.Holiday	-0.468***	-0.500**	0.989
	(0.106)	(0.197)	(0.709)
88.CountyNum#0b.Holiday	-0.398***	-0.535***	0.103
	(0.0200)	(0.0388)	(0.238)
88.CountyNum#1.Holiday	-0.393***	-0.299**	0.853
	(0.0727)	(0.137)	(0.608)
89.CountyNum#0b.Holiday	0.193***	-0.507***	-0.374
	(0.0386)	(0.106)	(1.004)
89.CountyNum#1.Holiday	0.599***	-0.0573	-15.64***
	(0.132)	(0.475)	(0.126)
90.CountyNum#0b.Holiday	-0.0700***	-0.182***	-0.0796
	(0.0107)	(0.0200)	(0.131)
90.CountyNum#1.Holiday	-0.230***	-0.206***	-0.501
	(0.0344)	(0.0599)	(0.475)
91.CountyNum#0b.Holiday	0.212***	0.354***	0.640***
	(0.0152)	(0.0282)	(0.162)
91.CountyNum#1.Holiday	0.337***	0.580***	0.987**
	(0.0499)	(0.105)	(0.471)
92.CountyNum#0b.Holiday	0.145***	-0.0247	-0.566***
	(0.00991)	(0.0168)	(0.109)
92.CountyNum#1.Holiday	-0.142***	-0.246***	-0.424**
	(0.0304)	(0.0377)	(0.197)
93.CountyNum#0b.Holiday	-0.118***	-0.0704	0.910***
	(0.0230)	(0.0471)	(0.235)
93.CountyNum#1.Holiday	0.181**	0.202	-0.00621
	(0.0739)	(0.136)	(1.000)
94.CountyNum#0b.Holiday	-0.199***	-0.362***	0.325
	(0.0281)	(0.0566)	(0.304)
94.CountyNum#1.Holiday	-0.186*	-0.411	0.504
	(0.106)	(0.281)	(0.997)
95.CountyNum#0b.Holiday	-0.00693	-0.333***	-0.0391
	(0.0158)	(0.0299)	(0.208)
95.CountyNum#1.Holiday	-0.173***	-0.370***	-18.24***
	(0.0613)	(0.116)	(0.126)
96.CountyNum#0b.Holiday	-0.00633	0.0969***	0.401***
	(0.0120)	(0.0221)	(0.135)
96.CountyNum#1.Holiday	-0.0718*	0.0836	-0.212
	(0.0385)	(0.0692)	(0.449)
97.CountyNum#0b.Holiday	-0.258***	-0.175***	0.325**
	(0.0151)	(0.0269)	(0.161)
97.CountyNum#1.Holiday	-0.370***	-0.287***	0.375
	(0.0491)	(0.0869)	(0.453)
98.CountyNum#0b.Holiday	0.0937***	0.109***	0.460***
	(0.0136)	(0.0252)	(0.151)
98.CountyNum#1.Holiday	0.122***	0.250***	0.544
	(0.0439)	(0.0731)	(0.382)
99.CountyNum#0b.Holiday	-0.233***	-0.374***	0.485***
	(0.0195)	(0.0355)	(0.185)
99.CountyNum#1.Holiday	-0.237***	-0.254*	0.442

	(0.0610)	(0.148)	(0.578)
100.CountyNum#0b.Holiday	-0.585***	-0.605***	0.405
	(0.0268)	(0.0541)	(0.253)
100.CountyNum#1.Holiday	-0.521***	-0.434**	0.0793
	(0.0966)	(0.177)	(1.002)
2014	0.0121***	0.00605	-0.00283
	(0.00447)	(0.00807)	(0.0432)
2015	0.102***	0.0954***	0.0680
	(0.00425)	(0.00798)	(0.0426)
2016	0.145***	0.133***	0.0965**
	(0.00427)	(0.00793)	(0.0419)
2017	0.169***	0.116***	0.0608
	(0.00409)	(0.00793)	(0.0424)
2018	0.183***	0.0769***	0.0876**
	(0.00417)	(0.00790)	(0.0421)
2019	0.181***	0.0695***	0.110***
	(0.00401)	(0.00788)	(0.0417)
February	-0.00961	0.0497***	-0.0236
	(0.00697)	(0.0113)	(0.0593)
March	-0.0252***	0.100***	0.0284
	(0.00625)	(0.0107)	(0.0580)
April	-0.0176***	0.164***	0.115**
	(0.00602)	(0.0104)	(0.0570)
May	0.0282***	0.222***	0.197***
	(0.00593)	(0.0104)	(0.0562)
June	0.00555	0.211***	0.243***
	(0.00592)	(0.0104)	(0.0557)
July	-0.0506***	0.151***	0.107*
	(0.00596)	(0.0106)	(0.0573)
August	-0.00632	0.202***	0.141**
	(0.00593)	(0.0104)	(0.0561)
September	0.0268***	0.208***	0.267***
	(0.00605)	(0.0104)	(0.0557)
October	0.183***	0.281***	0.291***
	(0.00584)	(0.0103)	(0.0548)
November	0.251***	0.228***	0.232***
	(0.00587)	(0.0104)	(0.0560)
December	0.149***	0.164***	0.105*
	(0.00620)	(0.0105)	(0.0568)
Monday	0.335***	0.205***	-0.211***
	(0.00438)	(0.00848)	(0.0424)
Tuesday	0.337***	0.197***	-0.184***
	(0.00435)	(0.00842)	(0.0419)
Wednesday	0.336***	0.194***	-0.162***
	(0.00433)	(0.00835)	(0.0417)
Thursday	0.341***	0.207***	-0.187***
	(0.00421)	(0.00825)	(0.0417)
Friday	0.506***	0.393***	0.00166
	(0.00428)	(0.00818)	(0.0399)
Saturday	0.219***	0.198***	0.0995**
	(0.00433)	(0.00851)	(0.0390)
lnalpha	-2.810***	-0.869***	0.867***
	(0.0189)	(0.00939)	(0.0537)
Constant	-10.07***	-10.79***	-15.11***
	(0.0106)	(0.0189)	(0.112)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Discovery Regression #3

nbreg Crashes i.CountyNum#(Vhot) i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store Discover3C
outreg2 using Discover3, word replace ctitle(Crashes, NB)
nbreg Injured i.CountyNum#(Vhot) i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)

```
estimates store Discover3I
outreg2 using Discover3, word append ctitle(Injuries, NB)
nbreg Killed i.CountyNum#(Vhot) i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store Discover3K
outreg2 using Discover3, word append ctitle(Fatalities, NB)
```

