THESIS

THE ECONOMIC CONSEQUENCES OF FLOOD ALERTS: EVIDENCE FROM EMPLOYMENT OUTCOMES

Submitted by

Diellza Muriqi

Department of Agricultural and Resource Economics

In partial fulfillment of the requirements

For the Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Summer 2025

Master's Committee:

Advisor: Christopher Goemans
Co-Advisor: Jordan F. Suter

Frances Davenport

ABSTRACT

THE ECONOMIC CONSEQUENCES OF FLOOD ALERTS: EVIDENCE FROM EMPLOYMENT OUTCOMES

Floods are some of the costliest and most common natural hazards in the United States. As the frequency and intensity of extreme weather events increase, flood alerts have become an important tool for reducing damages and saving lives. Previous studies show that early warning systems can reduce economic losses and protect lives, but their effectiveness depends on alert accuracy and public response. Most of the existing research has focused on how false alarms and missed alerts affect trust and compliance, especially in the context of tornadoes. Much less is known about their economic impacts, particularly for floods, despite the fact that issuing an alert involves tradeoffs. False alarms may generate unnecessary costs, while missed events can lead to unanticipated disruptions. Understanding the labor market impacts of these inaccuracies is important for agencies like the National Weather Service, which must balance risk communication under constrained resources.

This thesis investigates how flood alerts, false flood alarms, and missed flood events disrupt county-level employment outcomes in the United States. To answer this, I construct a county-by-month panel dataset from 2007 to 2023, combining data from the NOAA Storm Events Database, the Iowa Environmental Mesonet, and the Bureau of Labor Statistics. Using a two-way fixed effects model, I estimate how different combinations of alerts and flood events influence employment levels in total, as well as construction, and leisure & hospitality sectors.

The results show that flash flood days accompanied by both a warning and a notification are associated with small but statistically significant declines in employment. These effects are most pronounced in the leisure and hospitality sector, followed by construction. I find no evidence that false alarms or missed events have a significant impact on employment. Additional analyses reveal that effects vary by rural and urban classification, emerge over several months in some cases, and are robust to alternative alert groupings and proximity-based exposure definitions. These findings highlight the economic importance of alert accuracy and suggest that the type and layering of alerts, as well as local context, influence short-term labor market outcomes.

ACKNOWLEDGEMENTS

I would like to sincerely thank my main advisor, Dr. Chris Goemans, for his guidance, feedback, and patience throughout each stage of this project. I am equally grateful for my co-advisor, Dr. Jordan F. Suter, whose feedback shaped both the direction and quality of the work. Thank you as well to Dr. Frances Davenport for serving as my outside committee member and for offering perspectives that challenged me to think beyond the confines of my original approach.

This research greatly benefited from regular engagement with the broader flood research group. I appreciate the insights provided by Dr. Dale Manning, Dr. Jude Bayham, Dr. Judhajit Chakraborty, and Shuhang Lou during our weekly meetings. Their questions often revealed angles I had not considered before, and they helped refine the analysis.

This work would not have been possible without support from NOAA's National Weather Service. Thank you to Ms. Ji Sun Lee, JD, Dr. Jacob Fooks, Mr. Jeffery Adkins and Mr. Greg Heavener from NOAA, as well as Dr. Stan Rhodes, and Ms. Shelby Weder from the Cooperative Institute for Research in the Atmosphere. Your commitment to improving weather services continues to inspire the core motivation behind this thesis!

Finally, I would like to thank my cohort and friends in the department. Their willingness to listen, share ideas, and offer support made this process easier to navigate.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

Flood events are among the most damaging natural disasters worldwide. Their impacts include property losses, human casualties, and economic disruptions (Armal et al., 2020; Petrucci, 2022; Muriqi et al., 2025). In the U.S. alone, flood deaths average about 127 people per year (weather.gov, 2025b), and the total cost of flooding reaches billions of dollars annually. The U.S. Joint Economic Committee estimates that in 2023, the direct commercial impact of flooding was between $31.6 billion and $40 billion (US JEC, 2024).

One way of combating the impacts of flood events is through flood alert systems, which have proven to be effective in protecting lives and reducing monetary damages (Sadiq et al., 2023). However, this effectiveness depends on several attributes, such as alert accuracy, lead time, trust in the alert system, and how promptly the residents act (Kuller et al., 2021). When alert accuracy fails, two types of errors are possible: false alarms and missed events. False alarms represent the situation when an alert is issued, but a flood does not occur, and missed events are when no alert is issued, but the flood does occur. Such errors can result in more costs, such as a reduction in public trust or lower compliance with future warnings (Simmons & Sutter, 2009; Trainor et al., 2015).

A question that remains unanswered in the existing literature is how inaccuracies in flood alerts affect local employment outcomes. There are several channels through which false alarms and missed flood events might influence employment. On the labor supply side, inaccurate alerts may lead workers to stay home unnecessarily or encounter unexpected hazards when commuting, both of which could reduce workforce availability. On the demand side, businesses may experience reduced customer activity, operational delays, or temporary closures, depending on whether the alert is perceived as credible or whether flooding occurs without warning. These disruptions can affect hiring, work hours, and staffing decisions, especially in sectors that rely on in-person services or outdoor labor. This study addresses the question: "Do false alarms and missed flood events disrupt employment at the county level in the United States?" Specifically, I explore whether these inaccuracies in alerts influence employment counts per month.

Previous research has primarily examined other natural disasters, especially tornadoes, when studying false alarms or missed events (e.g. Simmons & Sutter, 2009; Ripberger et al., 2015; Trainor et al., 2015; Lim et al., 2019). In these studies, the emphasis has been placed on how alert inaccuracies influence public trust, individual protective behaviors, and outcomes such as injuries or fatalities. When it comes to flood events specifically, most of the work on alert accuracy has been conducted outside of the U.S. (e.g. Sawada et al., 2022; Kotani et al., 2023). In the U.S., research has mostly examined the impacts of flooding itself, rather than the potential consequences of inaccurate flood alerts.

Floods are usually separated into four categories: floods, flash floods, lakeshore floods, and coastal floods. Floods and flash floods differ primarily in speed and duration. Floods develop more gradually and can last for several days or even weeks. They mostly result from rising water in rivers, streams, or drainage systems. Flash floods, on the other hand, occur rapidly, usually within six hours of intense rainfall or sudden water release. They are characterized by swift, high-velocity flows that can cause immediate and severe damage (weather.gov, 2025c). This paper focuses specifically on floods and flash floods because these are the only flood types for which complete and consistent geolocation data are available. In contrast, coastal and lakeshore flood events often lack spatial detail or are recorded at broader forecast zones, which makes them unsuitable for county-level analysis.

This thesis makes three main contributions. First, it fills a gap in the literature by empirically analyzing the effects of false alarms and missed events on employment outcomes, using monthly county-level employment data from 2007 to 2023. Second, it disaggregates effects by flood type (general vs. flash flood), alert type (warning vs. notification), and employment sector (construction and leisure and hospitality). Third, it assesses heterogeneity in alert effects by rural-urban classifications and includes lagged models to examine medium-run effects.

To carry out this analysis, I construct a daily panel dataset of alerts and events and merge it with monthly employment counts from the U.S. Bureau of Labor Statistics. Alert-event combinations are categorized using binary and three-digit encodings to capture false alarms, missed events, and actualized alerts. I use a two-way fixed effects regression framework with county and state-by-year-by-month fixed effects, clustering standard errors at the county level.

The results show that not all alert-event combinations are associated with statistically significant changes in employment, but certain patterns do emerge. Employment effects are most pronounced when flash flood days are accompanied by both a warning and a notification, with statistically significant declines observed in total employment, as well as in construction and leisure and hospitality. False alarms and missed events, on the other hand, do not consistently affect employment levels. However, sectoral and geographic differences play an important role. For instance, the leisure and hospitality sector in urban counties appears especially sensitive to actualized alerts during flash flood days, while rural counties show more varied responses, including some positive employment effects. Additional analyses suggest that prior exposure to false alarms and the timing of alert-event combinations also shape the magnitude and direction of labor market impacts.

The remainder of this paper is organized as follows: The Conceptual Framework section outlines how false alarms and missed events can disrupt local economies and influence protective behaviors. The Background and Related Literature section delves deeper into flood alerts and the research on the performance of alert systems. It highlights studies on public trust, warning compliance, and the potential economic impacts of forecast errors. The Data and Methods section describes how various datasets, such as the Iowa Environmental Mesonet (IEM), the NOAA Storm Events Database, and the Quarterly Census of Employment and Wages (QCEW), are compiled to create a county-level monthly panel. That section also explains the econometric approach, which uses a two-way fixed-effects model to estimate the effects of misclassified alerts on employment outcomes. The paper concludes by discussing findings, implications, and directions for future research.

2. CONCEPTUAL FRAMEWORK

Flood alerts are intended to mitigate potential flood damage by providing advanced or real-time notice to residents and businesses (Van Houtven, 2024). However, false alarms and missed events may introduce uncertainty and unintended consequences, which could impact both the supply and demand of labor. These dynamics are shaped not only by the physical presence of flooding but also by the informational environment in which people and businesses make decisions. The conceptual framework in Figure 2.1 presents these relationships and outlines the different pathways through which flood alerts and events can influence employment outcomes.

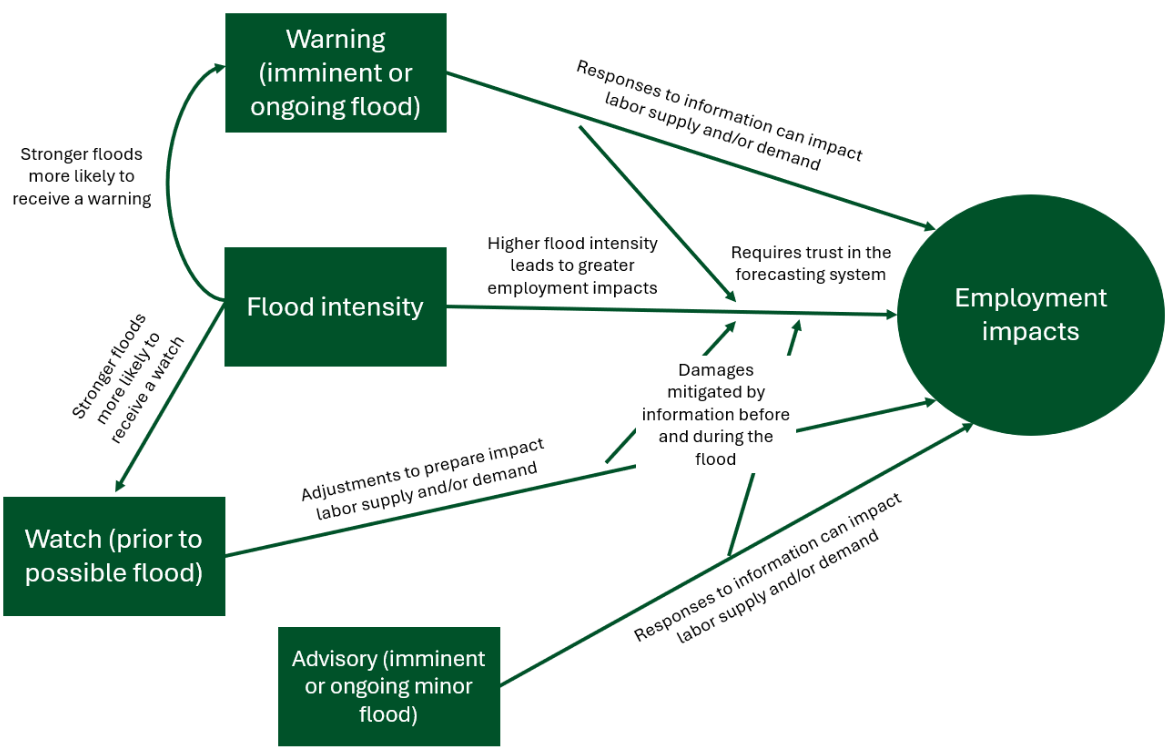

Figure 2.1: Conceptual framework linking flood alerts, flood events, and employment outcomes.

At the core of the framework is the relationship between flood intensity and job loss. More intense floods are expected to produce greater economic disruption, and they may lead to reductions in employment. This link reflects the direct physical and logistical challenges posed by flooding, such as damage to infrastructure, business closures, and mobility constraints.

However, the effects of flooding on employment are also mediated by the alert system. Alerts differ in timing and severity, ranging from watches issued prior the flood, to real-time alerts (advisories and warnings). Each of these alert types may trigger different behavioral responses, and they may affect both the supply and demand of labor. For example, an advisory might lead to heightened awareness and minor adjustments in travel or operations. A watch may prompt individuals to stay home from work or businesses to scale back operations in anticipation of flooding. A warning issued during the flood may trigger real-time decisions to shut down operations or evacuate. The formal definitions among these alert types are detailed in the Background section.

At the same time, the issuance of an alert is closely tied to the expected or observed severity of a weather event. For instance, flash flood warnings are typically issued when flooding is imminent or already occurring, based on radar estimates, local observations, or gauge thresholds (National Weather Service, 2021). This creates an important identification concern: alerts are not randomly assigned but are a function of underlying hazard conditions. As a result, it is difficult to disentangle the economic impact of alerts themselves from the damage caused by the events they accompany. To address this, the analysis compares different combinations of alerts and flood events, specifically, false alarms (alerts issued without a recorded flood), missed events (floods with no alert issued), and actualized alerts (alerts that coincide with recorded flood events).

Another consideration in the framework is the role of public trust. For alerts to be effective, recipients must view them as credible. If false alarms become frequent, businesses and workers may begin to discount future alerts, which lowers compliance and undermines the protective potential of the system. This can lead to worse outcomes when real floods occur and protective actions are not taken seriously. In this way, past exposure to false alerts may moderate the relationship between current alerts and employment responses. This mechanism is explored in the empirical analysis by interacting current alert-event combinations with a county-level measure of historical false alarm exposure. This allows the study to assess whether employment effects differ in places that have experienced more frequent false alarms in the past.

Finally, alerts may also mitigate the employment effects of flooding by enabling advanced or real-time adjustments that limit physical damage or business disruption. In the framework, this is captured by a feedback path in which information, either before or during the flood, dampens the link between flood intensity and employment impacts. However, such mitigation requires both accurate forecasting and behavioral responsiveness, which in turn depend on trust and institutional capacity.

One limitation of this framework is that it does not include a direct measure of flood severity. Although alerts are not issued randomly, they also do not provide a continuous or consistent signal of expected severity. Therefore, the presence of an alert does not directly quantify how severe a flood is or will be. This creates ambiguity in interpreting the estimated effects associated with those categories where a flood actually occurs and an alert is issued. That could either reflect the informational impact of the alert (e.g., people preparing based on perceived threat) or the physical impact of the flood (e.g., closures, damage, or access issues), or both. Expected severity and actual severity are not separable in the data, which makes it difficult to identify the exact mechanism behind observed employment responses. This limitation affects the interpretation of the coefficient estimates and points to the need for future work that includes direct or high-resolution proxies of severity to better distinguish expected and actual severity.

The elements in this framework highlight why it is important to move beyond event-based analysis and instead examine alert-event combinations. In doing so, this study provides a more complete picture of how the flood alert system, through its timing, content, and credibility, shapes labor market outcomes.

Drawing upon these insights, this study proposes two testable hypotheses. First, false alarms negatively affect short-term employment by disrupting normal economic activities through unnecessary precautionary actions. Second, missed events adversely influence medium-term employment due to unforeseen economic disruptions and prolonged recovery processes.

