Labor Market Impacts of Flooding in the United States*

Judhajit Chakraborty[1]†, Jude Bayham[1], Christopher Goemans[1], Dale Manning[2], Diellza Muriqi[1], Jordan Suter[1]

[1]Colorado State University, [2]University of Tennessee

Abstract

This study investigates the labor market consequences of floods – historically among the most lethal and expensive natural disasters in the United States. Using quarterly, county-level employment and wage data spanning 1996-2023, our empirical approach distinguishes between flash floods and floods with gradual, slower onset patterns (non-flash floods). The analysis explores how the impacts of flood events vary across temporal windows (sub-annual versus annual), location (inland versus coastal counties), sectors, and existing labor market conditions. Our results show that an additional day of flash floods in a quarter reduces county-level employment and wages by 0.13% and 0.15% respectively. We find that total wages decreased by $6.2 billion per year (in 2023 USD) between 1996 and 2023 as a result of flash and non-flash floods. Heterogeneous effects reveal that economically vulnerable counties experience larger negative impacts from both flood types and that both coastal and inland counties face negative economic disruptions. Our findings underscore that sub-annual impacts are crucial for understanding flood impacts and designing policies to build resilience against shocks.

Keywords: Flash Floods, Floods, Natural Hazards, Labor Markets, Employment, Wages
JEL Codes: E24, J21, J31, J40, Q54

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†Corresponding author at: Colorado State University, Fort Collins, Colorado.
Email address: judhajit.chakraborty@colostate.edu

1 Introduction

Flood events are one of the deadliest and most costly forms of natural disasters in the U.S., claiming approximately 100 lives and causing billions of dollars in damages annually (Davenport et al., 2021; NOAA National Severe Storms Laboratory, 2024). Studies project increases in flood magnitude and frequency and a higher population exposed to flooding (AECOM, 2013; Jia et al., 2025; Peralta and Scott, 2024). Therefore, it is increasingly important to quantify the full economic consequences of flood hazards, including labor market impacts[1]. The federal government allocates substantial resources to flood-affected regions through emergency assistance, recovery and adaptation programs. Allocating these public funds efficiently requires understanding how floods impact regional economies. Yet existing research has focused on annual impacts, large federally declared emergencies, and urban or coastal settings.

Recent literature using annual data finds that flood events reduce annual output with no contemporaneous effect on annual employment, a pattern interpreted as a productivity shock (Jia et al., 2025). However, this interpretation relies on annual aggregates that may obscure sub-annual labor market disruptions that are either offset through within-year reallocation or concealed by noise in the annual data. This is important because evidence from other natural hazards documents sub-annual labor market impacts. For example, Coulombe and Rao (2025) find that wildfire exposure depresses month-to-month employment growth, while Groen et al. (2020) document short-term earnings losses from Hurricanes Katrina and Rita. Moreover, recent labor market research documents substantial month-to-month income instability driven largely by firm-led demand fluctuations. Such instability is masked in annual data widely used in the literature (Ganong et al., 2025).

In this paper, we study the *sub-annual* labor market impact of flooding for the contiguous U.S.[2]. We leverage daily flood exposure data, linked with quarterly county-level labor market data spanning nearly three decades. We test for differences in impacts by flood type (flash floods versus slower-onset or “non-flash" floods[3]), sector (goods producing versus service producing), location (inland versus coastal counties), and local economic conditions (high versus low unemployment).

We construct a county–quarter panel by combining employment and wage data from the

[1]A growing literature documents the economic consequences of flooding and flood risk. Recent studies examine the effects of flood events on firm entry-exit and employment (Jia et al., 2025), establishment-level employment, wages, and adaptation following Hurricane Sandy–induced flooding in New York City (Indaco et al., 2021), and flood-related mortality (Chu et al., 2025). Others analyze impacts on agricultural and rural outcomes in both developed and developing countries (Kim et al., 2023; Kamble et al., 2024; Parida and Chowdhury, 2021), as well as broader effects on economic activity, productivity, income, and regional growth (Kocornik-Mina et al., 2020; Erda, 2024; Roth Tran and Wilson, 2025; Desmet et al., 2015). Another set of studies examines the role of flood risk in asset markets, particularly housing and property prices (Hennighausen and Suter, 2020; Beltrán et al., 2018).

[2]This includes the 48 contiguous states in the U.S., as well as the District of Columbia (DC).

[3]The SED classifies flash floods as rapid water rises, typically occurring "within minutes to a few hours", representing more sudden, violent upsurges. On the other hand, documented non-flash flood events are classified as those cases where the rise of water is slower and more gradual, typically "over hours to days".

Quarterly Census of Employment and Wages (QCEW), with corresponding flood exposure information from the National Oceanic and Atmospheric Administration's (NOAA's) Storm Events Database (SED). Our data span 1996–2023, and include information on over 160,000 flash and non-flash flood events. We use event dates to measure daily county-level flood exposure, then aggregate to quarterly exposure levels to match our labor market data. Unlike earlier research studying large federally-declared emergencies (Kocornik-Mina et al., 2020; Jia et al., 2025), the SED's comprehensive coverage allows us to capture a wider breadth of flooding events – from spatially and temporally limited incidents to large federally-declared flood disasters. We also include events across the contiguous U.S., unlike previous research which focuses on flood impacts in urban and coastal areas (Kocornik-Mina et al., 2020; Hallegatte et al., 2013) (see Figure A1).

Our empirical strategy uses a specification with county-level fixed effects to account for the unobserved time-invariant confounders that may affect exposure to flood events and economic outcomes simultaneously. We also include spatially varying time controls, such as state-quarter-year fixed effects, to account for state-specific seasonality and macroeconomic shocks that could coincide with flood exposure. Identification relies on *within-county* variation, after accounting for common state-quarter-year factors that affect all counties within a state.