VARIABLES	(1) Crashes NB	(2) Injuries NB	(3) Fatalities NB
1b.CountyNum#0b.Vhot	0	0	0
	(0)	(0)	(0)
1b.CountyNum#1.Vhot	-0.0471	-0.0171	0.0450
	(0.0338)	(0.0577)	(0.440)
2.CountyNum#0b.Vhot	-0.533***	-0.618***	0.186
	(0.0195)	(0.0399)	(0.206)
2.CountyNum#1.Vhot	-0.579***	-0.615***	0.648
	(0.0692)	(0.158)	(0.576)
3.CountyNum#0b.Vhot	-0.342***	-0.425***	0.385
	(0.0323)	(0.0636)	(0.303)
3.CountyNum#1.Vhot	-0.386***	-0.519**	0.786
	(0.125)	(0.227)	(1.004)
4.CountyNum#0b.Vhot	0.174***	0.303***	0.643***
	(0.0182)	(0.0355)	(0.200)
4.CountyNum#1.Vhot	0.230***	0.377***	-23.18***
	(0.0704)	(0.126)	(0.132)
5.CountyNum#0b.Vhot	-0.339***	-0.465***	0.344
	(0.0219)	(0.0430)	(0.217)
5.CountyNum#1.Vhot	-0.233***	-0.567***	-0.0748
	(0.0706)	(0.159)	(1.001)
6.CountyNum#0b.Vhot	-0.308***	-0.460***	-0.0972
	(0.0255)	(0.0503)	(0.303)
6.CountyNum#1.Vhot	-0.186**	-0.0965	-22.88***
	(0.0848)	(0.166)	(0.131)
7.CountyNum#0b.Vhot	-0.125***	-0.164***	0.417**
	(0.0159)	(0.0336)	(0.173)
7.CountyNum#1.Vhot	-0.165***	-0.250**	0.0623
	(0.0602)	(0.117)	(0.710)
8.CountyNum#0b.Vhot	-0.0871***	0.0575	1.221***
	(0.0225)	(0.0431)	(0.189)
8.CountyNum#1.Vhot	0.0181	0.207	1.621***
	(0.0792)	(0.140)	(0.501)
9.CountyNum#0b.Vhot	0.132***	0.203***	1.172***
	(0.0167)	(0.0348)	(0.169)
9.CountyNum#1.Vhot	0.147**	0.225*	1.068*
	(0.0634)	(0.127)	(0.617)
10.CountyNum#0b.Vhot	-0.168***	-0.286***	0.295**
	(0.0122)	(0.0234)	(0.139)
10.CountyNum#1.Vhot	-0.0503	-0.183**	0.396
	(0.0379)	(0.0776)	(0.398)
11.CountyNum#0b.Vhot	0.134***	-0.111***	0.0910
	(0.0107)	(0.0191)	(0.120)
11.CountyNum#1.Vhot	0.211***	-0.0366	-0.107
	(0.0239)	(0.0479)	(0.348)
12.CountyNum#0b.Vhot	-0.0793***	-0.0763***	0.349**
	(0.0139)	(0.0254)	(0.143)
12.CountyNum#1.Vhot	-0.112**	-0.0380	0.919**
	(0.0449)	(0.0776)	(0.462)
13.CountyNum#0b.Vhot	0.0771***	0.0103	-0.119
	(0.0111)	(0.0200)	(0.131)
13.CountyNum#1.Vhot	0.00701	-0.0619	-0.261
	(0.0308)	(0.0608)	(0.385)
14.CountyNum#0b.Vhot	-0.149***	-0.141***	0.0417
	(0.0138)	(0.0254)	(0.168)
14.CountyNum#1.Vhot	-0.0933**	-0.0541	0.690
	(0.0446)	(0.0887)	(0.433)
15.CountyNum#0b.Vhot	-0.354***	-0.668***	0.469

	(0.0317)	(0.0681)	(0.365)
15.CountyNum#1.Vhot	-0.291**	-0.233	-22.32***
	(0.137)	(0.224)	(0.132)
16.CountyNum#0b.Vhot	-0.256***	-0.375***	-0.164
	(0.0149)	(0.0283)	(0.190)
16.CountyNum#1.Vhot	-0.0156	-0.331***	0.310
	(0.0431)	(0.0981)	(0.495)
17.CountyNum#0b.Vhot	-0.276***	-0.340***	0.763***
	(0.0215)	(0.0419)	(0.193)
17.CountyNum#1.Vhot	-0.359***	-0.194	1.420**
	(0.0945)	(0.155)	(0.613)
18.CountyNum#0b.Vhot	0.166***	0.0350*	0.136
	(0.0118)	(0.0206)	(0.132)
18.CountyNum#1.Vhot	0.161***	0.0405	0.0365
	(0.0262)	(0.0579)	(0.434)
19.CountyNum#0b.Vhot	-0.187***	-0.498***	0.499***
	(0.0159)	(0.0290)	(0.154)
19.CountyNum#1.Vhot	-0.356***	-0.463***	0.0141
	(0.0471)	(0.0956)	(0.745)
20.CountyNum#0b.Vhot	-0.427***	-0.466***	0.723***
	(0.0212)	(0.0408)	(0.190)
20.CountyNum#1.Vhot	-0.390***	-0.506***	-0.197
	(0.0817)	(0.160)	(1.002)
21.CountyNum#0b.Vhot	-0.372***	-0.563***	0.479*
	(0.0282)	(0.0607)	(0.273)
21.CountyNum#1.Vhot	-0.505***	-0.781***	-22.66***
	(0.133)	(0.255)	(0.132)
22.CountyNum#0b.Vhot	-0.355***	-0.561***	0.386
	(0.0325)	(0.0654)	(0.326)
22.CountyNum#1.Vhot	-0.585***	-0.717***	0.773
	(0.132)	(0.266)	(1.004)
23.CountyNum#0b.Vhot	0.0888***	0.00463	0.574***
	(0.0129)	(0.0236)	(0.137)
23.CountyNum#1.Vhot	0.0200	-0.0472	0.654
	(0.0348)	(0.0767)	(0.401)
24.CountyNum#0b.Vhot	0.238***	0.407***	1.198***
	(0.0136)	(0.0273)	(0.133)
24.CountyNum#1.Vhot	0.273***	0.456***	1.461***
	(0.0457)	(0.0835)	(0.350)
25.CountyNum#0b.Vhot	-0.183***	-0.203***	0.198
	(0.0127)	(0.0240)	(0.146)
25.CountyNum#1.Vhot	-0.169***	-0.239***	-0.0654
	(0.0431)	(0.0788)	(0.500)
26.CountyNum#0b.Vhot	0.00246	0.0391**	0.200*
	(0.0108)	(0.0186)	(0.115)
26.CountyNum#1.Vhot	0.0415	0.0159	0.374*
	(0.0286)	(0.0486)	(0.227)
27.CountyNum#0b.Vhot	-0.499***	-0.587***	0.413*
	(0.0232)	(0.0469)	(0.224)
27.CountyNum#1.Vhot	-0.155**	-0.127	1.055
	(0.0744)	(0.197)	(0.756)
28.CountyNum#0b.Vhot	-0.129***	-0.208***	-0.0622
	(0.0204)	(0.0361)	(0.228)
28.CountyNum#1.Vhot	0.575***	0.444***	0.708
	(0.0493)	(0.106)	(0.582)
29.CountyNum#0b.Vhot	-0.145***	-0.124***	0.395***
	(0.0120)	(0.0216)	(0.124)
29.CountyNum#1.Vhot	-0.168***	-0.0861	0.640*
	(0.0311)	(0.0637)	(0.343)
30.CountyNum#0b.Vhot	-0.202***	-0.187***	0.345*
	(0.0198)	(0.0336)	(0.196)
30.CountyNum#1.Vhot	-0.228***	0.115	0.823*
	(0.0649)	(0.129)	(0.499)
31.CountyNum#0b.Vhot	0.241***	0.0631**	0.827***
	(0.0146)	(0.0300)	(0.156)
31.CountyNum#1.Vhot	0.198***	0.0830	1.778***
	(0.0475)	(0.0927)	(0.336)
32.CountyNum#0b.Vhot	0.264***	0.0647***	-0.214*
	(0.0104)	(0.0184)	(0.122)
32.CountyNum#1.Vhot	0.285***	0.0808*	0.159