3. BACKGROUND AND RELATED LITERATURE

The National Weather Service (NWS) is the primary issuing authority for flood alerts across the United States (United States Code, 2024). To determine when to issue an alert, the NWS considers several criteria, including recent wildfire activity, burn scars, soil saturation, and forecasted rainfall intensity. These factors influence how water accumulates and flows, especially in areas with impervious surfaces or highly saturated soils, where rapid runoff can cause localized flooding. For flash floods (i.e., rapid flooding lasting 6 hours or less), radar and meteorological data are used to track rainfall coverage and intensity, enabling the NWS to predict potential impacts on specific regions (Mr. Greg Heavener, Warning Coordination Meteorologist at NWS Boulder, personal communication, November 12, 2024). Once a warning is issued, the NWS distributes it through several systems, including the Federal Emergency Management Agency's (FEMA) Integrated Public Alert and Warning System (IPAWS), radios, and TV stations among others, who deliver it to the public (Mr. Greg Heavener, Warning Coordination Meteorologist at NWS Boulder, personal communication, November 12, 2024).

Flood alerts include warnings, watches, advisories, and statements, and they mostly vary based on the severity of the threat. A (flash) flood advisory is the least severe form of alerts. It is issued when flooding is expected to happen soon or is already occurring, but is not likely to cause major damage. However, even under an advisory, heavy rain can cause inconvenience and minor property damage if people are not prepared. A (flash) flood watch is more serious than an advisory. It is issued up to 36 hours in advance when weather conditions make flooding possible. A watch does not guarantee that flooding will happen, but indicates a higher level of concern than an advisory. A flood warning is the most severe alert of all. It is issued when flooding is either imminent or already happening. At this point, individuals in flood-prone areas are advised to move to higher ground. The warning may escalate to a flash flood warning if flooding becomes sudden and more intensive (weather.gov, 2025a). Lastly, there is also something called a flood statement. A flood statement provides updated information about ongoing flooding, particularly along main rivers or important creeks. These statements are meant to inform the public about the current situation and any changes in flood conditions (weather.gov, 2025b).

Previous studies have examined the benefits of flood alerts. Van Houtven (2024) explains that flood alerts help communities prepare for potential flooding, leading to fewer damages. Specifically, early warnings allow individuals and local governments to take precautionary actions such as evacuating vulnerable areas, relocating valuables, deploying temporary flood barriers, and adjusting traffic or infrastructure operations. These anticipatory responses can reduce both direct damages, such as property loss, and indirect damages, including business interruptions and public service disruptions. Li et al. (2021) highlight that successful flood warning systems depend on accurate data, hydrological models, and timely warnings, which help residents take action to reduce flood impacts. Priest et al. (2011) and Pappenberger et al. (2015) also find economic benefits from accurate flood warnings. However, they warn that false alarms and missed events can reduce the overall effectiveness and reliability of the alert systems. Perera et al. (2020) argue that flood forecasting systems need regular evaluation due to uncertainty and the potential for errors.

Studies about false alerts in other natural disasters in the U.S. emphasize several consequences. Simmons and Sutter (2009) studied the impact of false tornado alarms on the contiguous U.S. from 1986 to 2004. They found that tornadoes caused more injuries and fatalities in areas with frequent false tornado alarms, because people responded less seriously. Moreover, LeClerc and Joslyn (2015) examined the impact of false alarms on compliance with weather-related alerts through a controlled laboratory experiment. According to their results, too many false alarms made people less likely to respond to future alerts, known as the "cry wolf" effect. On top of false alarms, Ripberger et al. (2015) also studied the impact of missed events for tornadoes. Through a regional survey across tornado-prone areas of the U.S., authors found that both false alarms and missed events reduced trust in the National Weather Service (NWS). Perceptions of missed events had a slightly higher negative impact than perceptions of false alarms.

Although previous research has studied false alarms and missed events in the context of tornado warnings in the United States, little is known about their impact on the effectiveness of flood alerts. A recent study by Mao et al. (2024) provides experimental evidence by focusing on how drivers respond to automated flood-warning systems under different error conditions. In a between-subjects experimental design, the authors exposed participants to simulated driving scenarios with false alarms or missed alerts and varying levels of system reliability. Their results showed that both false alarms and missed events reduced perceived system reliability, and each type of error influenced behavior differently. Drivers exposed to false alarms were less likely to follow the system's recommendation, while those exposed to missed events tended to hesitate or remain undecided. The study demonstrates how different kinds of alert inaccuracy may shape trust and compliance behavior in real time, particularly in the context of transportation.

Two additional studies have been conducted in Japan. One of them is by Kotani et al. (2023), who examined how the performance of flood early warning systems influenced casualties and economic losses during the 2018 Japan Floods. The study used open data from the real-time flood warning map for 127 municipalities in 4 different prefectures. Using Bayesian regression models, they found that a higher false alarm ratio (FAR) was associated with more fatalities, injuries, and greater economic losses to general assets when prefecture-level differences were not controlled for. However, these relationships weakened when prefecture-specific effects were included. For the missed events ratio (MER), no clear relationship with flood damage was observed in either model.

Another Japanese-based study that analyzes false flood alarms is the work by Sawada et al. (2022). In this paper, the authors developed a stylized socio-hydrological model to simulate how false alarms can influence public trust in flood early warning systems (FEWS) and, ultimately, preparedness actions. The model shows that when false alarms are frequent, public trust in FEWS deteriorates, which decreases the likelihood that people take protective actions when real alerts are issued. Sawada et al. (2022) further find that this effect is especially strong in "technological societies", where floods are rare because of advanced flood control infrastructure, and social memory of disasters is low. In these cases, maintaining high trust in the warning system becomes even more important. The authors conclude that as forecasting technology improves, the efficiency of FEWS becomes increasingly sensitive to changes in public trust, meaning that forecasters need to balance between avoiding false alarms and missed events carefully. These findings provide important insights into warning system performance, though it remains unknown if the same patterns would hold in the U.S. context.

Beyond studies focused on public responses to alerts, other research has used employment as an indicator of economic outcomes after disasters. Jia et al. (2022) used U.S. data to study how both realized floods and rising flood risk affect firm entry, employment, and output between 1998 and 2018. Their results show that long-run increases in flood risk significantly reduce employment, firm entry, and GDP, while short-run flood events mainly reduce output without much effect on employment. The authors argue that the expectation of risk alters firms' and workers' decisions even when no flood occurs, such as when firms avoid high-risk areas and workers relocate or reduce labor supply. Using a spatial general equilibrium model, they estimate that flood risk in 2018 lowered U.S. aggregate output by about 0.5 percent, with most of that loss driven by behavioral adjustments to anticipated risk rather than direct damages from flood events themselves. Coulombe and Rao (2025) used employment data to study the economic impacts of wildfires in U.S. counties. They constructed a fire exposure measure based on satellite imagery and found that increased fire exposure slows county employment growth for about three years. On average, they estimated that fire exposure leads to a cumulative decline equivalent to about 15 percent of expected employment growth over that period. Part of the decline is linked to increased migration away from affected areas, especially when large fires burn significant portions of county land. Belasen & Polachek (2008) also used employment data to determine the impact of hurricanes in Florida. They found short-term employment losses due to reduced demand, even though earnings temporarily increased in some counties. Mendoza et al. (2020) studied earthquakes in Ecuador and found that disasters led more workers to join the informal sector, with effects differing by region and gender.

While previous studies have used employment to measure the economic impacts of disasters, little is known about how false alarms or missed events, in particular, influence local labor markets. In addition, most existing research emphasizes short-term outcomes of disasters or false alerts, leaving open questions about how employment patterns evolve over longer periods following inaccurate warnings. By addressing these gaps, this study provides new evidence on the economic significance of flood alert accuracy.

4. DATA AND METHODS

4.1. Study Area

This study focuses on counties located in the contiguous U.S. It excludes Alaska, Hawaii, and U.S. territories, but it retains Washington D.C., which is treated as a county equivalent. County-level shapefiles were obtained from the U.S. Census Bureau using the TIGER/Line dataset for the year 2020. The resulting county panel includes 3,108 unique counties.

4.2. Flood Event Data

County-level flood event data were sourced from the NOAA Storm Events Database. This database contains information for floods, flash floods, coastal floods, and lakeshore floods, in addition to other natural disasters. Although data is available from 1996, certain issues, such as missing geolocations and counties, limited the study period to only include years from 2007 to 2023. Moreover, coastal and lakeshore floods did not have reported geolocations. As a result, only events classified as "Flood" or "Flash Flood" and occurring in counties (not in forecast zones) were included. Minor corrections were made to ensure that updated FIPS codes, such as for Oglala Lakota County, South Dakota (formerly Shannon County), and Bedford County, Virginia (formerly Bedford City), matched modern county boundaries. I expanded each flood event to cover all active dates between its start and end dates to generate a complete daily sequence of flood occurrences per county.

4.3. Flood Alert Data

The flood alert data were collected from the Iowa Environmental Mesonet (IEM) archive, which contains storm-based warning polygons issued by the National Weather Service (NWS). I downloaded shapefiles for all flood-related alerts, including (flash) flood warnings, watches, advisories, and statements from 2007 to 2023. These shapefiles were combined into a single geospatial dataset after correcting invalid geometries. They were then merged with counties to determine where an alert occurred. Given that the flood event data is documented at the local time zone, time zones for flood alert data were adjusted from UTC to local time for each county based on the state's official time zone. Alerts were also expanded to cover all active dates.

4.4. Alert and Flood Event Panel Construction

A daily county-level panel was created, covering January 1, 2007, to December 31, 2023. Each county-date observation records whether a flood event occurred, and whether any warning, watch, or advisory was active. Watch periods were treated flexibly, allowing a two-day lead period to account for the fact that they can be issued up to 36 hours in advance.

Next, various binary indicators were created to capture whether a flood event was correctly alerted, falsely alerted, or missed. Combined indicators were generated to differentiate among situations where both floods and alerts occurred, only alerts occurred, or neither occurred. Separate indicators were also developed for flash floods and general floods.

In the case that a flood event extended over multiple days but the associated alert expired on the first day, then the subsequent days of the event were registered as missed events. This approach reflects the assumption that an expired alert does not continue to provide actionable guidance, and thus, for each day of the event, an active alert must be in effect to be counted as a correct alerting instance.

Although the alert data specifies the type of hazard for which they were issued (for instance, whether the alert was for a flood or for a flash flood), I encountered several inconsistencies when merging the alert data with the recorded event data. In a number of cases, the issued alert type did not match the classification of the flood event that occurred. For example, there were instances in which a general flood warning was issued, but a flash flood was later recorded for that same county and time period. Because of these inconsistencies, and in order to construct a consistent and interpretable framework for analysis, I combined alerts across flood types. All warnings were grouped together, regardless of whether they were originally issued for floods or flash floods. The same was done for watches and advisories. The data was then collapsed at the monthly level to show the number of days in each month that a category occurred.

To better understand how frequently different alerts and events occurred each year, I calculated the annual average number of days with flood advisories, watches, warnings, and events per county. The data were grouped by county and year, then aggregated to produce a time series showing how many days of each type occurred on average, per county, for each year from 2007 to 2023. This allows for a clearer view of temporal patterns and helps establish the broader context within which individual alerts and flood events occurred.

As Figure 4.1 shows, counties experienced warnings on more days than any other alert type, followed by watches and advisories. Note that the graph reflects the number of days on which events occurred, not the number of distinct events. Flood events tend to last over multiple days. However, the total number of flash flood events is higher than that of floods, but flash floods are shorter in duration.

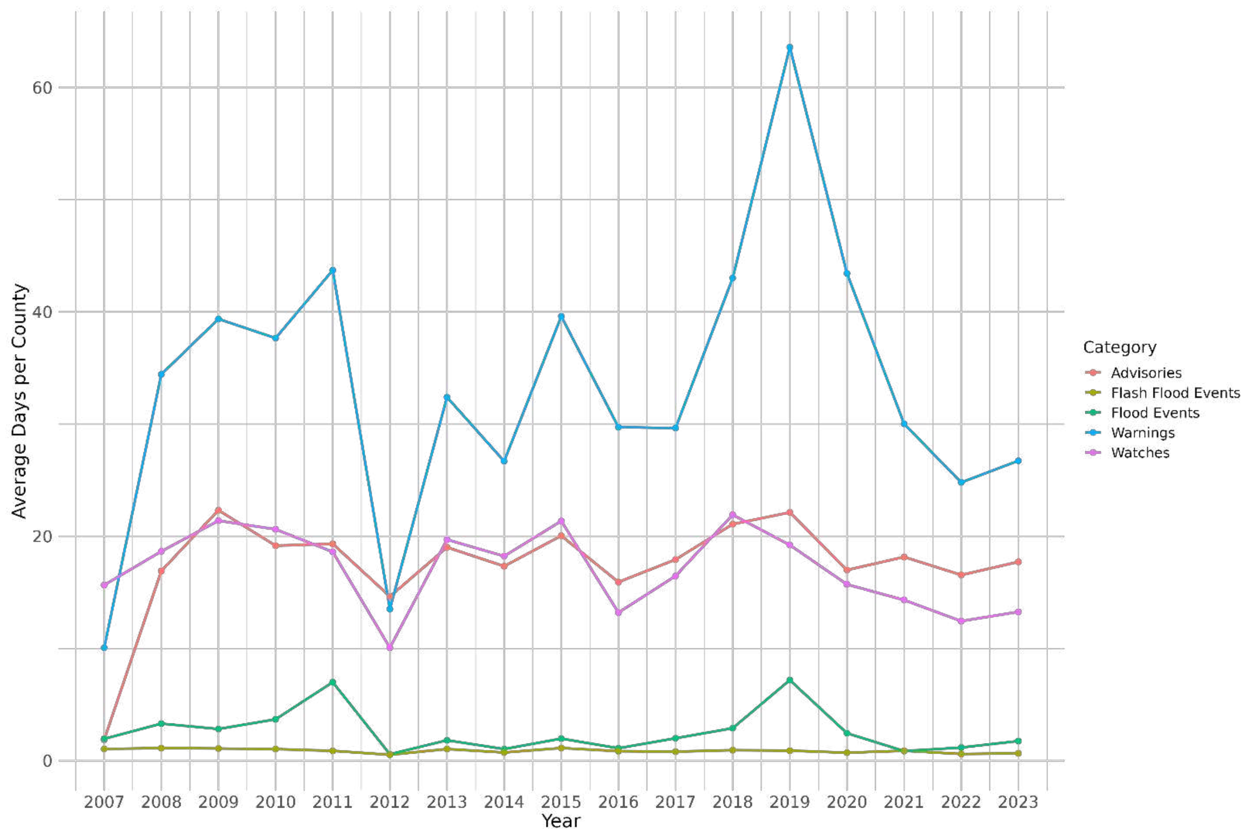

Figure 4.1: Average county annual trends in flood alerts and events (2007–2023).

Although the number of alert days varies across years, days with actual flood or flash flood events remain relatively rare. One reason for this discrepancy is that the National Weather Service (NWS) warning system is designed to be precautionary, prioritizing public safety even when flood outcomes are uncertain (National Weather Service, 2021). Issuing a warning does not require that a flood has already begun, but rather that forecasters judge flooding to be imminent or highly probable based on available information. This can include radar signatures, upstream rainfall accumulation, or modeled streamflow projections. The system is intentionally calibrated to issue alerts with enough lead time for protective actions to be taken, which means that warnings may be issued in cases where a flood ultimately does not occur. In addition, alerts are polygon-based and tied to specific geographic forecast zones, which increases the spatial resolution and the frequency with which alerts are triggered for any given county. Combined, these factors result in a situation where the alert system, by design, produces more warnings than there are verified flood events, particularly when storms develop rapidly or shift track (National Weather Service, 2021). As a result, many alerts end up being classified as false alarms from a post-event perspective, even if they were reasonable based on information available at the time.

4.5. Employment Data

Monthly county-level employment data were sourced from the U.S. Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW). I used private-sector employment counts for each month from 2007 to 2023. Only counties located in the contiguous United States were retained. Employment measures were further disaggregated by industry, but this study focuses primarily on total employment, construction employment, and leisure and hospitality employment.

The employment data were merged with the flood event-alert panel at the monthly level by matching county FIPS codes and year-month identifiers. A final panel was created that contains employment outcomes along with flood alerts and event combinations for 3,108 counties from January 2007 to December 2023, to make a total of 634,032 observations.