	(0.0234)	(0.0433)	(0.256)
33.CountyNum#0b.Vhot	-0.00680	0.0905***	0.595***
	(0.0152)	(0.0285)	(0.165)
33.CountyNum#1.Vhot	-0.0490	0.199**	-0.0686
	(0.0498)	(0.0934)	(0.707)
34.CountyNum#0b.Vhot	0.0809***	-0.0343*	-0.108
	(0.0114)	(0.0188)	(0.118)
34.CountyNum#1.Vhot	0.0813***	-0.0579	-0.104
	(0.0265)	(0.0409)	(0.354)
35.CountyNum#0b.Vhot	-0.273***	-0.235***	0.462***
	(0.0150)	(0.0279)	(0.152)
35.CountyNum#1.Vhot	-0.261***	-0.231**	0.0937
	(0.0495)	(0.104)	(0.583)
36.CountyNum#0b.Vhot	0.0758***	0.138***	0.198
	(0.0111)	(0.0194)	(0.121)
36.CountyNum#1.Vhot	0.106***	0.0567	-0.630
	(0.0296)	(0.0508)	(0.450)
37.CountyNum#0b.Vhot	-0.229***	-0.167***	0.932***
	(0.0290)	(0.0597)	(0.247)
37.CountyNum#1.Vhot	-0.367***	-0.336	1.459
	(0.116)	(0.218)	(1.008)
38.CountyNum#0b.Vhot	-0.207***	0.107**	1.468***
	(0.0331)	(0.0526)	(0.232)
38.CountyNum#1.Vhot	0.00722	0.469**	1.077
	(0.121)	(0.187)	(1.001)
39.CountyNum#0b.Vhot	-0.220***	-0.158***	0.732***
	(0.0160)	(0.0279)	(0.148)
39.CountyNum#1.Vhot	-0.276***	0.00504	0.188
	(0.0535)	(0.107)	(0.740)
40.CountyNum#0b.Vhot	-0.0685***	-0.210***	0.396
	(0.0211)	(0.0440)	(0.245)
40.CountyNum#1.Vhot	-0.131	0.315*	0.139
	(0.0854)	(0.168)	(0.997)
41.CountyNum#0b.Vhot	0.0955***	0.279***	0.00902
	(0.0106)	(0.0173)	(0.109)
41.CountyNum#1.Vhot	0.0426**	0.189***	-0.101
	(0.0213)	(0.0323)	(0.251)
42.CountyNum#0b.Vhot	0.135***	0.209***	0.768***
	(0.0148)	(0.0307)	(0.156)
42.CountyNum#1.Vhot	0.189***	0.317***	0.661
	(0.0477)	(0.101)	(0.615)
43.CountyNum#0b.Vhot	-0.302***	-0.239***	0.654***
	(0.0126)	(0.0232)	(0.125)
43.CountyNum#1.Vhot	-0.361***	-0.297***	0.350
	(0.0391)	(0.0696)	(0.357)
44.CountyNum#0b.Vhot	-0.269***	-0.215***	0.345**
	(0.0162)	(0.0283)	(0.168)
44.CountyNum#1.Vhot	-0.155***	-0.103	0.668
	(0.0572)	(0.0994)	(0.452)
45.CountyNum#0b.Vhot	-0.110***	-0.353***	-0.0105
	(0.0133)	(0.0246)	(0.149)
45.CountyNum#1.Vhot	-0.00927	-0.134*	-0.878
	(0.0384)	(0.0727)	(0.714)
46.CountyNum#0b.Vhot	-0.206***	0.110**	0.489**
	(0.0210)	(0.0428)	(0.210)
46.CountyNum#1.Vhot	-0.253***	-0.201	0.720
	(0.0886)	(0.153)	(0.713)
47.CountyNum#0b.Vhot	-0.377***	-0.120***	0.666***
	(0.0168)	(0.0310)	(0.161)
47.CountyNum#1.Vhot	-0.411***	-0.170	0.832
	(0.0603)	(0.108)	(0.667)
48.CountyNum#0b.Vhot	-0.333***	-0.963***	0.0472
	(0.0438)	(0.107)	(0.508)
48.CountyNum#1.Vhot	-0.370**	-0.913**	-21.62***
	(0.176)	(0.449)	(0.131)
49.CountyNum#0b.Vhot	-0.0188	0.0310	0.200
	(0.0123)	(0.0206)	(0.125)
49.CountyNum#1.Vhot	-0.0146	0.0205	-0.0384
	(0.0320)	(0.0538)	(0.382)
50.CountyNum#0b.Vhot	-0.252***	-0.355***	0.445**

	(0.0189)	(0.0330)	(0.188)
50.CountyNum#1.Vhot	-0.170***	-0.276**	0.490
	(0.0594)	(0.111)	(0.576)
51.CountyNum#0b.Vhot	-0.0739***	-0.0507**	0.416***
	(0.0119)	(0.0205)	(0.122)
51.CountyNum#1.Vhot	-0.119***	-0.197***	-0.517
	(0.0346)	(0.0644)	(0.449)
52.CountyNum#0b.Vhot	0.350***	0.105**	0.731**
	(0.0235)	(0.0519)	(0.291)
52.CountyNum#1.Vhot	0.404***	0.486***	0.896
	(0.0990)	(0.178)	(1.000)
53.CountyNum#0b.Vhot	0.0250*	-0.0253	0.631***
	(0.0145)	(0.0291)	(0.154)
53.CountyNum#1.Vhot	-0.0844	-0.315***	0.675
	(0.0519)	(0.105)	(0.659)
54.CountyNum#0b.Vhot	0.0507***	0.215***	0.520***
	(0.0149)	(0.0263)	(0.155)
54.CountyNum#1.Vhot	-0.0564	0.187**	0.918**
	(0.0481)	(0.0927)	(0.411)
55.CountyNum#0b.Vhot	-0.236***	-0.316***	0.309**
	(0.0154)	(0.0276)	(0.150)
55.CountyNum#1.Vhot	-0.147***	-0.289***	0.709*
	(0.0446)	(0.0949)	(0.429)
56.CountyNum#0b.Vhot	-0.202***	-0.271***	0.575***
	(0.0178)	(0.0338)	(0.178)
56.CountyNum#1.Vhot	0.0183	-0.114	0.300
	(0.0629)	(0.118)	(0.705)
57.CountyNum#0b.Vhot	-0.508***	-0.850***	0.536**
	(0.0248)	(0.0507)	(0.221)
57.CountyNum#1.Vhot	-0.450***	-0.698***	-23.07***
	(0.0961)	(0.183)	(0.131)
58.CountyNum#0b.Vhot	0.108***	0.0542	0.594***
	(0.0205)	(0.0380)	(0.207)
58.CountyNum#1.Vhot	-0.0120	-0.0263	-23.14***
	(0.0874)	(0.151)	(0.131)
59.CountyNum#0b.Vhot	0.0188	-0.212***	0.407**
	(0.0161)	(0.0310)	(0.185)
59.CountyNum#1.Vhot	0.00435	-0.226**	-0.642
	(0.0534)	(0.112)	(1.000)
60.CountyNum#0b.Vhot	0.295***	0.429***	-0.247**
	(0.00954)	(0.0164)	(0.105)
60.CountyNum#1.Vhot	0.330***	0.376***	-0.476**
	(0.0156)	(0.0236)	(0.219)
61.CountyNum#0b.Vhot	-0.449***	-0.276***	-0.223
	(0.0270)	(0.0495)	(0.411)
61.CountyNum#1.Vhot	-0.517***	-0.126	-22.72***
	(0.115)	(0.176)	(0.132)
62.CountyNum#0b.Vhot	-0.0305	-0.290***	0.923***
	(0.0191)	(0.0382)	(0.184)
62.CountyNum#1.Vhot	-0.0827	-0.331***	1.201**
	(0.0679)	(0.125)	(0.501)
63.CountyNum#0b.Vhot	-0.106***	-0.246***	0.477***
	(0.0134)	(0.0253)	(0.140)
63.CountyNum#1.Vhot	-0.237***	-0.324***	0.00594
	(0.0408)	(0.0888)	(0.610)
64.CountyNum#0b.Vhot	0.0581***	0.170***	0.832***
	(0.0133)	(0.0238)	(0.131)
64.CountyNum#1.Vhot	-0.0578	-0.0166	0.833**
	(0.0367)	(0.0813)	(0.335)
65.CountyNum#0b.Vhot	0.0566***	-0.0387**	-0.186
	(0.0108)	(0.0195)	(0.129)
65.CountyNum#1.Vhot	0.109***	-0.0949**	-0.425
	(0.0264)	(0.0460)	(0.479)
66.CountyNum#0b.Vhot	-0.0196	-0.0290	1.144***
	(0.0225)	(0.0436)	(0.187)
66.CountyNum#1.Vhot	0.109	0.172	1.772***
	(0.0744)	(0.175)	(0.449)
67.CountyNum#0b.Vhot	-0.193***	-0.271***	-0.00179
	(0.0114)	(0.0209)	(0.131)
67.CountyNum#1.Vhot	-0.215***	-0.277***	-0.510

	(0.0316)	(0.0622)	(0.452)
68.CountyNum#0b.Vhot	-0.218***	-0.354***	-0.287*
	(0.0127)	(0.0231)	(0.155)
68.CountyNum#1.Vhot	-0.314***	-0.489***	-0.752
	(0.0417)	(0.0761)	(0.580)
69.CountyNum#0b.Vhot	-0.486***	-0.715***	0.402
	(0.0300)	(0.0645)	(0.283)
69.CountyNum#1.Vhot	-0.648***	-0.602**	-22.54***
	(0.135)	(0.281)	(0.130)
70.CountyNum#0b.Vhot	-0.170***	-0.289***	-0.258
	(0.0169)	(0.0340)	(0.237)
70.CountyNum#1.Vhot	-0.168***	-0.258*	-0.509
	(0.0578)	(0.135)	(1.002)
71.CountyNum#0b.Vhot	0.0579***	-0.0293	1.056***
	(0.0142)	(0.0304)	(0.137)
71.CountyNum#1.Vhot	0.118***	0.0718	0.737
	(0.0442)	(0.0960)	(0.454)
72.CountyNum#0b.Vhot	-0.403***	-0.566***	0.420
	(0.0290)	(0.0638)	(0.319)
72.CountyNum#1.Vhot	-0.478***	-0.335	0.570
	(0.132)	(0.223)	(1.004)
73.CountyNum#0b.Vhot	-0.0550***	-0.164***	0.297
	(0.0175)	(0.0328)	(0.192)
73.CountyNum#1.Vhot	-0.272***	-0.533***	-23.68***
	(0.0605)	(0.141)	(0.132)
74.CountyNum#0b.Vhot	0.270***	0.326***	0.174
	(0.0112)	(0.0198)	(0.128)
74.CountyNum#1.Vhot	0.194***	0.200***	-1.997**
	(0.0300)	(0.0574)	(1.004)
75.CountyNum#0b.Vhot	-0.197***	-0.330***	0.534**
	(0.0224)	(0.0446)	(0.242)
75.CountyNum#1.Vhot	-0.186**	-0.429**	-23.01***
	(0.0888)	(0.198)	(0.131)
76.CountyNum#0b.Vhot	-0.0533***	-0.111***	0.440***
	(0.0124)	(0.0216)	(0.126)
76.CountyNum#1.Vhot	-0.164***	-0.192***	-0.169
	(0.0345)	(0.0681)	(0.449)
77.CountyNum#0b.Vhot	-0.000514	0.241***	0.722***
	(0.0163)	(0.0293)	(0.174)
77.CountyNum#1.Vhot	0.0958	0.253***	0.0764
	(0.0625)	(0.0947)	(0.706)
78.CountyNum#0b.Vhot	0.161***	0.425***	1.148***
	(0.0118)	(0.0207)	(0.117)
78.CountyNum#1.Vhot	0.168***	0.412***	1.169***
	(0.0368)	(0.0632)	(0.308)
79.CountyNum#0b.Vhot	-0.0930***	-0.236***	0.220
	(0.0133)	(0.0250)	(0.147)
79.CountyNum#1.Vhot	-0.132***	-0.126	0.861**
	(0.0389)	(0.0820)	(0.367)
80.CountyNum#0b.Vhot	-0.0364***	-0.0358*	0.283**
	(0.0122)	(0.0212)	(0.136)
80.CountyNum#1.Vhot	-0.0586*	0.00761	0.0131
	(0.0335)	(0.0700)	(0.475)
81.CountyNum#0b.Vhot	-0.207***	-0.204***	0.258
	(0.0149)	(0.0272)	(0.158)
81.CountyNum#1.Vhot	-0.253***	-0.182*	0.805
	(0.0526)	(0.0995)	(0.585)
82.CountyNum#0b.Vhot	0.108***	0.156***	0.905***
	(0.0141)	(0.0257)	(0.142)
82.CountyNum#1.Vhot	0.0616	0.0659	1.217***
	(0.0468)	(0.106)	(0.403)
83.CountyNum#0b.Vhot	-0.136***	0.235***	0.744***
	(0.0176)	(0.0320)	(0.176)
83.CountyNum#1.Vhot	-0.0590	0.319***	0.317
	(0.0735)	(0.118)	(0.713)
84.CountyNum#0b.Vhot	-0.125***	-0.258***	0.330*
	(0.0147)	(0.0295)	(0.169)
84.CountyNum#1.Vhot	-0.212***	-0.380***	0.610
	(0.0505)	(0.109)	(0.603)
85.CountyNum#0b.Vhot	-0.225***	-0.386***	0.397**

	(0.0174)	(0.0322)	(0.183)
85.CountyNum#1.Vhot	-0.427***	-0.502***	0.728
	(0.0693)	(0.171)	(0.506)
86.CountyNum#0b.Vhot	-0.141***	-0.0470*	0.605***
	(0.0147)	(0.0263)	(0.145)
86.CountyNum#1.Vhot	-0.0832	-0.0232	0.0307
	(0.0524)	(0.0832)	(0.584)
87.CountyNum#0b.Vhot	-0.541***	-0.633***	0.331
	(0.0285)	(0.0574)	(0.274)
87.CountyNum#1.Vhot	-0.182*	-0.0974	0.465
	(0.0990)	(0.191)	(1.001)
88.CountyNum#0b.Vhot	-0.403***	-0.533***	0.201
	(0.0201)	(0.0391)	(0.230)
88.CountyNum#1.Vhot	-0.195***	-0.264**	-0.319
	(0.0643)	(0.129)	(0.999)
89.CountyNum#0b.Vhot	0.217***	-0.525***	-0.382
	(0.0383)	(0.110)	(1.004)
89.CountyNum#1.Vhot	0.442***	0.214	-21.38***
	(0.155)	(0.351)	(0.132)
90.CountyNum#0b.Vhot	-0.0718***	-0.178***	-0.0971
	(0.0107)	(0.0200)	(0.131)
90.CountyNum#1.Vhot	-0.0907***	-0.229***	-0.0883
	(0.0282)	(0.0620)	(0.373)
91.CountyNum#0b.Vhot	0.231***	0.384***	0.698***
	(0.0152)	(0.0284)	(0.159)
91.CountyNum#1.Vhot	0.132**	0.121	0.0744
	(0.0547)	(0.0999)	(0.706)
92.CountyNum#0b.Vhot	0.137***	-0.0313*	-0.523***
	(0.0101)	(0.0169)	(0.108)
92.CountyNum#1.Vhot	0.110***	-0.0995***	-1.224***
	(0.0185)	(0.0303)	(0.316)
93.CountyNum#0b.Vhot	-0.0965***	-0.0669	0.815***
	(0.0228)	(0.0463)	(0.243)
93.CountyNum#1.Vhot	0.0193	0.234	1.600***
	(0.0885)	(0.175)	(0.610)
94.CountyNum#0b.Vhot	-0.199***	-0.379***	0.317
	(0.0280)	(0.0577)	(0.303)
94.CountyNum#1.Vhot	-0.0529	-0.102	0.730
	(0.114)	(0.219)	(0.999)
95.CountyNum#0b.Vhot	-0.0171	-0.341***	-0.0446
	(0.0160)	(0.0303)	(0.208)
95.CountyNum#1.Vhot	0.112**	-0.206**	-23.98***
	(0.0465)	(0.0901)	(0.131)
96.CountyNum#0b.Vhot	-0.00238	0.0992***	0.366***
	(0.0121)	(0.0222)	(0.136)
96.CountyNum#1.Vhot	-0.0326	0.0849	0.552*
	(0.0360)	(0.0647)	(0.332)
97.CountyNum#0b.Vhot	-0.256***	-0.171***	0.319**
	(0.0151)	(0.0269)	(0.159)
97.CountyNum#1.Vhot	-0.298***	-0.328***	0.558
	(0.0489)	(0.0825)	(0.534)
98.CountyNum#0b.Vhot	0.101***	0.122***	0.433***
	(0.0136)	(0.0251)	(0.151)
98.CountyNum#1.Vhot	0.109**	0.0961	0.973***
	(0.0425)	(0.0826)	(0.365)
99.CountyNum#0b.Vhot	-0.222***	-0.356***	0.499***
	(0.0193)	(0.0358)	(0.183)
99.CountyNum#1.Vhot	-0.331***	-0.513***	0.259
	(0.0727)	(0.137)	(0.708)
100.CountyNum#0b.Vhot	-0.579***	-0.606***	0.446*
	(0.0266)	(0.0523)	(0.246)
100.CountyNum#1.Vhot	-0.494***	-0.353	-22.90***
	(0.110)	(0.259)	(0.132)
2014	0.0121***	0.00599	-0.00274
	(0.00448)	(0.00809)	(0.0432)
2015	0.102***	0.0948***	0.0712*
	(0.00428)	(0.00801)	(0.0426)
2016	0.145***	0.132***	0.101**
	(0.00430)	(0.00797)	(0.0421)
2017	0.169***	0.116***	0.0620