4.6. Estimating Flood Alert Impacts Using Two-Way Fixed Effects

To estimate the effect of flood alerts and events on employment, I construct a series of monthly indicators that count the number of days in a given month during which a county experienced a particular combination of alert and event status. These combinations are defined using binary encodings, where each digit in the code refers to the presence or absence of a specific condition. For example, in the simplest specification, I define categories using a two-digit code: the first digit captures whether any type of flood event occurred, and the second digit captures whether any type of alert (regardless of type) was active. In this context, 10 corresponds to a missed event (flood without alert), 01 to a false alarm (alert without flood), and 11 to a actualized alert (both flood and alert). The goal of this first step is to assess whether the combinations of any form of flood alert with any type of flooding have a measurable relationship with monthly employment levels.

Next, I examine whether the type of flood impacts the relationship between floods, alerts, and employment. This step disaggregates the basic combinations discussed above into two types: flash floods paired with any alert, and general floods paired with any alert. By separating the analysis into flash flood and general flood categories, I aim to assess whether missed events carry different employment consequences depending on the nature of the flood hazard.

After establishing whether the type of flood matters, I then assess whether the type of alert plays a role in shaping employment outcomes. Watches and advisories are combined into a single category, referred to as notifications. That is because these types are generally issued for less severe (advisories) or less certain (watches) flooding conditions than warnings, and both are intended to increase awareness and encourage preparedness. In this part of the analysis, each model includes the number of days in the month that fall into combinations of flood presence, warning presence, and notification presence. This includes categories such as 010 (flood + warning + no notification), 011 (no flood + warning + notification), 100 (flood without any alert), and so on. These combinations are evaluated under both general flood and flash flood conditions. This step helps to understand whether the specificity or severity of the alert contributes to differences in economic outcomes.

Once these relationships are estimated for total employment, I then apply the same models to two industries that I hypothesize to be more sensitive to flood alerts and events due to their physical exposure and service characteristics. These industries are construction and leisure

& hospitality. Construction is likely to be impacted by flood alerts due to its dependence on outdoor work and infrastructure stability, while the leisure and hospitality sector may experience disruptions due to changes in consumer mobility and local travel during flood alerts.

In addition to evaluating sector-specific outcomes, I also consider the possibility that the estimated effects of flood alerts and events may be confounded by the presence of other natural hazards occurring simultaneously. To assess whether the alert-event coefficients capture flood-specific impacts or are instead driven by broader multi-hazard conditions, I estimate a robustness specification that includes controls for co-occurring natural disasters. I construct two additional variables to account for these cases. The first captures the presence of other flood-related natural hazards occurring on the same day and in the same county, when both a warning and a notification were issued. The second captures the presence of non-flood-related hazards again requiring both warning and notification. These binary indicators are included in the employment regressions alongside the flood alert-event categories to test whether the effects of flood alerts persist after accounting for other weather-related disruptions.

To examine geographic heterogeneity, I merge the 2023 Rural-Urban Continuum Codes (RUCC) with the county-level dataset. Counties are categorized as urban (RUCC 1–3), non-urban (RUCC 4–6), or rural (RUCC 7–9). I create interaction terms between each alert-event category and the rural or urban indicators and include them in the regression models to test whether employment responses differ by county type.

Another step I consider is historical exposure to false alarms. I examine whether past exposure to false flood alerts affects how current alerts influence employment outcomes. The main motivation for this analysis is that repeated exposure to false alarms may erode public responsiveness to alerts, either by lowering trust in the alert system or by shifting local behavioral patterns in ways that alter the relationship between alerts and labor market activity. To construct the exposure measure, I first subset the dataset to the years 2007 through 2013. During this period, I calculate the total number of false alarms, true alerts, and missed events for each county. These counts were used to calculate the share of false positives out of all alert-related experiences. Counties in the top 5% of this distribution are flagged as having high historical exposure to false alarms. An indicator variable, high_fp_county, is then created and merged back into the main dataset. To avoid reverse causality and ensure temporal separation between the exposure and the outcome periods, the regression analysis for this step was restricted to post-2013 data only.

I also look at whether the effects of flood alerts on employment are immediate or delayed, and I include lagged values of the alert-event indicators for up to six months in the regression models. For each combination, I construct six additional variables that count the number of days in the previous 1st through 6th months during which a county experiences that alert-event category. The regression specifications maintain the same fixed effects structure and clustering approach. These models help identify short- and medium-run employment responses to flood alerts.

In addition to the core specifications, I estimate a separate set of models that categorize flood and flash flood events by their duration. These models are designed to capture whether employment effects differ depending on how long a given flood event lasts. To construct the duration categories, I identify sequences of consecutive flood days for each county and classify them based on length: 1–3 days, 4–6 days, and 7 or more days. These sequences are defined separately for actualized and missed alerts to preserve alert-event combinations. The resulting event-level dataset is merged back into the main panel, and for each month, I calculate the number of days that fall into each duration category.

Lastly, to assess the robustness of the false alarm and missed event definitions, I construct a spatial adjacency matrix using county boundary shapefiles. For each county and date, I create an indicator that captures whether a flood occurs in any adjacent county. I then revise the definitions of false alarms to exclude cases in which flooding occurs in neighboring areas. The main regression models are re-estimated using these refined definitions to evaluate whether proximity to flooding alters the estimated effects of alerts on employment.

All regressions were estimated using the feols() function from the fixest package in R. Each model includes county fixed effects (α_i) to account for time-invariant county-specific characteristics, and state-by-month-by-year fixed effects (δ_{s+m+t}) to control for seasonality and statewide trends. Standard errors are clustered at the county level. The general structure of the model is:

$$\log(employment_{imt}) = \beta_0 + \sum_c \beta_c \times Days_{c,imt} + \alpha_i + \delta_{s+m+t} + \varepsilon_{imt}. \qquad (1)$$

Where $\log(\text{employment}_{imt})$ is the natural log of employment in county i, month m, and year t. $\text{Days}_{c,imt}$ represents the number of days in the month that the county experienced in category c. The fixed effects include α_i and δ_{s+m+t} as described above.

The analysis is structured to build step by step, beginning with the most general alert-event combinations, then moving into distinctions by flood and alert types and other heterogeneity analysis. As a result, the analysis proceeds in nine stages: (1) general combinations of flood alerts and events, (2) disaggregation by flood type, (3) disaggregation by alert type, (4) interaction of flood and alert types using three-digit encodings, (5) industry-specific models for construction and leisure and hospitality, (6) inclusion of controls for co-occurring natural hazards, (7) robustness checks using alternative alert groupings, (8) heterogeneity analysis by rural/urban county classification, (9) analysis by high historical exposure to false alarms, (10) models incorporating up to six-month lags to identify delayed effects, and (11) models that categorize flood events by duration to test for non-linear responses. A final sensitivity analysis includes flooding in neighboring counties. This sequence allows the study to gradually develop a more layered understanding of how different components of the flood alert system relate to changes in employment across U.S. counties.

4.7. Alert-Event Frequencies

To accompany the regression analysis, I also conducted a series of descriptive statistics and spatial visualizations. These include counts and averages of false alarms, missed events, and actualized alerts across counties and years, as well as maps displaying the geographic variation in alert-event patterns.

Using the daily panel dataset described earlier, I generated a histogram of how frequently each category occurred on average, per county, per year. I grouped the data by county and year, calculated the total number of days in which each category was observed, and then averaged those values across all counties and years from 2007 to 2023. The final dataset provides a view of the typical annual exposure counties have of each combination of flood or flash flood alerts and events. Figure 4.2 presents these results. The most frequent alert-event categories are 010 and 001. These correspond to false alarms, where warnings or notifications were issued even though no flooding occurred. On average, counties experienced approximately 20 days per year of warning-only false alarms (010) and 19 days per year of notification-only false alarms (001).

In contrast, actualized alerts (111) or missed flood events without any alert (100) were much less common.

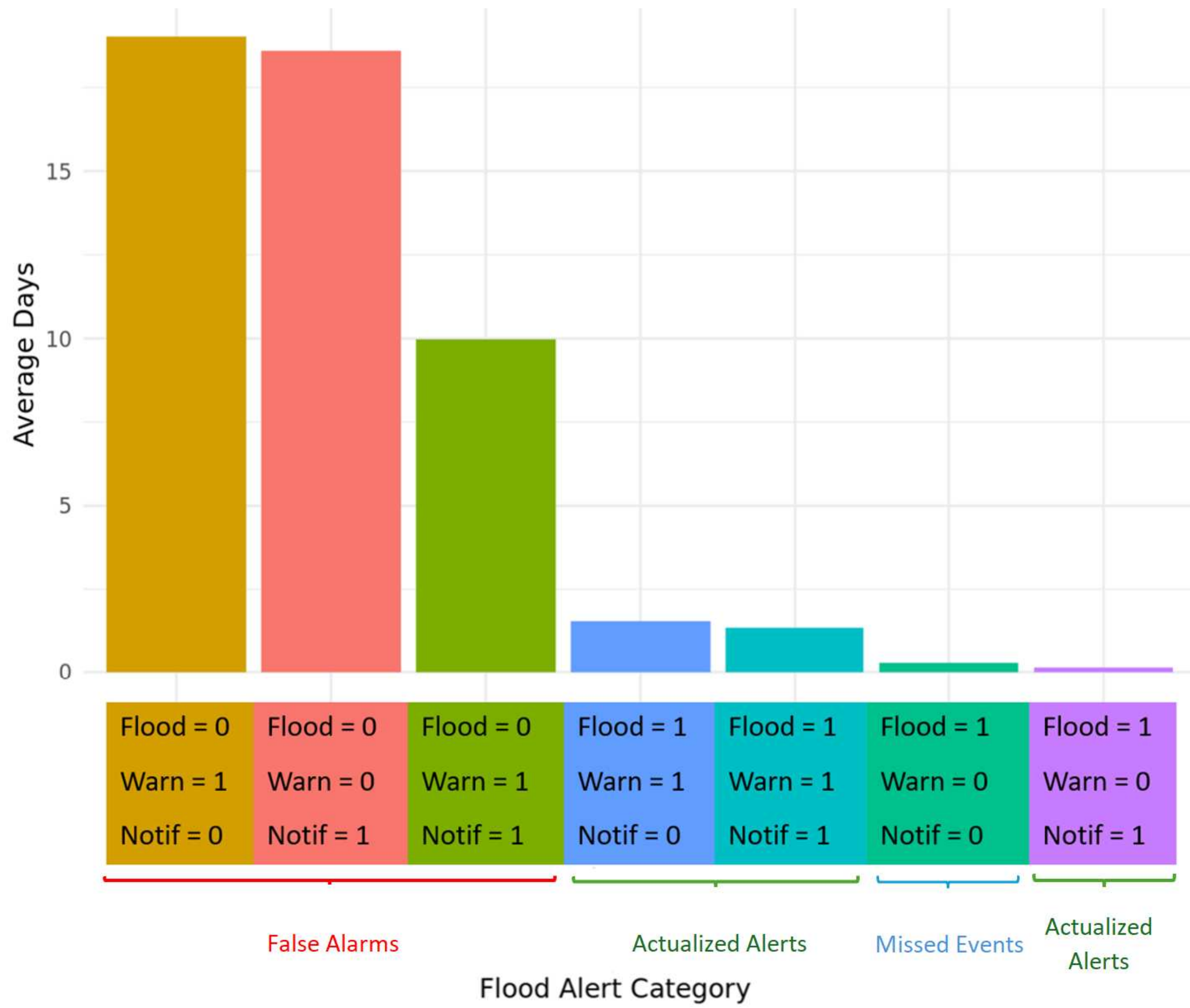

Figure 4.2: Average days per year per county by flood alert category.

I also created a spatial visualization to show how frequently different alert-event combinations occurred across counties in the contiguous U.S. Using the constructed monthly panel dataset, I calculated the share of all flood-related alert-event days from 2019 to 2023 that fell into each of the three categories. Specifically, for each county, I computed the ratio of days classified as false alarms, missed events, or actualized alerts to the total number of alert-event days involving any flood type. The goal was to examine not just how often these mismatches occurred in absolute terms, but how they compare to the overall alert-event activity in each location. To account for cases in which the alert is issued for a general flood, but the Storm Events Database ends up categorizing the event as a lakeshore flood, for instance, I included all types of floods and their respective alerts for this visual. Hence, false alarms include cases where no flood, flash flood, lakeshore flood, or coastal flood happened, but at least an alert for any of these events was issued. Similarly, a missed event includes cases where no alerts were issued but at least one type of flood (flood, flash flood, lakeshore flood, coastal flood) occurred.

The abovementioned ratios are displayed in Figure 4.3. The top panel shows the false alarm ratio, which is elevated across a large portion of the country. This widespread pattern reflects the relatively frequent issuance of alerts that are not followed by a confirmed flood event. The middle panel presents the actualized (matched) alert ratio, which dominates in areas with persistent flood risk, including much of the Midwest and sections of the Southeast. The bottom panel shows the missed event ratio, which is more spatially concentrated, with particularly high values in parts of the Northern Plains and Upper Midwest. Counties shaded in gray had no actualized alerts or missed events in those 5 years, respectively.

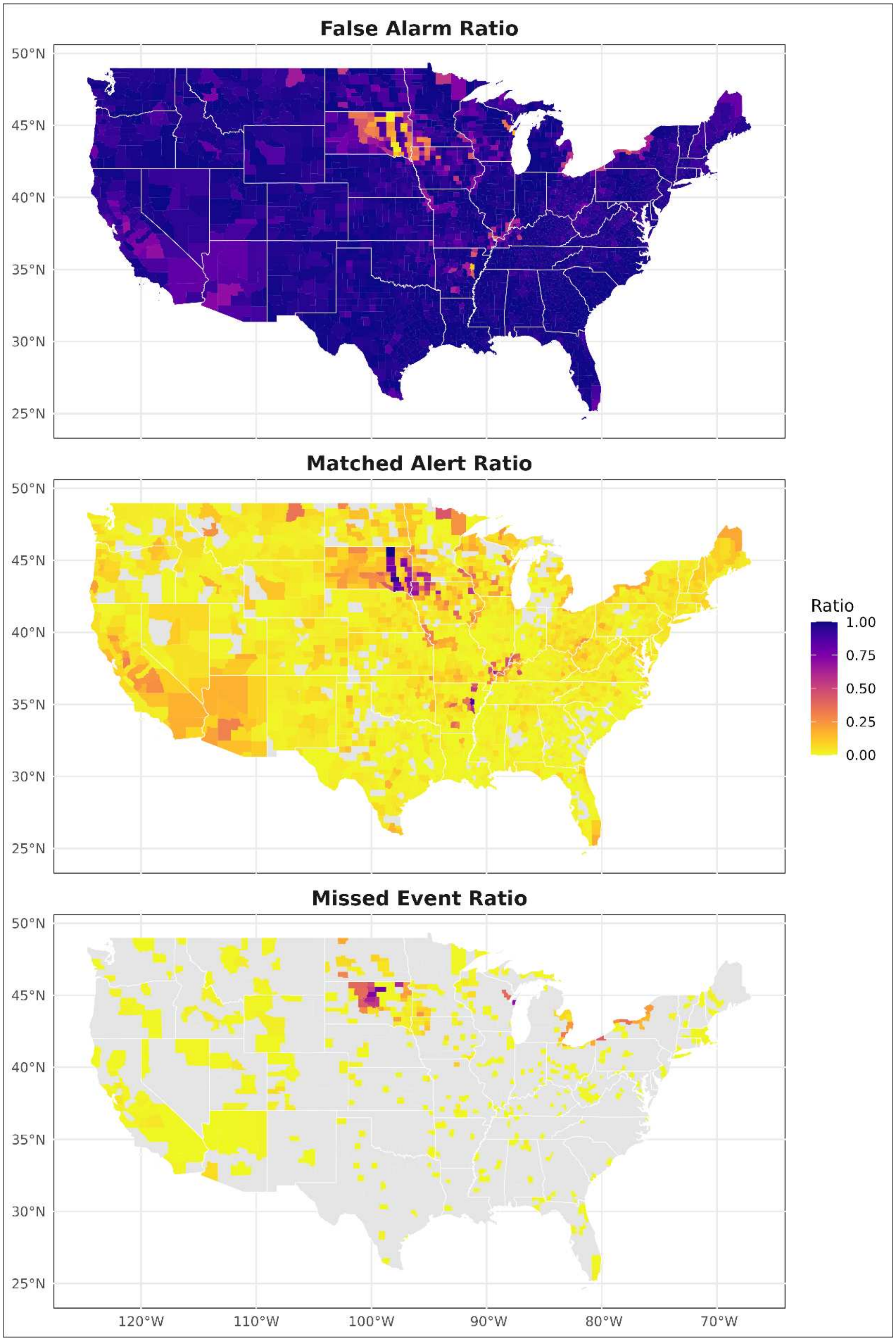

Figure 4.3: The ratio of flood alert-event combinations from 2019 to 2023 at the county-level.