	(0.00410)	(0.00794)	(0.0425)
2018	0.183***	0.0765***	0.0885**
	(0.00418)	(0.00791)	(0.0421)
2019	0.182***	0.0692***	0.113***
	(0.00403)	(0.00792)	(0.0418)
February	-0.00721	0.0507***	-0.0259
	(0.00698)	(0.0113)	(0.0593)
March	-0.0228***	0.101***	0.0262
	(0.00626)	(0.0107)	(0.0581)
April	-0.0152**	0.165***	0.113**
	(0.00603)	(0.0104)	(0.0571)
May	0.0149**	0.217***	0.209***
	(0.00592)	(0.0104)	(0.0554)
June	0.00579	0.210***	0.252***
	(0.00597)	(0.0105)	(0.0560)
July	-0.0581***	0.145***	0.134**
	(0.00620)	(0.0111)	(0.0594)
August	-0.00782	0.200***	0.153***
	(0.00598)	(0.0105)	(0.0568)
September	0.0218***	0.206***	0.274***
	(0.00608)	(0.0104)	(0.0556)
October	0.179***	0.279***	0.294***
	(0.00584)	(0.0103)	(0.0548)
November	0.248***	0.227***	0.234***
	(0.00589)	(0.0104)	(0.0561)
December	0.144***	0.163***	0.109*
	(0.00625)	(0.0105)	(0.0567)
Monday	0.337***	0.207***	-0.212***
	(0.00440)	(0.00849)	(0.0424)
Tuesday	0.344***	0.200***	-0.188***
	(0.00433)	(0.00839)	(0.0417)
Wednesday	0.341***	0.196***	-0.165***
	(0.00431)	(0.00833)	(0.0416)
Thursday	0.345***	0.209***	-0.188***
	(0.00421)	(0.00824)	(0.0415)
Friday	0.509***	0.395***	0.000783
	(0.00427)	(0.00818)	(0.0399)
Saturday	0.222***	0.200***	0.0987**
	(0.00433)	(0.00851)	(0.0389)
lnalpha	-2.788***	-0.869***	0.865***
	(0.0185)	(0.00937)	(0.0537)
Constant	-10.08***	-10.79***	-15.12***
	(0.0107)	(0.0189)	(0.110)
Observations	255,600	255,600	255,600

Stata Prompt and Results for Discovery Regression #4

nbreg Crashes i.CountyNum#(DST) i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store Discover4C
outreg2 using Discover4, word replace ctitle(Crashes, NB)
nbreg Injured i.CountyNum#(DST) i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store Discover4I
outreg2 using Discover4, word append ctitle(Injuries, NB)
nbreg Killed i.CountyNum#(DST) i.Year i.MoY i.DoW, vce(robust) exposure(YearPop)
estimates store Discover4K
outreg2 using Discover4, word append ctitle(Fatalities, NB)

	(1)	(2)	(3)
	Crashes	Injuries	Fatalities
VARIABLES	NB	NB	NB

1b.CountyNum#0b.DST	0	0	0
	(0)	(0)	(0)
1b.CountyNum#1.DST	0.0940**	0.141	-0.916
	(0.0451)	(0.145)	(0.706)
2.CountyNum#0b.DST	-0.530***	-0.609***	0.145
	(0.0194)	(0.0392)	(0.201)
2.CountyNum#1.DST	-0.509***	-0.669***	0.956
	(0.0766)	(0.180)	(0.732)
3.CountyNum#0b.DST	-0.335***	-0.410***	0.344
	(0.0321)	(0.0623)	(0.302)
3.CountyNum#1.DST	-0.409***	-0.815**	1.083
	(0.144)	(0.317)	(0.997)
4.CountyNum#0b.DST	0.174***	0.307***	0.603***
	(0.0181)	(0.0345)	(0.199)
4.CountyNum#1.DST	0.384***	0.471***	-19.21***
	(0.0718)	(0.172)	(0.142)
5.CountyNum#0b.DST	-0.326***	-0.483***	0.305
	(0.0217)	(0.0428)	(0.216)
5.CountyNum#1.DST	-0.344***	-0.0666	0.196
	(0.0836)	(0.140)	(0.999)
6.CountyNum#0b.DST	-0.293***	-0.425***	-0.227
	(0.0252)	(0.0491)	(0.315)
6.CountyNum#1.DST	-0.347***	-0.540**	0.595
	(0.106)	(0.234)	(0.994)
7.CountyNum#0b.DST	-0.126***	-0.167***	0.377**
	(0.0159)	(0.0329)	(0.173)
7.CountyNum#1.DST	-0.00502	-0.0515	0.344
	(0.0542)	(0.124)	(0.707)
8.CountyNum#0b.DST	-0.0725***	0.0728*	1.260***
	(0.0221)	(0.0418)	(0.181)
8.CountyNum#1.DST	-0.145	0.0599	-18.98***
	(0.106)	(0.217)	(0.142)
9.CountyNum#0b.DST	0.140***	0.213***	1.168***
	(0.0166)	(0.0340)	(0.167)
9.CountyNum#1.DST	0.114*	0.149	0.0242
	(0.0686)	(0.150)	(1.001)
10.CountyNum#0b.DST	-0.154***	-0.272***	0.291**
	(0.0121)	(0.0226)	(0.136)
10.CountyNum#1.DST	-0.192***	-0.303***	-0.227
	(0.0409)	(0.0836)	(0.583)
11.CountyNum#0b.DST	0.146***	-0.100***	0.0396
	(0.0106)	(0.0181)	(0.119)
11.CountyNum#1.DST	0.106***	-0.108**	0.386
	(0.0323)	(0.0542)	(0.283)
12.CountyNum#0b.DST	-0.0718***	-0.0798***	0.361**
	(0.0138)	(0.0246)	(0.143)
12.CountyNum#1.DST	-0.148***	0.195**	0.391
	(0.0558)	(0.0829)	(0.503)
13.CountyNum#0b.DST	0.0758***	0.00398	-0.201
	(0.0110)	(0.0191)	(0.131)
13.CountyNum#1.DST	0.171***	0.219***	0.656**
	(0.0300)	(0.0585)	(0.317)
14.CountyNum#0b.DST	-0.140***	-0.128***	0.0751
	(0.0136)	(0.0247)	(0.163)
14.CountyNum#1.DST	-0.122**	-0.171*	-0.231
	(0.0512)	(0.0900)	(0.703)
15.CountyNum#0b.DST	-0.346***	-0.637***	0.340
	(0.0317)	(0.0671)	(0.386)
15.CountyNum#1.DST	-0.306**	-0.549**	1.168
	(0.136)	(0.240)	(1.001)
16.CountyNum#0b.DST	-0.236***	-0.368***	-0.280
	(0.0148)	(0.0275)	(0.186)
16.CountyNum#1.DST	-0.255***	-0.327***	1.199**
	(0.0561)	(0.112)	(0.514)
17.CountyNum#0b.DST	-0.276***	-0.325***	0.800***
	(0.0215)	(0.0411)	(0.189)
17.CountyNum#1.DST	-0.221**	-0.321*	0.330
	(0.0881)	(0.192)	(0.993)
18.CountyNum#0b.DST	0.171***	0.0363*	0.109
	(0.0116)	(0.0195)	(0.131)

18.CountyNum#1.DST	0.192***	0.172**	0.0195
	(0.0372)	(0.0684)	(0.443)
19.CountyNum#0b.DST	-0.194***	-0.492***	0.469***
	(0.0159)	(0.0282)	(0.153)
19.CountyNum#1.DST	-0.0513	-0.421***	-0.0884
	(0.0465)	(0.108)	(0.710)
20.CountyNum#0b.DST	-0.420***	-0.472***	0.632***
	(0.0210)	(0.0398)	(0.194)
20.CountyNum#1.DST	-0.389***	-0.233	1.242**
	(0.0929)	(0.204)	(0.577)
21.CountyNum#0b.DST	-0.373***	-0.567***	0.313
	(0.0282)	(0.0595)	(0.290)
21.CountyNum#1.DST	-0.345***	-0.565	1.522**
	(0.125)	(0.361)	(0.706)
22.CountyNum#0b.DST	-0.347***	-0.556***	0.424
	(0.0322)	(0.0642)	(0.312)
22.CountyNum#1.DST	-0.703***	-0.752**	-18.42***
	(0.154)	(0.381)	(0.142)
23.CountyNum#0b.DST	0.0908***	0.00547	0.539***
	(0.0128)	(0.0227)	(0.136)
23.CountyNum#1.DST	0.110***	0.0773	0.849**
	(0.0380)	(0.0870)	(0.381)
24.CountyNum#0b.DST	0.246***	0.423***	1.221***
	(0.0135)	(0.0264)	(0.130)
24.CountyNum#1.DST	0.244***	0.236***	-0.509
	(0.0509)	(0.0909)	(0.998)
25.CountyNum#0b.DST	-0.179***	-0.200***	0.199
	(0.0127)	(0.0232)	(0.143)
25.CountyNum#1.DST	-0.116***	-0.148*	-20.66***
	(0.0416)	(0.0851)	(0.142)
26.CountyNum#0b.DST	0.0105	0.0423**	0.189*
	(0.0107)	(0.0175)	(0.113)
26.CountyNum#1.DST	0.0145	0.0986**	0.0675
	(0.0308)	(0.0472)	(0.353)
27.CountyNum#0b.DST	-0.470***	-0.543***	0.472**
	(0.0229)	(0.0468)	(0.218)
27.CountyNum#1.DST	-0.561***	-0.793***	-19.28***
	(0.0916)	(0.208)	(0.142)
28.CountyNum#0b.DST	-0.0551***	-0.140***	-0.103
	(0.0200)	(0.0348)	(0.227)
28.CountyNum#1.DST	-0.646***	-0.662***	1.003*
	(0.0893)	(0.151)	(0.579)
29.CountyNum#0b.DST	-0.140***	-0.115***	0.408***
	(0.0118)	(0.0206)	(0.122)
29.CountyNum#1.DST	-0.136***	-0.140*	-0.526
	(0.0400)	(0.0773)	(0.582)
30.CountyNum#0b.DST	-0.196***	-0.160***	0.391**
	(0.0195)	(0.0330)	(0.187)
30.CountyNum#1.DST	-0.206**	-0.224	-19.76***
	(0.0867)	(0.150)	(0.142)
31.CountyNum#0b.DST	0.243***	0.0763***	0.871***
	(0.0145)	(0.0291)	(0.151)
31.CountyNum#1.DST	0.292***	-0.0867	1.129**
	(0.0496)	(0.108)	(0.535)
32.CountyNum#0b.DST	0.270***	0.0684***	-0.217*
	(0.0102)	(0.0174)	(0.119)
32.CountyNum#1.DST	0.308***	0.161***	-0.160
	(0.0282)	(0.0511)	(0.399)
33.CountyNum#0b.DST	-0.0111	0.0891***	0.525***
	(0.0150)	(0.0275)	(0.167)
33.CountyNum#1.DST	0.182***	0.400***	0.917*
	(0.0637)	(0.114)	(0.499)
34.CountyNum#0b.DST	0.0858***	-0.0279	-0.137
	(0.0113)	(0.0177)	(0.117)
34.CountyNum#1.DST	0.119***	-0.0587	-0.0374
	(0.0301)	(0.0495)	(0.330)
35.CountyNum#0b.DST	-0.271***	-0.229***	0.433***
	(0.0148)	(0.0271)	(0.150)
35.CountyNum#1.DST	-0.142**	-0.198	0.0104
	(0.0606)	(0.125)	(0.707)

36.CountyNum#0b.DST	0.0825***	0.136***	0.145
	(0.0109)	(0.0183)	(0.121)
36.CountyNum#1.DST	0.110***	0.248***	0.0432
	(0.0339)	(0.0632)	(0.380)
37.CountyNum#0b.DST	-0.232***	-0.172***	0.982***
	(0.0289)	(0.0591)	(0.244)
37.CountyNum#1.DST	-0.148	-0.0975	-18.44***
	(0.127)	(0.243)	(0.142)
38.CountyNum#0b.DST	-0.175***	0.149***	1.464***
	(0.0325)	(0.0512)	(0.227)
38.CountyNum#1.DST	-0.600***	-0.258	-18.15***
	(0.178)	(0.295)	(0.142)
39.CountyNum#0b.DST	-0.221***	-0.141***	0.690***
	(0.0158)	(0.0272)	(0.147)
39.CountyNum#1.DST	-0.111*	-0.180	0.502
	(0.0601)	(0.116)	(0.582)
40.CountyNum#0b.DST	-0.0756***	-0.166***	0.397*
	(0.0209)	(0.0434)	(0.239)
40.CountyNum#1.DST	0.152	-0.255	-19.07***
	(0.0985)	(0.226)	(0.142)
41.CountyNum#0b.DST	0.0967***	0.277***	-0.00688
	(0.0104)	(0.0162)	(0.108)
41.CountyNum#1.DST	0.153***	0.367***	-0.505
	(0.0365)	(0.0407)	(0.384)
42.CountyNum#0b.DST	0.143***	0.212***	0.752***
	(0.0147)	(0.0266)	(0.154)
42.CountyNum#1.DST	0.176***	0.433	0.240
	(0.0501)	(0.303)	(0.706)
43.CountyNum#0b.DST	-0.301***	-0.233***	0.622***
	(0.0124)	(0.0221)	(0.124)
43.CountyNum#1.DST	-0.254***	-0.318***	0.409
	(0.0570)	(0.0965)	(0.467)
44.CountyNum#0b.DST	-0.255***	-0.196***	0.378**
	(0.0160)	(0.0274)	(0.162)
44.CountyNum#1.DST	-0.315***	-0.368***	-20.14***
	(0.0640)	(0.117)	(0.142)
45.CountyNum#0b.DST	-0.0960***	-0.331***	-0.0771
	(0.0132)	(0.0236)	(0.149)
45.CountyNum#1.DST	-0.152***	-0.377***	0.134
	(0.0380)	(0.0878)	(0.496)
46.CountyNum#0b.DST	-0.202***	0.101**	0.447**
	(0.0209)	(0.0421)	(0.210)
46.CountyNum#1.DST	-0.194**	0.120	1.021
	(0.0939)	(0.183)	(0.696)
47.CountyNum#0b.DST	-0.369***	-0.121***	0.676***
	(0.0166)	(0.0302)	(0.160)
47.CountyNum#1.DST	-0.461***	-0.00349	-0.456
	(0.0641)	(0.117)	(1.004)
48.CountyNum#0b.DST	-0.317***	-0.947***	0.00652
	(0.0433)	(0.106)	(0.508)
48.CountyNum#1.DST	-0.632***	-1.153**	-17.66***
	(0.233)	(0.520)	(0.142)
49.CountyNum#0b.DST	-0.0120	0.0372*	0.165
	(0.0121)	(0.0196)	(0.124)
49.CountyNum#1.DST	-0.0208	0.0317	0.101
	(0.0463)	(0.0652)	(0.407)
50.CountyNum#0b.DST	-0.236***	-0.350***	0.441**
	(0.0186)	(0.0320)	(0.184)
50.CountyNum#1.DST	-0.371***	-0.202	-0.263
	(0.0767)	(0.153)	(1.001)
51.CountyNum#0b.DST	-0.0715***	-0.0534***	0.340***
	(0.0117)	(0.0196)	(0.122)
51.CountyNum#1.DST	-0.0322	0.000692	0.703**
	(0.0453)	(0.0696)	(0.290)
52.CountyNum#0b.DST	0.357***	0.140***	0.754***
	(0.0234)	(0.0508)	(0.281)
52.CountyNum#1.DST	0.406***	-0.00330	-18.30***
	(0.113)	(0.228)	(0.142)
53.CountyNum#0b.DST	0.0191	-0.0360	0.613***
	(0.0144)	(0.0285)	(0.154)