5. RESULTS

This section presents the results from the fixed effects models used to estimate the relationship between flood alert accuracy and county-level employment. As outlined earlier, the analysis proceeds in multiple stages:

5.1. Baseline Model Estimates: The Average Effect of Flood Alerts and Events on Employment

The first model evaluates whether general combinations of flood alerts and events influence monthly employment. As shown in Table 5.1, column (1), none of the coefficients are statistically significant. This suggests that at an aggregate level, employment does not respond strongly to either accurate matches between alerts and flood events or to mismatches such as false alarms and missed events. This could mean that general mismatches, when not disaggregated by flood or alert type, are too coarse to capture measurable disruptions in the labor market.

5.2. Does the Average Effect on Employment Vary by Type of Flood?

The second model separates the results for flash floods and general floods. As seen in Table 5.1, column (2), the coefficient for actualized alerts during flash floods is statistically significant and negative, which suggests that an additional day of a flash flood with an accompanying alert leads to a decrease in employment counts by 0.13%, holding all else constant. This could reflect temporary closures or reductions in work hours due to the combined effects of an actual flash flood and the mobilization prompted by an alert. The effect of missed flash floods is positive but not statistically significant, and the coefficients for false alarms and actualized alerts in the general flood model are also not significant. The implication is that employment effects may be more noticeable during actualized alerts for flash floods than for general floods, though more disaggregated specifications are needed to clarify these patterns.

Table 5.1: Regression results for two-way fixed effect models 1 and 2.

Variables		Estimated Change in Log Employment	
		(1)	**(2)**
Flood	**Alert**		
Any Flood	No	4.344e-04	
		(4.835e-04)	
No	Yes	-5.295e-05	
		(6.471e-05)	
Any Flood	Yes	-7.495e-05	
		(1.230e-04)	
Flash Flood	No		7.317e-04
			(3.940e-03)
Flash Flood	Yes		-1.321e-03**
			(5.732e-04)
Flood	No		4.337e-04
			(4.872e-04)
Flood	Yes		-4.252e-06
			(1.241e-04)
No	Yes		-4.661e-05
			(6.460e-05)
Observations		631,032	631,032
Adj. R^2		0.996	0.996
Within R^2		1.04e-5	2.737e-5
County Fixed Effects		3,106 levels	3,106
State by Year by Month Fixed Effects		9,996 levels	9,996

* p < 0.1, ** p < 0.05, *** p < 0.01

5.3. Does How the Alert is Categorized Impact Employment Outcomes?

The third model introduces combinations that distinguish between warnings and notifications (advisories and watches). As Table 5.2, column (3) shows, only one of the categories has a statistically significant coefficient. Specifically, an additional day of actualized alerts involving both a warning and a notification during a flood is associated with a small but significant decline in employment (-0.058%, $p < 0.05$). This finding suggests that when both types of alerts are issued and a flood does occur, the impact on employment is more noticeable. None of the other combinations, such as isolated warnings without floods or floods without any alerts, are statistically significant, which could suggest that mismatches, such as false alarms or missed events, do not, on their own, generate significant negative consequences for employment in this setting.

5.4. Do Employment Impacts Differ by Both Flood and Alert Type?

The final model disaggregates the results by both flood type (flash flood vs. general flood) and alert type (warning vs. notification). Table 5.2, column (4), displays the resulting estimates. Three combinations under flash flood conditions show statistically significant relationships with employment.

First, an additional day of a flash flood event with notifications but without warnings is associated with a statistically significant increase in employment of 0.54% ($p<0.05$). This may reflect recovery-related labor demand following low-severity flash floods that triggered only a notification. Second, an additional day of a flash flood event with warnings but no notifications shows a negative and statistically significant association with employment (-0.18%, $p<0.05$). Third, the marginal effect of a day with flash flood events, as well as both warnings and notifications is also linked to a statistically significant decrease in employment (-0.14%, $p<0.05$), consistent with the idea that compounded alert activity during a flood corresponds with broader work interruptions or economic slowdowns. While both combinations involving warnings are associated with negative effects, the magnitude is slightly smaller when a notification is also present. Nevertheless, the difference between the two coefficients is not statistically significant.

This suggests that the presence of a notification does not meaningfully change the employment response during flash flood event days when a warning is issued.

None of the combinations under general flood conditions are statistically significant. This implies that general employment responses are more likely to occur under flash flood conditions than during general floods, possibly due to differences in duration, visibility, or preparedness levels associated with each flood type.

Table 5.2: Regression results for two-way fixed effect models 3 and 4.

Dependent Variable: Log Employment			**(3)**	**(4)**	
Category			**All Floods**	**Flash Floods**	**Floods**
Flood	**Warning**	**Notification**			
No	No	Yes	-6.300e-05	-6.424e-05	
			(1.042e-04)	(1.042e-04)	
No	Yes	No	-5.026e-05	-4.450e-05	
			(8.438e-05)	(8.441e-05)	
No	Yes	Yes	-3.992e-05	-3.181e-05	
			(1.213e-04)	(1.209e-04)	
Yes	No	No	3.339e-04	3.694e-04	3.622e-04
			(4.483e-04)	(4.097e-03)	(4.492e-04)
Yes	No	Yes	1.288e-03	5.388e-03*	9.592e-04
			(8.770e-04)	(2.933e-03)	(9.326e-04)
Yes	Yes	No	7.964e-05	-1.802e-03*	9.940e-05
			(1.560e-04)	(9.717e-04)	(1.575e-04)
Yes	Yes	Yes	-5.810e-04**	-1.350e-03**	-3.692e-04
			(2.452e-04)	(6.414e-04)	(2.514e-04)
Observations			631,032	631,032	
Adj. R²			0.996	0.996	
Within R²			2.62E-05	4.543e-5	
County Fixed Effects			3,106 levels	3,106 levels	
State by Year by Month Fixed Effects			9,996 levels	9,996 levels	

* p < 0.1, ** p < 0.05, *** p < 0.01

5.5. Do Employment Outcomes of Flood Alerts and Events Change in Different Sectors?

After estimating the models for all employment, I also ran the same models for two sectors that I hypothesize to be more exposed to flooding and flood alerts: construction and leisure and hospitality. Table 5.3 shows the results for general floods and flash floods, disaggregated by alert type.

Table 5.3: Regression results for two-way fixed effect models for all employment, construction, and leisure and hospitality.

Variables			Estimated Change in Log Employment		
Flood	**Warning**	**Notification**	**All Employment**	**Construction**	**Leisure & Hospitality**
No	No	Yes	-6.42e-05	-2.17e-04	-1.86e-04
			(1.04e-04)	(2.23e-04)	(1.74e-04)
No	Yes	No	-4.45e-05	2.75e-04	-1.13e-04
			(8.44e-05)	(2.18e-04)	(1.34e-04)
No	Yes	Yes	-3.18e-05	-1.76e-05	1.65e-04
			(1.21e-04)	(2.71e-04)	(1.99e-04)
Flash Flood	No	No	3.69e-04	3.42e-03	-4.49e-03
			(4.10e-03)	(5.50e-03)	(3.47e-03)
Flash Flood	No	Yes	5.39e-03*	-2.93e-03	1.47e-03
			(2.93e-03)	(6.44e-03)	(3.87e-03)
Flash Flood	Yes	No	-1.80e-03*	4.08e-04	-4.33e-03**
			(9.72e-04)	(2.20e-03)	(1.70e-03)
Flash Flood	Yes	Yes	-1.35e-03**	-2.38e-03*	-3.44e-03***
			(6.41e-04)	(1.26e-03)	(9.53e-04)
Flood	No	No	3.62e-04	1.14e-03	-6.46e-04
			(4.49e-04)	(1.14e-03)	(5.58e-04)
Flood	No	Yes	9.59e-04	1.36e-03	-2.38e-03
			(9.33e-04)	(3.82e-03)	(1.57e-03)
Flood	Yes	No	9.94e-05	4.05e-05	-5.26e-04
			(1.57e-04)	(4.98e-04)	(3.33e-04)
Flood	Yes	Yes	-3.69e-04	-2.82e-03***	-3.68e-04
			(2.51e-04)	(8.05e-04)	(4.56e-04)
Observations			631,032	565,713	617,124
Adj. R^2			0.996	0.979	0.991
Within R^2			4.522e-05	8.466e-05	9.58e-05
County Fixed Effects			3,106 levels	3,060	3,082
State by Year by Month Fixed Effects			9,996 levels	9,984	9,996

* p < 0.1, ** p < 0.05, *** p < 0.01

For construction, two combinations showed statistically significant results. The first one was for general floods that were accompanied by both a warning and a notification. An additional day of this category was associated with a 0.28% decrease in employment ($p<0.001$), holding all else constant. The second significant result for construction occurred under flash flood conditions when both warning and notification were issued, where an additional day of this category suggests a decline in employment by 0.24% ($p<0.1$). This result also suggests that construction activity slows down when flash floods are combined with multiple alerts. Given that both alerts are likely to signal high risk or uncertainty, workers or firms may take additional precautionary measures, such as delaying projects or reducing site operations.

For leisure and hospitality, the largest and most statistically significant effect was also for the category where a flash flood occurs, and both a warning and a notification are issued. An additional day of this category is associated with a decline of 0.34% in employment ($p<0.01$). One possible explanation is that residents and visitors reduce non-essential activities, such as dining out, shopping, or traveling, due to flood conditions and the perception of danger. Businesses in this sector may respond by reducing hours or temporarily closing. The fact that both alerts were issued might make the flood feel more severe.

Another statistically significant result for leisure and hospitality was for the category which includes flash floods with a warning but no notification. This result suggests that an additional day of a flash flood with only a warning being issued (with no prior watch or advisory) leads to the sector experiencing a stronger negative shock of -0.43% ($p<0.05$). This could be because the warning came with little anticipation, making it harder for businesses to prepare.

When comparing the results across sectors, some important differences emerge. First, actualized alerts during flash floods have negative effects that are statistically significant in all three employment measures, but the size of the effect is largest in leisure and hospitality, followed by construction, and then all employment. Second, construction is more sensitive to general floods, especially when both alerts are active, while the leisure and hospitality sector is more sensitive to flash floods, particularly when alerts are mismatched or compounded.

Most other coefficients in the table are not statistically significant. This means that, although some alert-event combinations do influence employment, many of them do not produce measurable effects in the data. One possible reason is that monthly employment numbers may not fully capture short-term responses, especially if layoffs are avoided or hours are adjusted instead. Another reason is that counties may vary in their sensitivity to floods depending on geography, preparedness, or economic structure. It is also possible that some alerts are seen as routine, especially in counties that receive them frequently, and therefore do not trigger strong responses. Results for all other sectors reported in the QCEW data are reported in Appendix I for completeness. Sectors with greater physical or outdoor exposure, similar to construction and leisure and hospitality, tend to exhibit more pronounced employment responses to flood alerts, whereas sectors with more remote or office-based work are less affected.

5.6. Do Co-occurring Natural Hazards Explain the Effects of Flood Alerts on Employment?

One concern raised in the interpretation of the alert-event coefficients, particularly the larger effects associated with flash flood warnings, is the possibility that these results may be confounded by co-occurring natural hazards. For instance, flash floods can occur alongside hail, severe thunderstorms, or windstorms, which could contribute independently to local employment disruptions. To address this concern, I estimate a robustness specification that adds controls for the presence of other weather events.

Specifically, I include two additional variables. The first captures whether a flood-related natural hazard (e.g., hurricanes, coastal floods, seiches, hail, tsunamis, lakeshore floods, cyclones, surges, severe storms, heavy rain, and wind) occurred on the same day and county, accompanied by both a warning and a notification (Other Flood-Related Natural Disasters). The second captures similar combinations for non-flood hazards (e.g., tornadoes, wildfires, snowstorms, ice, cold, fog, smoke, rip currents, debris flows, dust storms, low tides, avalanches, and droughts), labeled Non-Flood-Related Natural Disasters.

The results from this robustness check are presented in Table 5.4. The coefficients on the flash flood alert-event combinations remain statistically significant and negative, particularly for the leisure and hospitality sector. For example, an additional day of flash flooding with a warning and a notification being issued for leisure and hospitality employment remains large (-0.321%) and highly significant ($p<0.01$), even after controlling for other natural disasters. This suggests that the employment losses identified in earlier specifications are not solely due to confounding by multi-hazard events. The coefficients on the co-occurrence variables themselves also carry expected signs. For instance, the presence of other flood-related hazards is associated with employment reductions in leisure and hospitality (-0.201%, $p<0.05$), while non-flood-related events are positively associated with construction employment, which could reflect an increase in construction work due to seasonal weather events.

Overall, the robustness results confirm that the main findings are not driven by omitted co-occurring hazard events. These results strengthen the interpretation that the employment effects identified in prior sections can be attributed to the specific combinations of flood alerts and flood events, particularly flash floods.

Table 5.4: Robustness check: controlling for co-occurring natural hazards.

Variables			**Estimated Change in Log Employment**		
Flood	**Warning**	**Notification**	**All Employment**	**Construction**	**Leisure & Hospitality**
No	No	Yes	-5.874e-05	-2.103e-04	-1.640e-04
			(1.040e-04)	(2.230e-04)	(1.731e-04)
No	Yes	No	-4.274e-05	2.774e-04	-1.058e-04
			(8.444e-05)	(2.180e-04)	(1.341e-04)
No	Yes	Yes	-2.457e-05	-1.534e-05	1.929e-04
			(1.203e-04)	(2.701e-04)	(1.983e-04)
Flash Flood	No	No	3.904e-04	3.384e-03	-4.412e-03
			(4.096e-03)	(5.471e-03)	(3.454e-03)
Flash Flood	No	Yes	5.476e-03*	-2.752e-03	1.824e-03
			(2.935e-03)	(6.446e-03)	(3.863e-03)
Flash Flood	Yes	No	-1.735e-03*	3.903e-04	-4.068e-03**
			(9.720e-04)	(2.199e-03)	(1.697e-03)
Flash Flood	Yes	Yes	-1.291e-03**	-2.446e-03*	-3.205e-03***
			(6.428e-04)	(1.281e-03)	(9.355e-04)
Flood	No	No	3.629e-04	1.146e-03	-6.430e-04
			(4.491e-04)	(1.142e-03)	(5.580e-04)
Flood	No	Yes	9.673e-04	1.347e-03	-2.343e-03
			(9.315e-04)	(3.816e-03)	(1.572e-03)
Flood	Yes	No	1.002e-04	4.311e-05	-5.235e-04
			(1.575e-04)	(4.978e-04)	(3.332e-04)
Flood	Yes	Yes	-3.610e-04	-2.814e-03***	-3.362e-04
			(2.509e-04)	(8.048e-04)	(4.551e-04)
Other Flood-Related Natural Disasters	Yes	Yes	-5.116e-04	1.808e-04	-2.011e-03**
			(4.513e-04)	(8.028e-04)	(9.151e-04)
Other Non-Flood-Related Natural Disasters	Yes	Yes	1.918e-04	1.217e-03*	7.392e-04
			(2.907e-04)	(6.273e-04)	(4.763e-04)
Observations			631032	565713	617124
Adj. R^2			0.996	0.979	0.991
Within R^2			5.508e-5	1.111e-4	1.487e-4
County Fixed Effects			3,106	3,060	3,082
State by Year by Month Fixed Effects			9,996	9,984	9,996

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.7. Do Different Alert Groupings Alter the Estimated Effects on Employment?

The results discussed so far used a grouping where warnings were treated separately, and both advisories and watches were combined into a single category labeled as "notification." To evaluate whether this choice affected the estimated relationships between alert-event combinations and employment, I estimated two additional models using alternative groupings of alerts. In Table 5.5, column (2), warnings and watches were grouped and compared against advisories. In column (3), warnings and advisories were grouped and compared against watches. The results help evaluate whether the way alerts are bundled influences the estimated labor market impacts of flood-alert combinations.

Overall, the alternative specifications yield findings that are generally consistent with column (1) in terms of direction, but the statistical significance of some categories shifts depending on the grouping. Most notably, the category that represents flash flood days with only one type of alert was statistically significant in both column (1) (-0.18%, $p<0.1$) and column (2) (-0.24%, $p<0.01$) but not significant in column (3). This suggests that the negative effect of warning-only flash flood events on employment is robust when warnings are grouped with watches, but becomes less precise when warnings are grouped with advisories.

A similar pattern holds for the category which captures flash floods accompanied by both alert types. An additional day of this category in column (1) is associated with a 0.14% decrease in employment ($p<0.05$) and remains significant in column (3) (-0.26%, $p<0.01$), but loses significance in column (2). Despite the loss of statistical significance in (2), the coefficient remains negative and of similar magnitude. This suggests that the direction of the effect is robust, but that the precision of the estimate depends on how alerts are grouped.

Table 5.5: Regression results for two-way fixed effect models with different alert groupings.

Variables			**Estimated Change in Log Employment (All Sectors)**		
Flood	**Alert 1**	**Alert 2**	**(1) 1. Warning + 2. Watch&Advisory**	**(2) 1.Warning&Watch + 2. Advisory**	**(3) 1.Warning&Advisory + 2. Watch**
No	No	Yes	-6.424e-05	-1.970e-04	6.764e-05
			(1.042e-04)	(1.448e-04)	(1.320e-04)
No	Yes	No	-4.450e-05	-4.347e-05	-5.321e-05
			(8.441e-05)	(7.426e-05)	(6.998e-05)
No	Yes	Yes	-5.971e-05	7.735e-05	-6.216e-05
			(1.958e-04)	(1.591e-04)	(1.262e-04)
Flash Flood	No	No	3.694e-04	8.273e-04	3.434e-04
			(4.097e-03)	(3.945e-03)	(4.072e-03)
Flash Flood	No	Yes	5.388e-03*	3.520e-03	6.089e-03
			(2.933e-03)	(3.483e-03)	(6.689e-03)
Flash Flood	Yes	No	-1.802e-03*	-2.405e-03***	-5.997e-04
			(9.717e-04)	(8.612e-04)	(6.633e-04)
Flash Flood	Yes	Yes	-1.350e-03**	-6.853e-04	-2.579e-03***
			(6.414e-04)	(7.350e-04)	(7.921e-04)
Flood	No	No	3.622e-04	4.467e-04	2.727e-04
			(4.492e-04)	(4.758e-04)	(4.453e-04)
Flood	No	Yes	9.592e-04	-2.610e-04	3.005e-03*
			(9.324e-04)	(1.477e-03)	(1.559e-03)
Flood	Yes	No	9.940e-05	4.514e-05	3.908e-05
			(1.575e-04)	(1.382e-04)	(1.456e-04)
Flood	Yes	Yes	-3.692e-04	-2.456e-04	-2.962e-04
			(2.514e-04)	(3.362e-04)	(3.131e-04)
Observations			631,032	631,032	631,032
Adj. R^2			0.996	0.996	0.996
Within R^2			4.52E-05	4.65E-05	4.92E-05
County Fixed Effects			3,106	3,106	3,106
State by Year by Month Fixed Effects			9,996	9,996	9,996

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In contrast, the category of flash flood days with notification-type alerts but no warnings is statistically significant in column (1) but not in either column (2) or (3). This lack of robustness suggests that the initially observed positive effect may be sensitive to how notifications are defined and may not reflect a consistent economic pattern.

Only one general flood category showed a statistically significant relationship in columns (2) or (3). In column (3), the category with a general flood day and a watch issued in the last 36 hours is positive and significant (0.3%, $p<0.1$), whereas it is not significant in either Model 1 or Model 2. This result is not central to the main findings, but it may suggest that under certain grouping structures, general flood alerts that fall short of a warning might still stimulate economic activity.

Across both alternative models, most flood-alert combinations remain statistically insignificant. This mirrors the pattern in Model 1 and supports the broader conclusion that employment effects are concentrated in a small subset of flood-alert combinations, particularly those involving compound alerts during flood events.

Taken together, the results from Models 2 and 3 show that while some coefficients lose or gain significance depending on alert classification, the overall patterns are directionally consistent with the baseline specification. The strongest and most stable effects occur for flash floods with both alerts (Model 3) and flash floods with a warning but no accompanying advisory (Model 2). Although the significance of individual categories fluctuates slightly depending on the alert grouping scheme, the overall patterns suggest that alert layering, especially under flash flood conditions, remains a potentially important channel through which flood alerts influence short-term labor market activity.

5.8. Do Employment Impacts of Flood Alerts Differ Between Rural and Urban Counties?

To explore whether the relationship between flood alerts and employment differs between rural and urban counties, I used the 2023 Rural-Urban Continuum Codes (RUCC) to classify each county into rural, urban, and baseline categories and then create the flood-alert combinations for each to estimate whether the impacts of alerts differ depending on area characteristics. The baseline category includes RUCC codes 4, 5, and 6, which represent counties that are nonmetro but adjacent to metro areas or that have urban populations of at least 2,500. These counties are not as isolated as rural counties (RUCC 7, 8, and 9), but also do not exhibit the same degree of urbanization as metro counties (RUCC 1, 2, and 3).

Before introducing the full interaction models by alert and flood type, I estimated the baseline specification with rural and urban county interactions to examine whether the null result in the pooled model earlier masks opposing effects across space. The results are shown in Table 5.6.

In baseline counties, several statistically significant effects are observed. Days with flood alerts but no actual flooding, i.e., false alarms, are associated with a small but statistically significant decline in all employment ($p<0.01$) and a decline in leisure and hospitality employment ($p<0.05$). These findings suggest that even when flooding does not occur, the issuance of alerts in baseline counties may disrupt local labor markets, perhaps due to anticipatory behavioral responses or temporary changes in mobility, scheduling, or demand.

Additionally, actualized flood-alert days in baseline counties are associated with a statistically significant decline in leisure and hospitality employment ($p<0.05$), while the estimates for all employment and construction are not significant. These results indicate that baseline counties exhibit sensitivity to both false alarms and actual flood events, particularly in sectors like leisure and hospitality that may be more vulnerable to uncertainty or short-term disruptions.

Table 5.6: Regression results for two-way fixed effect models for rural and urban counties. Note: Coefficients for rural and urban counties reflect the sum of the baseline effect and the relevant interaction term.

Variables			Estimated Change in Log Employment		
Flood	**Alert**	**Metro Area**	**All Employment**	**Construction**	**Leisure & Hospitality**
Yes	No	Baseline	1.173e-03	1.490e-03	7.029e-04
			(8.610e-04)	(1.269e-03)	(1.714e-03)
No	Yes	Baseline	-2.654e-04***	-3.003e-04	-3.258e-04**
			(8.054e-05)	(2.040e-04)	(1.472e-04)
Yes	Yes	Baseline	5.602e-05	1.147e-03	-7.811e-04**
			(2.008e-04)	(7.967e-04)	(3.193e-04)
Yes	No	Rural	1.192e-03	1.528e-03	-3.065e-04
			(1.389e-03)	(2.569e-03)	(2.565e-03)
No	Yes	Rural	-1.397e-04	-6.133e-05	2.490e-04
			(1.266e-04)	(3.358e-04)	(2.464e-04)
Yes	Yes	Rural	2.078e-04	-9.626e-04	-1.834e-04
			(3.137e-04)	(1.256e-03)	(5.957e-04)
Yes	No	Urban	-8.748e-04	1.030e-03	-1.948e-03
			(1.290e-03)	(2.077e-03)	(2.472e-03)
No	Yes	Urban	1.724e-04	5.174e-04	-2.980e-04
			(1.389e-04)	(3.403e-04)	(2.188e-04)
Yes	Yes	Urban	-6.877e-04**	-1.736e-03	-1.341e-03**
			(3.522e-04)	(1.209e-03)	(5.436e-04)
Observations			629553	564270	61549
Adj. R^2			0.996	0.979	0.991
Within R^2			1.833e-4	1.435e-4	1.706e-4
County Fixed Effects			3,098	3,052	3,074
State by Year by Month Fixed Effects			9,792	9,780	9,792

* p < 0.1, ** p < 0.05, *** p < 0.01

In urban counties, actualized flood-alert combinations are associated with statistically significant declines in both all employment ($p<0.05$) and leisure and hospitality employment ($p<0.05$), reinforcing the idea that the compounding presence of both a warning and an actual flood imposes measurable labor market costs. These declines are small but consistent across sectors.

In contrast, in rural counties, none of the alert-event combinations are statistically significant. Across all employment sectors, the coefficients for false alarms, actualized alerts, and missed events are small and estimated with considerable uncertainty. This lack of statistical significance does not imply the absence of effects, but it does suggest that employment responses in rural counties are either more variable or more muted in response to the types of alerts and flood configurations considered here. The divergence across space highlights that the null results observed in the pooled model may be averaging out statistically significant negative effects in baseline and urban counties with non-significant or directionally mixed effects in rural areas.

I next estimate fully disaggregated models that distinguish between flood types (general versus flash), alert types (warnings versus notifications), and their combinations. The results are shown in a coefficient plot (Figure 5.1).

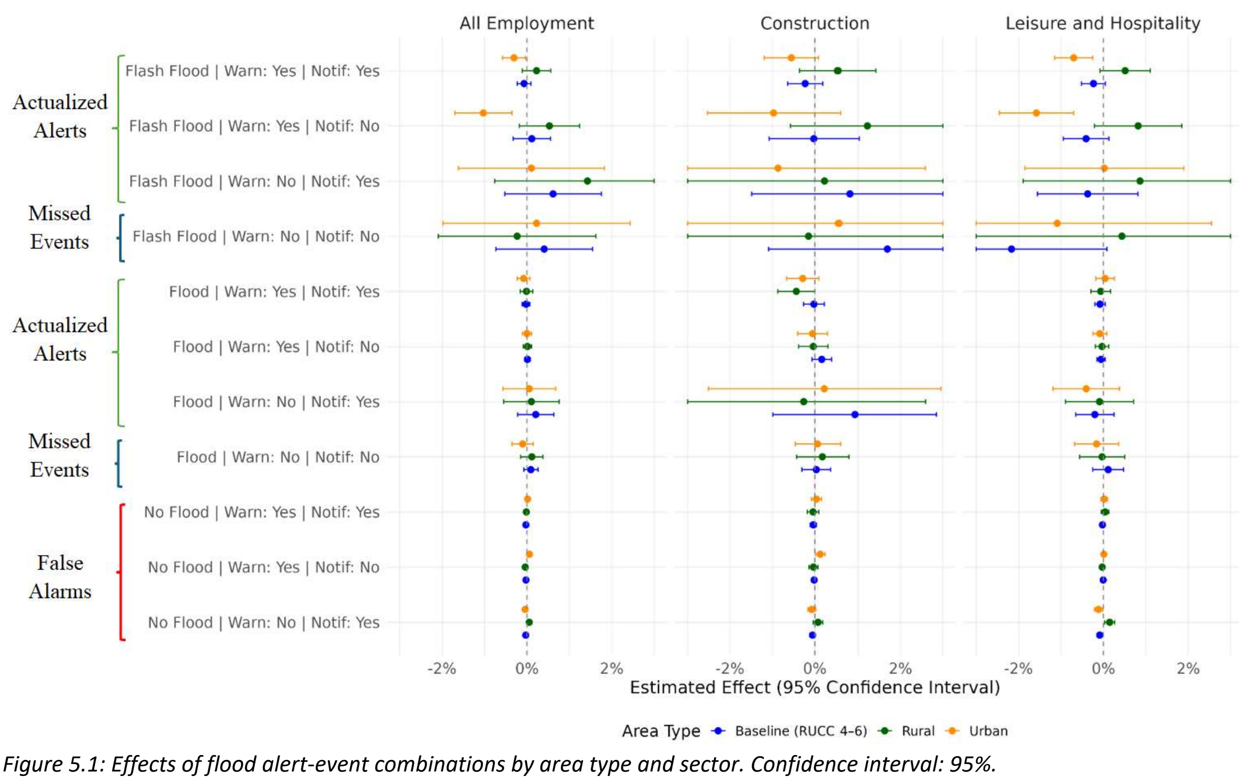

Figure 5.1: Effects of flood alert-event combinations by area type and sector. Confidence interval: 95%.

In rural counties, several combinations involving false alarms are associated with positive employment effects. For instance, an additional day with only a notification (false alarm) is linked to a 0.054% increase in overall employment ($p<0.1$) and a 0.147% increase in leisure and hospitality employment ($p<0.05$). Similarly, a warning-only false alarm in rural areas is associated with a 0.041% increase in total employment ($p<0.05$), although the sector-specific effects are not statistically significant. These results may reflect increased local activity or precautionary behaviors following alerts, even when flooding does not occur.

Additionally, actualized alert-event combinations in rural counties show positive associations with employment. In particular, a flash flood accompanied by both a warning and a notification is associated with a 0.512% increase in leisure and hospitality employment ($p<0.1$). The direction of the effect contrasts with the patterns seen in urban counties, where the same alert-event combination is associated with losses. In rural areas, these increases may reflect local recovery efforts, emergency mobilization, or temporary economic stimulus following flood events.

In contrast, urban counties show declines in employment under several flood-alert scenarios. An additional flash flood day, accompanied by only a warning (no notification), leads to a 1.03% decrease in total employment ($p<0.01$) and a 1.58% decrease in leisure and hospitality ($p<0.01$). When both a warning and notification are present during a flash flood day, the effects remain negative: -0.307 % in all employment ($p<0.05$), -0.553% in construction ($p<0.01$), and -0.701% in leisure and hospitality ($p<0.01$). These findings suggest that in urban areas, alerts during flood events are more disruptive, possibly because higher population density and infrastructure dependence make these areas more vulnerable to even short-term disruptions.

Urban counties also exhibit some positive effects in response to false alarms. A warning-only false alarm increases total employment by 0.059% ($p<0.01$) and construction employment by 0.127% ($p<0.05$). These findings are consistent with those observed in rural counties, possibly indicating precautionary adjustments or short-term economic activity generated by alerts, even in the absence of flooding. However, false alarms involving only a notification show the opposite pattern. Although the effects are negative across all three outcomes, they are only statistically significant for leisure and hospitality, where employment declines by 0.117% ($p<0.05$). This suggests that watches or advisories can have measurable effects in urban service sectors, possibly due to changes in consumer behavior, staffing decisions, or event cancellations that occur when a flood is anticipated but does not materialize.

Taken together, these results point to meaningful geographic variation in how flood-alert combinations affect employment outcomes. Rural counties tend to experience positive employment responses, especially in construction and service sectors, following actualized alerts and even in some cases following false alarms. In contrast, urban counties are more vulnerable to job losses in cases of flash floods, especially when those events are accompanied by only warnings or all alerts. These findings emphasize the importance of tailoring alert systems by regional characteristics and economic structure.