53.CountyNum#1.DST	0.179***	0.0624	0.472
	(0.0499)	(0.103)	(0.578)
54.CountyNum#0b.DST	0.0480***	0.217***	0.533***
	(0.0148)	(0.0255)	(0.151)
54.CountyNum#1.DST	0.139***	0.283***	0.134
	(0.0505)	(0.0997)	(0.706)
55.CountyNum#0b.DST	-0.226***	-0.315***	0.303**
	(0.0153)	(0.0269)	(0.148)
55.CountyNum#1.DST	-0.213***	-0.143	0.456
	(0.0484)	(0.103)	(0.497)
56.CountyNum#0b.DST	-0.173***	-0.238***	0.555***
	(0.0175)	(0.0327)	(0.176)
56.CountyNum#1.DST	-0.486***	-0.870***	-0.0899
	(0.0786)	(0.180)	(1.003)
57.CountyNum#0b.DST	-0.499***	-0.823***	0.456**
	(0.0246)	(0.0493)	(0.224)
57.CountyNum#1.DST	-0.480***	-1.187***	0.421
	(0.115)	(0.295)	(1.000)
58.CountyNum#0b.DST	0.108***	0.0611	0.519**
	(0.0205)	(0.0374)	(0.210)
58.CountyNum#1.DST	0.132	-0.0674	0.342
	(0.0814)	(0.160)	(1.000)
59.CountyNum#0b.DST	0.0310*	-0.207***	0.384**
	(0.0159)	(0.0302)	(0.183)
59.CountyNum#1.DST	-0.151**	-0.173	-19.83***
	(0.0619)	(0.135)	(0.142)
60.CountyNum#0b.DST	0.302***	0.430***	-0.293***
	(0.00940)	(0.0152)	(0.103)
60.CountyNum#1.DST	0.329***	0.515***	-0.0712
	(0.0203)	(0.0300)	(0.245)
61.CountyNum#0b.DST	-0.442***	-0.263***	-0.263
	(0.0268)	(0.0482)	(0.411)
61.CountyNum#1.DST	-0.549***	-0.203	-18.74***
	(0.140)	(0.257)	(0.142)
62.CountyNum#0b.DST	-0.0342*	-0.300***	0.917***
	(0.0189)	(0.0372)	(0.180)
62.CountyNum#1.DST	0.130	0.0269	0.901
	(0.0796)	(0.160)	(0.704)
63.CountyNum#0b.DST	-0.110***	-0.248***	0.417***
	(0.0133)	(0.0244)	(0.139)
63.CountyNum#1.DST	-0.00188	-0.132	0.728
	(0.0500)	(0.0982)	(0.531)
64.CountyNum#0b.DST	0.0542***	0.162***	0.809***
	(0.0131)	(0.0229)	(0.129)
64.CountyNum#1.DST	0.165***	0.290***	0.742
	(0.0550)	(0.0940)	(0.483)
65.CountyNum#0b.DST	0.0662***	-0.0371**	-0.227*
	(0.0107)	(0.0185)	(0.128)
65.CountyNum#1.DST	0.0467	0.0146	-0.130
	(0.0308)	(0.0491)	(0.465)
66.CountyNum#0b.DST	-0.00792	-0.0139	1.164***
	(0.0223)	(0.0426)	(0.181)
66.CountyNum#1.DST	0.0365	0.0814	1.208*
	(0.0922)	(0.242)	(0.704)
67.CountyNum#0b.DST	-0.187***	-0.260***	-0.0783
	(0.0113)	(0.0199)	(0.131)
67.CountyNum#1.DST	-0.200***	-0.389***	0.492
	(0.0359)	(0.0717)	(0.313)
68.CountyNum#0b.DST	-0.221***	-0.357***	-0.294*
	(0.0126)	(0.0223)	(0.152)
68.CountyNum#1.DST	-0.118**	-0.280***	-21.00***
	(0.0473)	(0.0797)	(0.142)
69.CountyNum#0b.DST	-0.494***	-0.724***	0.358
	(0.0300)	(0.0640)	(0.282)
69.CountyNum#1.DST	-0.337***	-0.257	-18.56***
	(0.130)	(0.293)	(0.142)
70.CountyNum#0b.DST	-0.166***	-0.283***	-0.299
	(0.0168)	(0.0334)	(0.236)
70.CountyNum#1.DST	-0.110*	-0.247*	-0.211
	(0.0623)	(0.133)	(0.999)