5.9. Do Employment Effects of Flood Alerts Differ Based on Prior Exposure to False Alarms?

In this step, I estimated a set of regressions that interact each alert-event category with an indicator for high historical false positive exposure to assess whether long-term exposure to false alarms shapes how current alerts affect employment. As outlined in the Data and Methods section, counties were flagged as high exposure if they fell in the top 5% of false alarm share during the 2007–2013 period. The regressions were then run for data from 2014 onward, separately for total employment, construction, and leisure and hospitality.

Figure 5.2 shows that the employment responses to current alerts differ in counties with high past false alarm exposure, though the direction and magnitude of effects vary by sector. In particular, an additional day of flash flood events with both a warning and a notification is associated with a statistically significant employment decline of 0.23% (p<0.01) in counties without high false alarm exposure. In counties with high exposure, the estimated decline is larger at 0.66%, but this difference is not statistically significant. While the direction is consistent with the idea that frequent historical false alarms may reduce preparedness or delay response, the statistical evidence is limited.

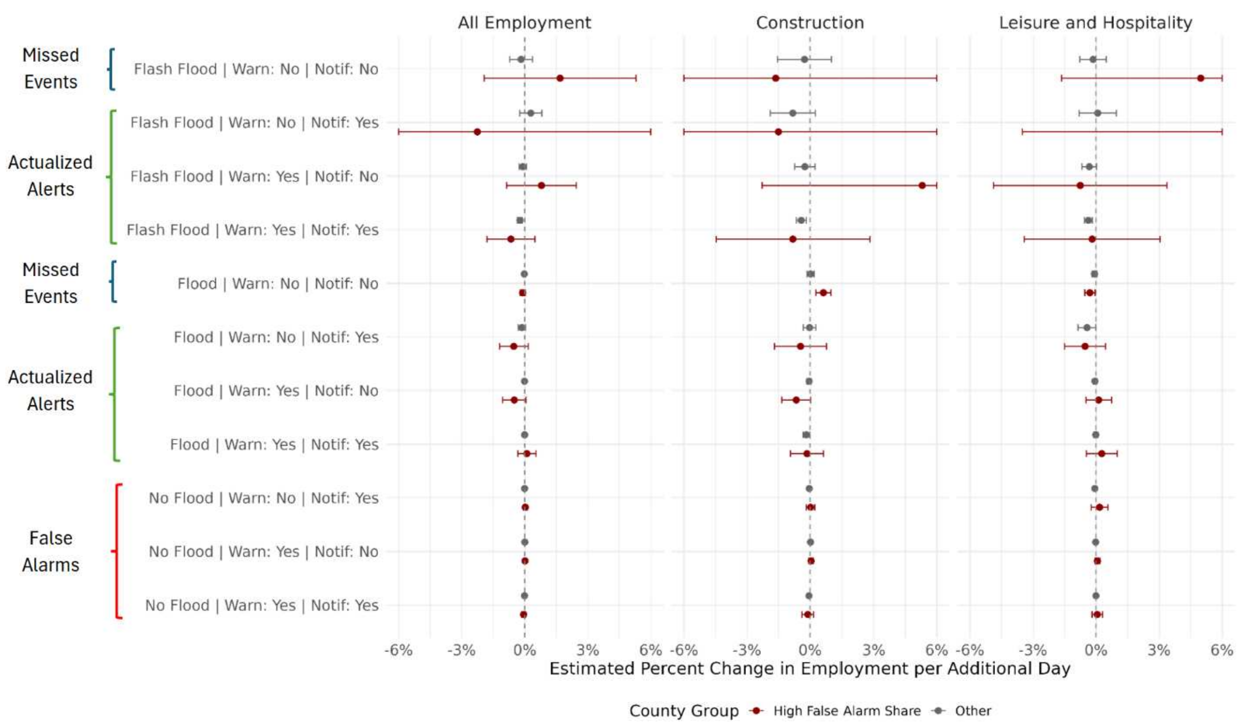

Figure 5.2: Effects of flood alert-event combinations by false alarm history. Confidence interval: 95%.

In the construction sector, effects are especially pronounced. In high-exposure counties, an additional general flood event day with no alerts is associated with a statistically significant 0.63% increase in construction employment (p<0.01), compared to no significant change in non-high-exposure counties. One possible interpretation is that firms operating in high false alarm environments may continue work even during flood conditions, especially when no alert is issued, suggesting a decline in perceived credibility of the alert system. However, this pattern may also reflect delayed or reactive labor demand during post-flood recovery in areas accustomed to inaccurate alerts.

By contrast, the leisure and hospitality sector shows more negative responses. In counties with high false alarm exposure, a general flood with no alert corresponds with a statistically significant 0.29% decline in employment ($p<0.05$). This sector may remain more sensitive to actual flood conditions, regardless of whether alerts are issued, given its reliance on consumer-facing services and mobility. Additionally, in counties without high false alarm exposure, notification-only false alarms are associated with a statistically significant 0.057% decline in employment in this sector ($p<0.01$), while no such effect is observed in high-exposure counties. A similar pattern is observed in the construction sector. In counties without high exposure to false alarms, an additional day of no flood but with a warning and notification issued is associated with a 0.054% decrease in employment ($p<0.05$). Again, false alarms in this sector do not have a statistically significant effect in counties with high false alarm exposure. This could indicate desensitization, where repeated exposure to false alerts weakens behavioral responses to real flood risks or partial alerts.

Together, these findings highlight that long-term exposure to false alarms can alter how local economies interpret and respond to flood alerts. While some sectors may become less reactive to warnings over time, this desensitization can potentially increase vulnerability during real flood events, particularly when alerts are missed or partial. These dynamics point to the broader consequences of over-warning, where declining trust in the alert system may erode its effectiveness as a public safety tool.

5.10. Do the Employment Effects of Flood Alerts Emerge Immediately or Over Time?

To evaluate whether the labor market effects of flood alerts manifest immediately or accumulate over time, I estimated models with lags of up to six months for each alert-event combination. This lag structure allows for the detection of delayed responses and the identification of persistent effects that might not be apparent in contemporaneous estimates.

The clearest lagged result appears for the category with flash floods and a warning but no notification (Figure 5.3). In the leisure and hospitality sector, the coefficient for the current period is negative and statistically significant (-0.48%, $p<0.01$), and the sixth lag remains negative and significant (-0.32%, $p<0.01$). This suggests that these mismatched flash flood alerts cause immediate and sustained reductions in employment in this sector.

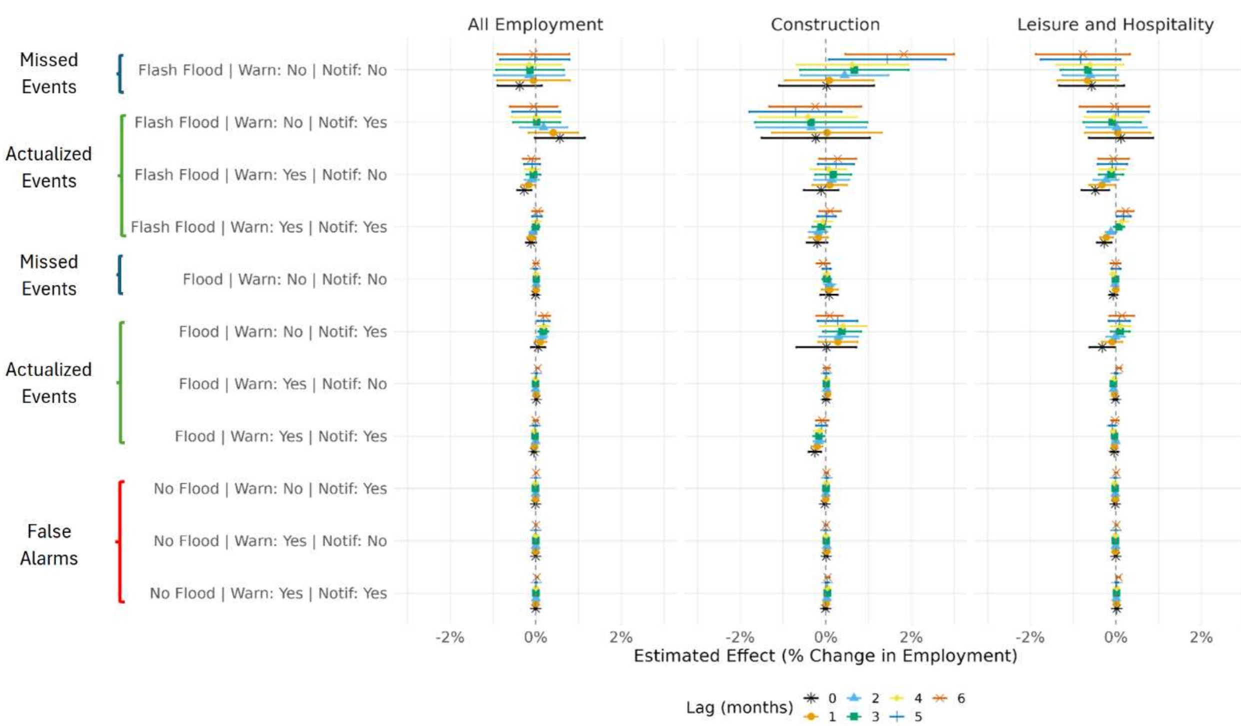

Figure 5.3: Lagged effects of flood alert-event combinations on employment outcomes. Confidence interval: 95%.

Another robust pattern emerges for the category with flash floods and both warnings and notifications. While the contemporaneous coefficient for all employment is negative and significant (-0.11%, $p<0.1$), lag one also shows a significant decline in employment (-0.1%,

$p<0.05$), and lags 4 to 6 show positive and significant effects in leisure and hospitality (e.g., lag 6: 0.23%, $p<0.01$). This pattern suggests an initial shock in all employment, followed by a potential recovery period, especially in service-oriented sectors.

For the category with general flood events and notifications but no warnings, lags 2 through 6 in the employment model are positive and statistically significant, with the sixth lag showing the strongest effect (0.21%, $p<0.01$). This could suggest that general floods accompanied by alerts not as severe as warnings may stimulate employment over time, potentially due to rebuilding or cleanup activities.

The category with general floods and warnings but no notifications also shows positive and significant effects at lag 6, both in all employment (0.05%, $p<0.01$) and in leisure and hospitality (0.08%, $p<0.01$). These findings again point to a potential cumulative effect where formal employment adjustments unfold gradually following the initial event.

In contrast, false alarms show more limited delayed effects. The sixth lag for alerts without a flood is negative and significant for employment (-0.006%, $p<0.01$), but the magnitude is relatively small. In the case of notification and warning issued but no flood, leisure and hospitality employment shows positive and statistically significant effects at lags 4 through 6 (e.g., lag 6: 0.1%, $p<0.01$).

Overall, the lagged specifications confirm that the labor market effects of flood alerts vary in timing and duration. Immediate shocks are most evident for actualized alerts during flash floods, particularly in leisure and hospitality, while delayed gains are concentrated in general floods accompanied by at least one form of alert.

5.11. Do Employment Effects Differ by Duration of Flood Events?

One of the main concerns with modeling flood alerts and events using daily exposure counts is that the structure may mask the cumulative nature of flooding. That is, general floods often last for several consecutive days, and the economic disruption they cause may build over time. By estimating marginal effects per additional day, earlier specifications may dilute or miss non-linear patterns, especially if the consequences of multi-day events are more than just additive. In other words, a five-day flood may not have five times the impact of a one-day flood, may have more, or may have less, depending on how businesses and workers respond to prolonged disruption.

To address this, I estimate an additional set of models that categorize flood and flash flood events by duration, distinguishing between events that lasted 1–3 days, 4–6 days, and 7 or more days. I construct these categories by identifying sequences of consecutive days where a given county experienced either a flood or flash flood event with the same alert status (actualized or missed). These event sequences are grouped using a cumulative identifier and then summarized to determine their start and end dates. The resulting event-level dataset is then merged back to the monthly panel to count the number of days in a given month that fall into each duration category.

Table 5.7 reports the estimated effects from this duration-based model. Several patterns emerge. First, for flash flood events that also had alerts, short-duration events (1–3 days) are associated with statistically significant declines in employment. The largest effect occurs in the leisure and hospitality sector (–0.37%, $p<0.01$), followed by construction (–0.23%, $p<0.05$) and all employment (–0.16%, $p<0.01$). These results are in line with the idea that short, high-intensity flash floods, when accompanied by an alert, may trigger responses in employment.

Table 5.7: Regression results for two-way fixed effect models with flood events disaggregated by duration and alert status.

Variables			**Estimated Change in Log Employment**		
			All Employment	**Construction**	**Leisure & Hospitality**
Flood	**Alert**	**Flood Duration**			
Flash Flood	Yes	1–3 days	-1.633e-03***	-2.256e-03**	-3.728e-03***
			(6.019e-04)	(1.147e-03)	(9.602e-04)
Flash Flood	Yes	4–6 days	2.294e-03	5.811e-03	-7.399e-04
			(1.722e-03)	(4.301e-03)	(2.844e-03)
Flash Flood	Yes	7+ days	7.050e-04	1.828e-03	-9.135e-04
			(8.321e-04)	(2.735e-03)	(2.243e-03)
Flash Flood	No	1–3 days	-1.069e-03	2.543e-03	-1.022e-02
			(3.895e-03)	(7.527e-03)	(6.729e-03)
Flash Flood	No	4–6 days	4.499e-04	2.626e-02***	6.795e-04
			(6.481e-03)	(5.071e-03)	(9.107e-03)
Flash Flood	No	7+ days	1.810e-03	-4.606e-04	4.500e-05
			(7.804e-03)	(9.028e-03)	(2.453e-03)
No	Yes	-	-4.772e-05	1.235e-04	-7.591e-05
			(6.469e-05)	(1.628e-04)	(1.066e-04)
Flood	Yes	1–3 days	6.462e-04	-2.215e-03*	-6.110e-04
			(4.852e-04)	(1.192e-03)	(8.805e-04)
Flood	Yes	4–6 days	-1.338e-04	-1.443e-03	4.191e-05
			(4.265e-04)	(1.138e-03)	(7.572e-04)
Flood	Yes	7+ days	-1.777e-05	-5.927e-04	-5.345e-04**
			(1.262e-04)	(4.616e-04)	(2.713e-04)
Flood	No	1–3 days	1.071e-03	4.908e-03	-2.502e-03
			(1.726e-03)	(4.337e-03)	(2.847e-03)
Flood	No	4–6 days	-1.540e-03	9.030e-04	-3.384e-03
			(1.596e-03)	(3.475e-03)	(2.377e-03)
Flood	No	7+ days	5.122e-04	1.239e-03	-5.709e-04
			(5.092e-04)	(1.107e-03)	(6.393e-04)
Observations			631032	565713	617124
Adj. R^2			0.996	0.979	0.991
Within R^2			4.393e-5	5.088e-5	9.17e-5
County Fixed Effects			3106	3060	3082
State by Year by Month Fixed Effects			9996	9984	9996

* p < 0.1, ** p < 0.05, *** p < 0.01

The only other statistically significant estimate for flash floods is found for missed flash flood events lasting 4–6 days, which are associated with a 2.6% increase in construction employment ($p<0.01$). This positive response is difficult to interpret definitively, but it may reflect post-flood repairs or temporary labor demand in construction that arises in the absence of a formal alert.

For general floods, the effects are much weaker overall. The only statistically significant coefficient is for actualized alerts for general floods lasting 7 or more days, which is associated with a small but statistically significant decline in leisure and hospitality employment (–0.05%, $p<0.05$). No other general flood categories show statistically significant effects across sectors. These findings are broadly consistent with earlier models and may reflect the fact that general floods are slower to develop, more predictable, and less disruptive in the short term than flash floods.

Altogether, these results indicate that the most acute employment disruptions occur during short, high-intensity flash floods that are actively alerted for, and that the effect of duration is not linear. For general floods, the evidence of disruption is limited and largely concentrated in the leisure and hospitality sector during long-duration, actualized alerts.

5.12. Sensitivity Analysis: Neighboring Counties

A sensitivity analysis was carried out to examine whether the presence of flood events in neighboring counties influences the effects of false alarms on local employment outcomes. In the original specification, alert-event combinations were constructed using only the flood event and alert data recorded within a given county. To evaluate whether proximity to actual flooding alters how false alarms are interpreted, I extended the daily panel dataset to include a new variable capturing whether a flood event occurred in any adjacent county on the same date. County adjacency was determined using geospatial relationships, and flood event data for neighboring counties were merged accordingly. Using this expanded panel, I redefined the false alarm categories to include only cases where a flood did not occur in the target county or any of its neighbors. I then re-ran the two-way fixed effects regression model for all employment to compare these results against the original specifications that did not account for neighboring conditions.

As Figure 5.4 shows, the inclusion of adjacent-county flood events did not change the results. Coefficients remained similar in magnitude and direction, and most remained statistically insignificant. These findings indicate that when no flooding is present locally or nearby, false alarms do not produce large disruptions in employment, and that the results are robust to an expanded geographic definition of flood exposure. Similar results were found for the construction and leisure & hospitality sectors (Appendix II).

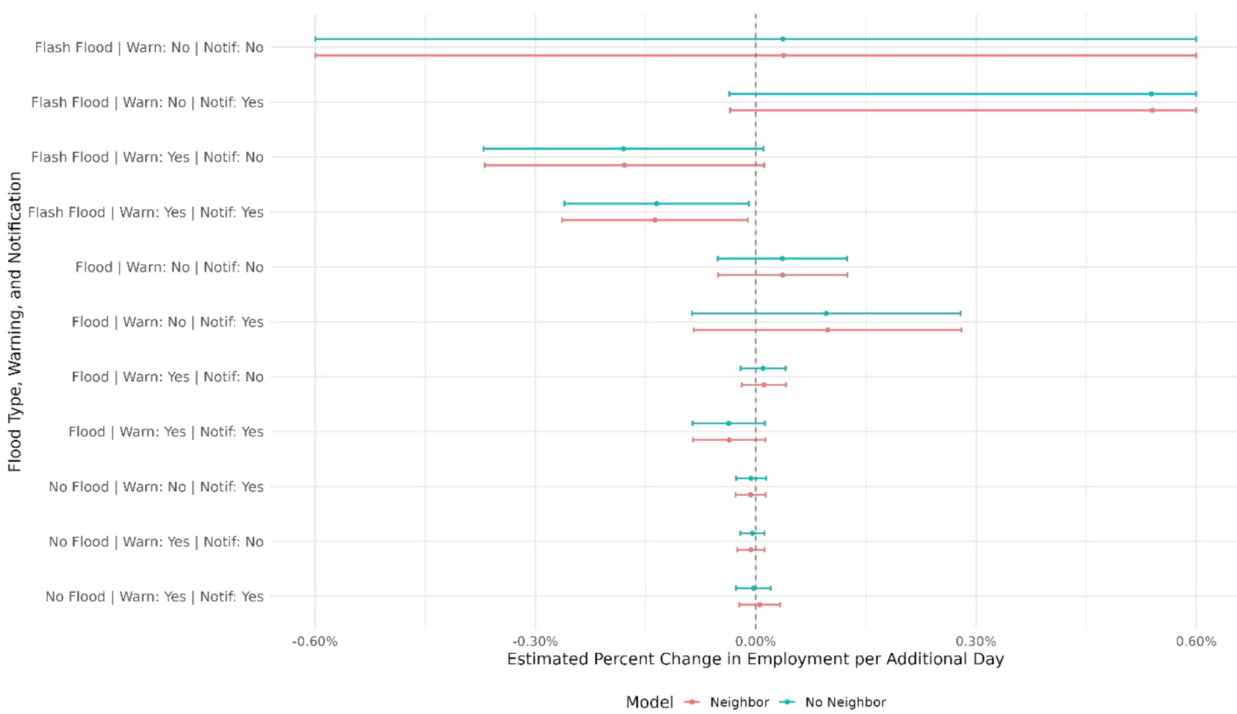

Figure 5.4: Event effects with and without neighboring alerts for all employment. Confidence interval: 95%.

5.13. Study Limitations

Several limitations need to be acknowledged when interpreting the results of this study. The first limitation concerns the measurement of flood events. This thesis relies on the NOAA Storm Events Database to identify when and where floods occurred. While this is the most comprehensive and publicly available dataset for historical flood records in the U.S., it may not capture all flood events equally across counties and years. In particular, minor floods that were not reported or that occurred in less populated areas may be underrepresented. Additionally, data on the severity of each flood was not available. In the current setup, employment changes following an actualized alert-event may be interpreted as the effect of the alert, the event, or both, but the relative contribution of each is unknown. Future work should explore strategies for separating expected severity from actual severity, such as incorporating crowd-sourced flood reports, satellite imagery, or damage assessments.

Another related limitation is that the analysis is conducted at the daily level, using the number of days per month during which a county experienced a specific flood-alert category. This approach assumes that each day contributes equally to the observed employment effects. However, many floods span multiple consecutive days, and it is possible that employment disruptions only emerge once flood duration reaches a certain threshold. To address this concern, I include additional models that categorize events by duration (1–3, 4–6, and 7+ days), which allows for the possibility of non-linear effects. While those models show that employment responses are concentrated during short-duration flash floods, the broader point remains that monthly employment totals may not fully capture more gradual or delayed labor market adjustments to prolonged flood exposure.

Furthermore, this study uses employment counts, reported by the Bureau of Labor Statistics' QCEW, as the primary indicator of local economic activity. While employment is a widely used and reliable economic metric, it does not capture all dimensions of economic disruption. Businesses may reduce hours worked, delay hiring, or shift to informal arrangements in response to flood alerts and events, none of which would be observed in monthly employment counts. Moreover, small-scale disruptions such as missed workdays or temporary closures could go unrecorded in the data if they did not lead to changes in formal employment status. A more complete picture of economic outcomes would include additional indicators, such as wages, hours worked, business revenue, or unemployment insurance claims. These were not available at the same spatial and temporal resolution as employment counts, which limited the analysis to employment numbers alone. For example, while the QCEW also reports wage data, these are available only at the quarterly level.

Apart from that, the data used for alerts and events does not allow for insight into how residents or businesses responded to each type of alert. For instance, the Iowa Environmental Mesonet does not include information on whether alerts were received, understood, or acted upon. Nor does it include measures of trust in the alert system or public compliance. As a result, the mechanisms through which alerts influence employment, such as absenteeism, closures, or precautionary actions, are inferred indirectly through employment changes rather than measured directly. Future research that combines administrative data with survey-based measures of behavior and perception would be better positioned to unpack these mechanisms.

Finally, the matching of alerts and events was based on administrative boundaries at the county level, and some mismatch was inevitable. Flood alerts are often issued based on storm-based polygons that do not align perfectly with county borders, and flood events may begin in one part of a county and have uneven impacts across space. Although I took several steps to reduce inconsistencies, such as adjusting time zones and resolving geometry errors, some spatial or temporal misalignment may remain.

Overall, while this study uses the best available data, these limitations should be kept in mind when interpreting the findings. Additional data on flood severity, response behaviors, and broader economic indicators would allow for a more complete understanding of how inaccurate flood alerts influence local economies.

Future research could build on this study by incorporating flood intensity metrics, survey data on alert compliance, and alternative measures of economic activity such as business revenue or hours worked. Additionally, studies that examine the longer-run consequences of false alarms, such as firm relocation, capital investment decisions, or changes in land use, would help clarify how sustained exposure to inaccurate alerts influences regional economic trajectories.

6. CONCLUSION

The purpose of this thesis is to examine whether inaccuracies in flood alerts, specifically false alarms and missed events, have measurable effects on local employment outcomes in the United States. Using county-level data from 2007 to 2023, the analysis relies on a two-way fixed effects approach to estimate how different alert-event combinations affect employment across all sectors, with a particular focus on construction and leisure and hospitality. The results show that not all alert-event combinations lead to significant changes in employment, but there are clear patterns in certain conditions. Most notably, when both a warning and a notification are issued during a flash flood, employment tends to decline. These effects are strongest in the leisure and hospitality sector, followed by construction. In contrast, false alarms and missed events on their own do not show consistent or statistically significant effects, especially when flood severity is not accounted for.

The results offer partial support for the hypotheses proposed in the conceptual framework. The first hypothesis stated that false alarms would disrupt short-term employment through precautionary behaviors such as absenteeism or reduced business operations. This hypothesis was not supported in the main models. Across specifications, whether general, disaggregated by flood or alert type, or evaluated separately by sector, false alarms did not produce statistically significant declines in employment. However, when disaggregated by rural–urban classification, the analysis reveals that false alarms are not neutral in all contexts. In rural counties, false alarms, particularly those involving only a warning, are associated with increases in employment. This may reflect elevated engagement in public works, emergency response, or repair activities in rural areas.

The second hypothesis proposed that missed events would reduce employment over the medium term by introducing unanticipated disruption and extending recovery periods. The results do not show strong support for this hypothesis when missed events are analyzed on their own. However, the strongest and most consistent negative employment effects appear when flood events are accompanied by both a warning and a notification, especially under flash flood conditions. These actualized alerts were associated with declines in total employment and in both the construction and leisure and hospitality sectors. The lagged models also reinforce this interpretation. For example, actualized alerts during flash floods showed a negative impact in the first lag, followed by delayed rebounds in later months for the leisure and hospitality sector. These results suggest that it is not the absence of alerts alone, but the compounded presence of both alerts and flooding, that creates the conditions for labor market disruptions.

These findings provide useful guidance for policymakers deciding when and how to issue flood alerts. While the results do not suggest that alerts alone cause employment changes, they do indicate that alerts issued during actual flood events, particularly flash floods, are associated with measurable declines in employment. For agencies like the National Weather Service, which must weigh the risks of false alarms against the costs of missed events, these results emphasize the value of timely and context-sensitive alerts that provide sufficient lead time for precautionary behavior.

In terms of issuing alerts, the evidence suggests that alerts should not be withheld during flood events for fear of causing economic disruption. Rather, the presence of both a warning and a notification during a flood appears to signal a level of severity that is already economically disruptive. In this context, withholding alerts would not prevent disruption but may instead reduce public readiness. Therefore, the findings support continued issuance of alerts when flooding is likely, especially when there is potential for severe impacts. At the same time, the weak or null effects observed for false alarms, particularly in the short run, suggest that the costs of over-warning may be limited in the employment domain, though caution is warranted if such patterns erode public trust over time or are associated with other economic disruptions.

These results also inform decisions about whether to invest in improving the accuracy of alerts. Investments that enhance the spatial precision, lead time, or coordination of alerts may help improve their alignment with underlying flood severity, though further research is needed to establish the extent to which such improvements would translate into measurable economic benefits.

I also evaluate whether the observed employment effects may be confounded by the presence of other natural hazards, where I control for the co-occurrence of other flood-related and non-flood-related hazards in the same county and day, conditional on both a warning and notification being issued. The results remain robust to these controls. Flash flood alert-event combinations, particularly those involving both alerts, continue to show significant employment effects in all sectors. This confirms that the main findings are not driven by overlapping hazards. Nonetheless, the presence of other hazards does contribute modestly to employment changes. For example, construction employment increases slightly during non-flood-related hazard events, likely due to post-event repairs. Future work could extend this analysis by disaggregating specific hazard combinations (e.g., flash floods and hail, or floods and tornadoes) to better understand whether certain multi-hazard pairings produce compounding effects on local labor markets.

When evaluating robustness across alternative alert groupings, I find that the results hold. General floods with both alerts and general floods with warnings but no notifications remain consistently associated with employment declines, regardless of how alerts are grouped. The only exception is the positive effect of flash floods with a notification but no warning, which becomes statistically insignificant in some specifications. This suggests that estimates for that category may be sensitive to how notifications are defined.

The urban and rural heterogeneity analysis reveals several differences. In urban counties, actualized alerts during flash floods are associated with employment losses, particularly in the leisure and hospitality sector. In contrast, rural counties show the opposite pattern. Employment increases in response to the same alert-event combination. Rural areas also experience positive effects in response to false alarms and warning-only events. These results could reflect differences in labor market structures, flood response mechanisms, or the role of public works and infrastructure repair in smaller communities.

Lagged models show that alert-event combinations can have delayed effects on employment. For example, the actualized alert category for flash floods is associated with an immediate drop in employment, followed by a positive rebound in the leisure and hospitality sector after four to six months. Similarly, general floods accompanied by a notification but no warning lead to a delayed increase in employment in the following months. These patterns likely reflect short-term disruption followed by recovery activity, including rehiring, repair work, or reopening of businesses.

The analysis on flood duration vs. flood days shows that short-duration flash flood events (1–3 days) with actualized alerts are associated with significant declines in employment, especially in leisure and hospitality and construction. In contrast, general floods yield weaker effects overall. These findings indicate that the intensity and immediacy of short flash flood events may prompt stronger labor market responses than longer, slower-moving general floods.

The neighboring county sensitivity analysis shows that the results are not driven by flood exposure in adjacent counties. When redefining false alarms to exclude cases where neighboring counties experienced flooding, the main results do not change. This suggests that local conditions, rather than regional proximity, shape employment responses to alerts.

Improving the accuracy and communication of flood alerts remains important not just for saving lives, but also for minimizing economic disruptions. As the frequency and variability of extreme weather increase, understanding the labor market consequences of warning system failures will become even more relevant for policymakers, employers, and communities. This thesis offers a first step in that direction by showing that certain types of alert-event mismatches do affect employment, and that these effects depend on the type of alert, the type of flood, and the characteristics of the local economy.