71.CountyNum#0b.DST	0.0627***	-0.0163	1.024***
	(0.0141)	(0.0295)	(0.136)
71.CountyNum#1.DST	0.168***	-0.0449	0.805
	(0.0484)	(0.112)	(0.492)
72.CountyNum#0b.DST	-0.412***	-0.538***	0.442
	(0.0292)	(0.0626)	(0.307)
72.CountyNum#1.DST	-0.170	-0.765***	-18.61***
	(0.111)	(0.268)	(0.142)
73.CountyNum#0b.DST	-0.0694***	-0.172***	0.203
	(0.0172)	(0.0321)	(0.196)
73.CountyNum#1.DST	0.167**	-0.197	0.514
	(0.0844)	(0.165)	(0.712)
74.CountyNum#0b.DST	0.269***	0.320***	0.117
	(0.0111)	(0.0188)	(0.128)
74.CountyNum#1.DST	0.350***	0.463***	-0.550
	(0.0379)	(0.0619)	(0.584)
75.CountyNum#0b.DST	-0.196***	-0.341***	0.450*
	(0.0223)	(0.0445)	(0.246)
75.CountyNum#1.DST	-0.0665	-0.0607	0.497
	(0.0932)	(0.171)	(1.002)
76.CountyNum#0b.DST	-0.0552***	-0.115***	0.368***
	(0.0122)	(0.0206)	(0.125)
76.CountyNum#1.DST	0.0152	0.0351	0.829*
	(0.0463)	(0.0806)	(0.430)
77.CountyNum#0b.DST	0.00824	0.251***	0.695***
	(0.0162)	(0.0284)	(0.172)
77.CountyNum#1.DST	0.0681	0.151	-0.317
	(0.0657)	(0.125)	(0.994)
78.CountyNum#0b.DST	0.166***	0.429***	1.124***
	(0.0117)	(0.0197)	(0.115)
78.CountyNum#1.DST	0.204***	0.489***	1.118***
	(0.0422)	(0.0685)	(0.379)
79.CountyNum#0b.DST	-0.0951***	-0.224***	0.214
	(0.0129)	(0.0240)	(0.143)
79.CountyNum#1.DST	0.0532	-0.211**	0.745
	(0.0648)	(0.108)	(0.573)
80.CountyNum#0b.DST	-0.0354***	-0.0321	0.249*
	(0.0119)	(0.0203)	(0.135)
80.CountyNum#1.DST	0.0627	0.0948	0.134
	(0.0597)	(0.0759)	(0.452)
81.CountyNum#0b.DST	-0.206***	-0.199***	0.264*
	(0.0148)	(0.0265)	(0.159)
81.CountyNum#1.DST	-0.149***	-0.132	0.389
	(0.0537)	(0.101)	(0.572)
82.CountyNum#0b.DST	0.114***	0.161***	0.913***
	(0.0140)	(0.0251)	(0.139)
82.CountyNum#1.DST	0.0652	0.0718	0.467
	(0.0466)	(0.101)	(0.578)
83.CountyNum#0b.DST	-0.130***	0.242***	0.739***
	(0.0176)	(0.0315)	(0.172)
83.CountyNum#1.DST	-0.0377	0.347***	-19.59***
	(0.0707)	(0.108)	(0.142)
84.CountyNum#0b.DST	-0.127***	-0.262***	0.316*
	(0.0146)	(0.0285)	(0.169)
84.CountyNum#1.DST	-0.0437	-0.172	0.465
	(0.0491)	(0.154)	(0.579)
85.CountyNum#0b.DST	-0.230***	-0.381***	0.413**
	(0.0173)	(0.0321)	(0.178)
85.CountyNum#1.DST	-0.172**	-0.491***	-0.335
	(0.0735)	(0.141)	(0.999)
86.CountyNum#0b.DST	-0.135***	-0.0412	0.565***
	(0.0146)	(0.0254)	(0.145)
86.CountyNum#1.DST	-0.0658	0.00667	0.306
	(0.0529)	(0.107)	(0.579)
87.CountyNum#0b.DST	-0.500***	-0.578***	0.352
	(0.0279)	(0.0560)	(0.266)
87.CountyNum#1.DST	-0.882***	-0.856***	-18.70***
	(0.149)	(0.298)	(0.142)
88.CountyNum#0b.DST	-0.375***	-0.510***	0.160
	(0.0197)	(0.0380)	(0.230)

88.CountyNum#1.DST	-0.661***	-0.507***	-0.0107
	(0.0956)	(0.177)	(1.008)
89.CountyNum#0b.DST	0.235***	-0.455***	-0.422
	(0.0382)	(0.108)	(1.004)
89.CountyNum#1.DST	0.240	-0.708	-17.40***
	(0.156)	(0.460)	(0.142)
90.CountyNum#0b.DST	-0.0697***	-0.178***	-0.122
	(0.0107)	(0.0191)	(0.130)
90.CountyNum#1.DST	0.00710	-0.0826	-0.131
	(0.0266)	(0.0580)	(0.414)
91.CountyNum#0b.DST	0.231***	0.376***	0.656***
	(0.0151)	(0.0276)	(0.159)
91.CountyNum#1.DST	0.281***	0.431***	0.386
	(0.0577)	(0.126)	(0.694)
92.CountyNum#0b.DST	0.141***	-0.0331**	-0.575***
	(0.00994)	(0.0157)	(0.107)
92.CountyNum#1.DST	0.178***	0.0899***	-0.609**
	(0.0229)	(0.0343)	(0.276)
93.CountyNum#0b.DST	-0.0901***	-0.0514	0.805***
	(0.0226)	(0.0456)	(0.238)
93.CountyNum#1.DST	0.0459	0.164	1.608**
	(0.110)	(0.197)	(0.749)
94.CountyNum#0b.DST	-0.185***	-0.352***	0.356
	(0.0279)	(0.0568)	(0.292)
94.CountyNum#1.DST	-0.188	-0.462*	-18.49***
	(0.120)	(0.264)	(0.142)
95.CountyNum#0b.DST	0.00120	-0.324***	-0.114
	(0.0157)	(0.0292)	(0.210)
95.CountyNum#1.DST	-0.128**	-0.408***	-0.501
	(0.0639)	(0.142)	(1.000)
96.CountyNum#0b.DST	0.000416	0.0980***	0.353***
	(0.0119)	(0.0212)	(0.133)
96.CountyNum#1.DST	0.0474	0.266***	0.310
	(0.0428)	(0.0786)	(0.453)
97.CountyNum#0b.DST	-0.246***	-0.169***	0.263
	(0.0149)	(0.0260)	(0.160)
97.CountyNum#1.DST	-0.385***	-0.262**	1.051***
	(0.0614)	(0.106)	(0.403)
98.CountyNum#0b.DST	0.104***	0.127***	0.475***
	(0.0135)	(0.0243)	(0.146)
98.CountyNum#1.DST	0.188***	0.140	-0.894
	(0.0502)	(0.0855)	(1.001)
99.CountyNum#0b.DST	-0.224***	-0.374***	0.459**
	(0.0193)	(0.0353)	(0.182)
99.CountyNum#1.DST	-0.144*	-0.00776	0.543
	(0.0764)	(0.134)	(0.704)
100.CountyNum#0b.DST	-0.563***	-0.570***	0.357
	(0.0263)	(0.0524)	(0.252)
100.CountyNum#1.DST	-0.710***	-1.026***	0.591
	(0.147)	(0.292)	(1.007)
2014	0.0119***	0.00579	-0.00355
	(0.00448)	(0.00808)	(0.0432)
2015	0.102***	0.0952***	0.0675
	(0.00427)	(0.00796)	(0.0425)
2016	0.145***	0.133***	0.0960**
	(0.00428)	(0.00793)	(0.0419)
2017	0.168***	0.116***	0.0610
	(0.00410)	(0.00794)	(0.0424)
2018	0.183***	0.0767***	0.0878**
	(0.00418)	(0.00790)	(0.0421)
2019	0.182***	0.0695***	0.109***
	(0.00402)	(0.00788)	(0.0417)
February	-0.00723	0.0508***	-0.0258
	(0.00698)	(0.0113)	(0.0593)
March	-0.0304***	0.0901***	0.0400
	(0.00637)	(0.0109)	(0.0597)
April	-0.0153**	0.165***	0.113**
	(0.00603)	(0.0104)	(0.0570)
May	0.0148**	0.217***	0.208***
	(0.00592)	(0.0104)	(0.0554)

June	0.00553	0.210***	0.244***
	(0.00594)	(0.0104)	(0.0557)
July	-0.0576***	0.149***	0.113**
	(0.00597)	(0.0106)	(0.0571)
August	-0.00744	0.202***	0.142**
	(0.00593)	(0.0104)	(0.0561)
September	0.0215***	0.206***	0.272***
	(0.00608)	(0.0104)	(0.0555)
October	0.179***	0.279***	0.293***
	(0.00584)	(0.0103)	(0.0548)
November	0.240***	0.215***	0.250***
	(0.00611)	(0.0109)	(0.0581)
December	0.144***	0.163***	0.109*
	(0.00625)	(0.0105)	(0.0566)
Monday	0.337***	0.206***	-0.212***
	(0.00440)	(0.00846)	(0.0424)
Tuesday	0.344***	0.200***	-0.189***
	(0.00433)	(0.00838)	(0.0416)
Wednesday	0.341***	0.197***	-0.167***
	(0.00431)	(0.00832)	(0.0416)
Thursday	0.346***	0.209***	-0.190***
	(0.00421)	(0.00823)	(0.0416)
Friday	0.509***	0.395***	-0.000644
	(0.00427)	(0.00817)	(0.0399)
Saturday	0.222***	0.200***	0.0975**
	(0.00433)	(0.00850)	(0.0389)
lnalpha	-2.787***	-0.868***	0.867***
	(0.0185)	(0.00934)	(0.0536)
Constant	-10.08***	-10.79***	-15.09***
	(0.0105)	(0.0178)	(0.109)
Observations	255,600	255,600	255,600