REFERENCES

Armal, S., Porter, J. R., Lingle, B., Chu, Z., Marston, M. L., & Wing, O. E. J. (2020). Assessing Property Level Economic Impacts of Climate in the US, New Insights and Evidence from a Comprehensive Flood Risk Assessment Tool. *Climate*, *8*(10), Article 10. https://doi.org/10.3390/cli8100116

Belasen, A. R., & Polachek, S. W. (2008). How Hurricanes Affect Wages and Employment in Local Labor Markets. *American Economic Review*, *98*(2), 49–53. https://doi.org/10.1257/aer.98.2.49

Coulombe, R. G., & Rao, A. (2025). Fires and local labor markets. *Journal of Environmental Economics and Management*, *130*, 103109. https://doi.org/10.1016/j.jeem.2024.103109

Jia, R., Ma, X., & Xie, V. W. (2022). *Expecting Floods: Firm Entry, Employment, and Aggregate Implications* (Working Paper 30250). National Bureau of Economic Research. https://doi.org/10.3386/w30250

Kotani, H., Ogawa, W., & Matsushima, K. (2023). *Does the Performance of Flood Early Warning System Affect Casualties and Economic Losses? Empirical Analysis Using Open Data from the 2018 Japan Floods*. *2023*, NH13B-0683. https://ui.adsabs.harvard.edu/abs/2023AGUFMNH13B0683O

Kuller, M., Schoenholzer, K., & Lienert, J. (2021). Creating effective flood warnings: A framework from a critical review. *Journal of Hydrology*, *602*, 126708. https://doi.org/10.1016/j.jhydrol.2021.126708

LeClerc, J., & Joslyn, S. (2015). The Cry Wolf Effect and Weather-Related Decision Making. *Risk Analysis*, *35*(3), 385–395. https://doi.org/10.1111/risa.12336

Li, D., Fang, Z. N., & Bedient, P. B. (2021). Flood early warning systems under changing climate and extreme events. In *Climate Change and Extreme Events* (pp. 83–103). Elsevier. https://doi.org/10.1016/B978-0-12-822700-8.00002-0

Lim, J. R., Liu, B. F., & Egnoto, M. (2019). *Cry Wolf Effect? Evaluating the Impact of False Alarms on Public Responses to Tornado Alerts in the Southeastern United States*. https://doi.org/10.1175/WCAS-D-18-0080.1

Mao, T., Garcia, K. R., & Chen, J. (2024). Assessing Driver's Trust, Compliance, and Reliance in an Automated Flood Warning System: Effects of Error Types and System Reliability. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *68*(1), 859–860. https://doi.org/10.1177/10711813241276493

Mendoza, C. A., Breglia, G., & Jara, B. (2020). Regional labor markets after an earthquake. Short-term emergency reactions in a cross-country perspective. Cases from Chile, Ecuador, Italy. *Review of Regional Research*, *40*(2), 189–221. https://doi.org/10.1007/s10037-020-00144-5

Muriqi, D., Bayham, J., Goemans, C., Manning, D. T., & Suter, J. F. (2025). Inland flooding in the United States: A review of research related to risk management, economic behavior, and data resources. *Environmental Research Letters*, *20*(6), 063003. https://doi.org/10.1088/1748-9326/add35e

National Weather Service. (2021). *Valid Time Event Code (VTEC): National Weather Service Instruction 10-1703*. Department of Commerce, National Oceanic and Atmospheric Administration. https://www.weather.gov/directives

Pappenberger, F., Cloke, H. L., Parker, D. J., Wetterhall, F., Richardson, D. S., & Thielen, J. (2015). The monetary benefit of early flood warnings in Europe. *Environmental Science & Policy*, *51*, 278–291. https://doi.org/10.1016/j.envsci.2015.04.016

Perera, D., Agnihotri, J., Seidou, O., & Djalante, R. (2020). Identifying societal challenges in flood early warning systems. *International Journal of Disaster Risk Reduction*, *51*, 101794. https://doi.org/10.1016/j.ijdrr.2020.101794

Petrucci, O. (2022). Review article: Factors leading to the occurrence of flood fatalities: a systematic review of research papers published between 2010 and 2020. *Natural Hazards and Earth System Sciences*, *22*(1), 71–83. https://doi.org/10.5194/nhess-22-71-2022

Priest, S. J., Parker ,Dennis J., & and Tapsell, S. M. (2011). Modelling the potential damage-reducing benefits of flood warnings using European cases. *Environmental Hazards*, *10*(2), 101–120. https://doi.org/10.1080/17477891.2011.579335

Ripberger, J. T., Silva, C. L., Jenkins-Smith, H. C., Carlson, D. E., James, M., & Herron, K. G. (2015). False Alarms and Missed Events: The Impact and Origins of Perceived Inaccuracy in Tornado Warning Systems. *Risk Analysis*, *35*(1), 44–56. https://doi.org/10.1111/risa.12262

Sadiq, A.-A., Dougherty, R. B., Tyler, J., & Entress, R. (2023). Public alert and warning system literature review in the USA: Identifying research gaps and lessons for practice. *Natural Hazards*, *117*(2), 1711–1744. https://doi.org/10.1007/s11069-023-05926-x

Sawada, Y., Kanai, R., & Kotani, H. (2022). Impact of cry wolf effects on social preparedness and the efficiency of flood early warning systems. *Hydrology and Earth System Sciences*, *26*(16), 4265–4278. https://doi.org/10.5194/hess-26-4265-2022

Simmons, K. M., & Sutter, D. (2009). False Alarms, Tornado Warnings, and Tornado Casualties. *Weather, Climate, and Society*, *1*(1), 38–53. https://doi.org/10.1175/2009WCAS1005.1

Trainor, J. E., Nagele, D., Philips, B., & Scott, B. (2015). *Tornadoes, Social Science, and the False Alarm Effect*. https://doi.org/10.1175/WCAS-D-14-00052.1

United States Code. (2024). *15 USC Ch. 9: NATIONAL WEATHER SERVICE*. https://uscode.house.gov/view.xhtml?path=/prelim@title15/chapter9&edition=prelim

US JEC, U. S. J. E. (2024). *Flooding Costs the U.S. Between $179.8 and $496.0 Billion Each Year—Flooding Costs the U.S. Between $179.8 and $496.0 Billion Each Year—United States Joint Economic Committee*. https://www.jec.senate.gov/public/index.cfm/democrats/2024/6/flooding-costs-the-u-s-between-179-8-and-496-0-billion-each-year

Van Houtven, G. (2024). Economic Value of Flood Forecasts and Early Warning Systems: A Review. *Natural Hazards Review*, *25*(4), 03124002. https://doi.org/10.1061/NHREFO.NHENG-2094

weather.gov. (2025b). *Severe Weather Awareness Week—Flash Flood Safety*. NOAA's National Weather Service. https://www.weather.gov/shv/awarenessweek_severe_flashflood

weather.gov. (2025a). *Watch Warning Advisory Explained*. NOAA's National Weather Service. https://www.weather.gov/sjt/WatchWarningAdvisoryExplained

APPENDIX I: IMPACTS OF FLOOD-ALERT CATEGORIES FOR ALL SECTORS REPORTED IN THE QCEW DATA

Table A1.1: Regression results for two-way fixed effect models for goods-producing, natural resources and mining, manufacturing, and service-providing sectors.

Variables			Estimated Change in Log Employment			
Flood	Warn	Notif	Goods-Producing	Natural Resources and Mining	Manufacturing	Service-Providing
No Flood	No	Yes	-4.30e-05	-1.02e-04	-4.48e-05	-1.22e-04
			(1.75e-04)	(3.50e-04)	(2.31e-04)	(1.09e-04)
No Flood	Yes	No	-5.67e-05	-4.49e-04**	-4.24e-05	-8.46e-05
			(1.46e-04)	(2.28e-04)	(1.81e-04)	(7.50e-05)
No Flood	Yes	Yes	-7.81e-05	-6.21e-04*	-4.56e-05	3.11e-05
			(2.13e-04)	(3.71e-04)	(2.62e-04)	(1.17e-04)
Flash Flood	No	No	9.39e-03	9.11e-03	1.67e-02	-1.88e-03
			(1.03e-02)	(1.32e-02)	(1.18e-02)	(2.99e-03)
Flash Flood	No	Yes	4.09e-03	9.45e-03	3.68e-03	3.14e-03
			(5.61e-03)	(8.93e-03)	(5.99e-03)	(2.32e-03)
Flash Flood	Yes	No	4.22e-04	-4.05e-03	-3.44e-04	-1.90e-03**
			(1.73e-03)	(2.99e-03)	(2.81e-03)	(9.55e-04)
Flash Flood	Yes	Yes	-8.78e-04	-3.56e-04	-7.35e-04	-1.09e-03*
			(1.16e-03)	(2.06e-03)	(1.10e-03)	(5.91e-04)
Flood	No	No	9.32e-04	9.27e-05	-9.21e-04	4.50e-05
			(9.11e-04)	(1.40e-03)	(8.15e-04)	(4.52e-04)
Flood	No	Yes	2.43e-03	2.55e-03	1.33e-03	8.45e-04
			(1.78e-03)	(2.15e-03)	(1.59e-03)	(7.49e-04)
Flood	Yes	No	-4.70e-05	-1.37e-04	1.12e-04	6.26e-05
			(3.16e-04)	(6.27e-04)	(4.38e-04)	(1.55e-04)
Flood	Yes	Yes	-8.61e-04*	-1.08e-03	-7.32e-04	-1.11e-04
			(4.73e-04)	(8.30e-04)	(6.18e-04)	(2.57e-04)
Num.Obs.			627777	574506	559905	629649
R^2 Adj.			0.988	0.945	0.985	0.997
AIC			-350565.9	267948.5	-112526.1	-1081767.5
BIC			-201756.8	413196.3	32580.7	-932896.6
RMSE			0.18	0.30	0.21	0.10
Std.Errors			by: FIPS	by: FIPS	by: FIPS	by: FIPS
FE: FIPS			X	X	X	X
FE: year_month_state			X	X	X	X

Table A1.2: Regression results for two-way fixed effect models for trade, transportation and utilities, information, and financial activities sectors.

Variables			Estimated Change in Log Employment		
Flood	**Warn**	**Notif**	**Trade, Transportation, and Utilities**	**Information**	**Financial Activities**
No Flood	No	Yes	-7.71E-05	-2.95e-04	2.30e-04
			(1.25e-04)	(3.10e-04)	(1.75e-04)
No Flood	Yes	No	-1.18e-04	-2.30e-04	-2.97e-05
			(8.99e-05)	(2.37e-04)	(1.16e-04)
No Flood	Yes	Yes	4.61e-05	-4.94e-05	-5.37e-05
			(1.31e-04)	(3.61e-04)	(1.59e-04)
Flash Flood	No	No	5.24e-04	-2.04e-04	4.89e-03
			(2.63e-03)	(4.79e-03)	(6.53e-03)
Flash Flood	No	Yes	2.17e-03	7.39e-03	-1.75e-03
			(2.84e-03)	(6.43e-03)	(3.63e-03)
Flash Flood	Yes	No	-1.68e-03	-1.66e-03	-1.47e-03
			(1.03e-03)	(2.75e-03)	(1.35e-03)
Flash Flood	Yes	Yes	-1.63e-03***	-1.68e-03	-8.70e-04
			(6.13e-04)	(1.46e-03)	(7.92e-04)
Flood	No	No	-9.36e-05	1.15e-04	-1.51e-04
			(7.25e-04)	(1.29e-03)	(6.13e-04)
Flood	No	Yes	1.58e-03	6.54e-04	-8.03e-04
			(1.26e-03)	(2.45e-03)	(1.34e-03)
Flood	Yes	No	-8.82e-05	4.58e-04	6.50e-04**
			(1.98e-04)	(5.33e-04)	(2.83e-04)
Flood	Yes	Yes	-1.47e-04	1.99e-05	-7.74e-04**
			(3.05e-04)	(7.30e-04)	(3.82e-04)
Num.Obs.			631953	488166	604191
R^2 Adj.			0.995	0.977	0.992
AIC			-869433.2	107623.3	-554002.5
BIC			-720525.9	249860.5	-406012.2
RMSE			0.12	0.26	0.15
Std.Errors			by: FIPS	by: FIPS	by: FIPS
FE: FIPS			X	X	X
FE: year_month_state			X	X	X

Table A1.3: Regression results for two-way fixed effect models for professional and business services, education and health services, and other services sectors.

Variables			Estimated Change in Log Employment		
			Professional and Business Services	**Education and Health Services**	**Other Services**
Flood	**Warn**	**Notif**			
No Flood	No	Yes	-4.77e-04*	1.85e-04	-2.20e-05
			(2.58e-04)	(1.73e-04)	(2.15e-04)
No Flood	Yes	No	-2.70e-05	4.84e-05	-1.23e-04
			(1.91e-04)	(1.25e-04)	(1.46e-04)
No Flood	Yes	Yes	1.13e-04	2.78e-04	1.02e-04
			(2.96e-04)	(1.89e-04)	(2.63e-04)
Flash Flood	No	No	-9.05e-03*	-8.91e-03***	-7.38e-04
			(4.68e-03)	(3.28e-03)	(3.55e-03)
Flash Flood	No	Yes	8.77e-04	7.25e-04	1.19e-02**
			(5.64e-03)	(3.23e-03)	(5.17e-03)
Flash Flood	Yes	No	-3.47e-03	-4.14e-03***	2.20e-03
			(2.66e-03)	(1.46e-03)	(2.46e-03)
Flash Flood	Yes	Yes	-6.25e-04	2.11e-04	-4.73e-04
			(1.24e-03)	(7.30e-04)	(1.02e-03)
Flood	No	No	9.79e-04	3.68e-04	5.84e-04
			(1.59e-03)	(6.24e-04)	(8.54e-04)
Flood	No	Yes	2.36e-03	-2.71e-05	5.21e-03***
			(2.77e-03)	(1.13e-03)	(1.50e-03)
Flood	Yes	No	5.68e-04	5.42e-04**	3.33e-04
			(5.45e-04)	(2.41e-04)	(4.18e-04)
Flood	Yes	Yes	-1.44e-04	-2.38e-04	1.08e-03**
			(8.10e-04)	(4.44e-04)	(5.42e-04)
Num.Obs.			596832	609195	568143
R^2 Adj.			0.984	0.992	0.986
AIC			111417.0	-495989.9	-189122.2
BIC			259371.2	-347914.4	-41948.1
RMSE			0.26	0.16	0.20
Std.Errors			by: FIPS	by: FIPS	by: FIPS
FE: FIPS			X	X	X
FE: year_month_state			X	X	X

APPENDIX II: EVENT EFFECTS WITH AND WITHOUT NEIGHBORING ALERTS FOR ALL EMPLOYMENT, CONSTRUCTION, AND LEISURE & HOSPITALITY

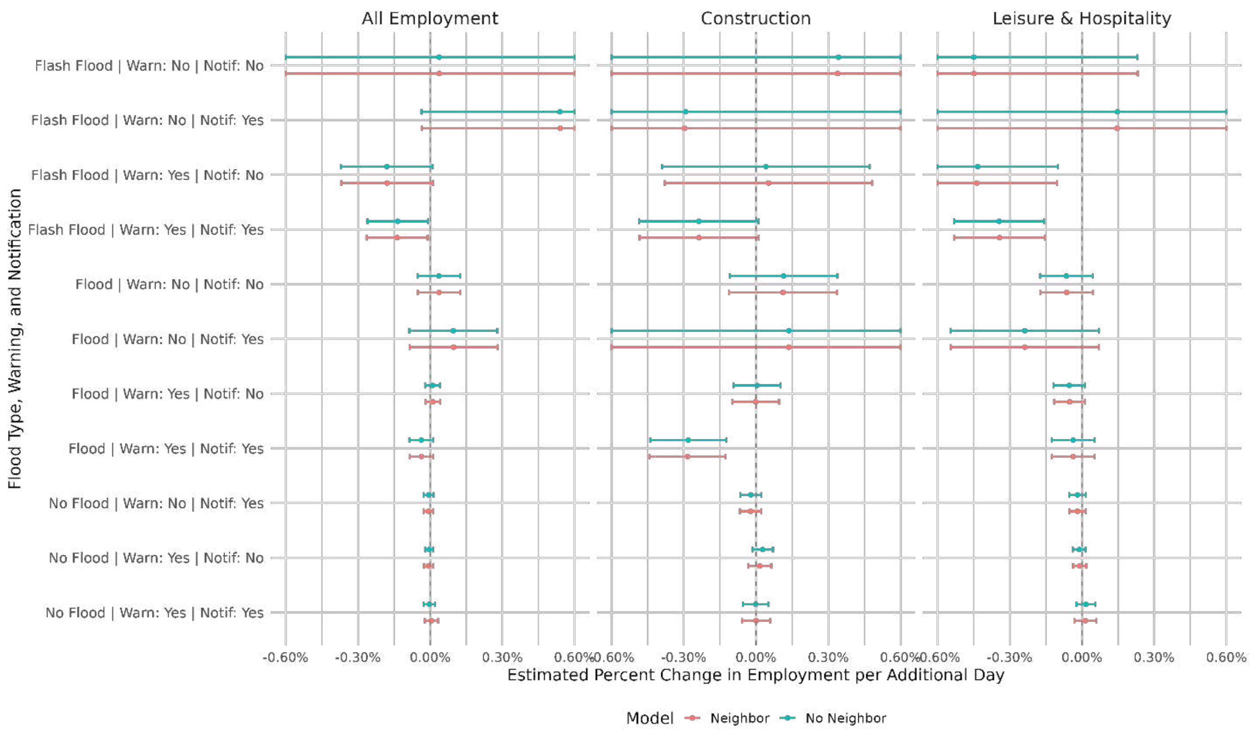

Figure A2.1: Event effects with and without neighboring alerts for all employment, construction, and leisure & hospitality. Confidence interval: 95%.