Understanding sub-annual effects of flooding is critical for both policy design and assessing impacts at the household level. Policy responses to productivity shocks, such as capital investments or business recovery loans at the firm level differ fundamentally from those addressing labor market disruptions, which may require household-level relief and income support to prevent deeper economic distress. This is especially true for vulnerable households and communities who face disproportionate flood impacts (Masozera et al., 2007). These households may also lack capacity to absorb transitory income losses.

Conceptually, floods can affect sub-annual employment through both labor demand and supply channels. On the demand side, physical capital destruction can initially reduce labor demand, though this may reverse during reconstruction. Floods can also affect labor demand due to lower consumer demand, i.e., through limited consumer mobility and foot traffic. On the labor supply side, flood exposure can prevent workers from reaching workplaces, while severe flooding may increase mortality or trigger out-migration. Although, out-migration may be a less salient channel given our sub-annual analysis window.

We find that an additional day of flash flooding reduces county-level private employment by 0.13% and total wages by 0.15%, conditional on county and state-quarter-year fixed effects and controlling for contemporaneous average precipitation and average temperature. The effect for slow-onset floods is negative but statistically insignificant, suggesting that sudden, violent flash flooding has more severe immediate impacts. Counterfactual analysis indicates total wage losses due to flash and non-flash floods averaged approximately $6.2 billion annually (in real 2023 USD) over 1996-2023. Importantly, when we aggregate the quarterly data to the annual level, these effects are not statistically distinguishable from zero, which is consistent with prior literature finding no annual employment effects (Jia et al., 2025). These results suggest that sub-annual labor market disruptions due to flash flooding exist, but are masked by intra-annual variation in labor market data.

We find heterogeneous effects across several dimensions. First, we estimate employment and wage effects by sector, including retail trade, leisure and hospitality, and construction sectors. Negative impacts across multiple sectors suggests that labor market disruptions span both the goods-producing and service-providing sectors.

Next, we explore heterogeneity by labor market slack (i.e., by high or low-unemployment). Since unemployment rates could interact with contemporaneous flood exposure, we use past unemployment rates to classify counties as high-or- low-slack counties. We find that both flash and non-flash floods have a larger negative effect on employment and total wages in high-slack counties. These differences are statistically significant for both flood types, indicating that economically vulnerable areas face disproportionate labor market consequences, with even slower-onset floods causing meaningful disruptions in local economies with weak labor market conditions.

Our results are robust to controlling for all other contemporaneous natural hazards occurring within a county in a given quarter-year, allowing for spatial clustering, conducting the analysis at the commuting-zone level, controlling for extreme rainfall anomalies, documenting that the baseline average effects are not driven solely by quarters with high reported damages or by quarters that coincide with FEMA-declared flood-emergency periods, and placebo analyses.

This paper advances the literature in several ways. First, we use sub-annual data to document labor-market impacts of flooding that previous annual analyses could not identify. Existing research primarily uses data at annual frequencies (Boustan et al., 2020; Jia et al., 2025; Roth Tran and Wilson, 2025; Erda, 2024), but sub-annual frequencies may better capture some labor-market outcomes. We are the first study to examine flood-related labor market impacts at a sub-annual level. Our findings indicate that meaningful sub-annual labor market shocks exist, suggesting a combined labor market and productivity shock rather than only a productivity shock (Jia et al., 2025). Our sub-annual analysis also addresses a gap identified in recent reviews of the inland flooding literature (Muriqi et al., 2025), which calls for temporally disaggregated research on flood impacts.

Second, we explore the impact of a wider range of flood events than is commonly considered in the natural hazard- and flood-related literature. This literature is skewed towards studying economic impacts for large and federally declared flood disasters in the U.S. (Boustan et al., 2020; Jia et al., 2025; Roth Tran and Wilson, 2025). This is despite the fact that the overwhelming majority of flood events are not recorded as federally declared events, as they are limited in spatial scope and duration. For example, in our sample, 94% of all flash flood days and 80% of all non-flash flood days occur outside of FEMA (Federal Emergency Management Agency)-declared flood emergency periods. Such non-declared events could be disruptive for local economies. Incorporating flood events across all spatial-temporal intensities avoids treatment misclassification and selection bias, capturing more typical flood experiences rather than analyzing an atypical subset of rare, declared disasters that may not represent more frequent local impacts. We show that flash flood days outside of FEMA-declared flood emergency periods also have economically meaningful labor market impacts that are similar in magnitude to our baseline average effects. We also expand the flood literature by distinguishing between the impacts of flash floods and slower-onset, non-flash floods, as well as examining heterogeneity in the impacts across specific sectors.

Finally, this paper reveals an important avenue through which floods can affect welfare in impacted communities. A large majority of the U.S. workforce depends on hourly work that can fluctuate due to firm-led demand variability (Ganong et al., 2025). We show that natural hazards such as flash and non-flash floods add to this volatility. To contextualize our findings, Davenport et al. (2021) find an annual average of $6.63 billion in property, crop, and other damages (in real 2020 USD over 1988-2017) caused by flooding. Additionally, Hallegatte et al. (2013) estimate asset-based flood damages at $6 billion USD annually in 2005 for 136 global coastal cities, projected to reach $52 billion by 2050. The significant labor market impacts we find ($>$ 6 billion per year in wages losses) could have important welfare implications as labor income and economic activity are disrupted (Hsiang et al., 2017).

2 Data

The datasets used in this analysis combine information on flood events at the daily level with quarterly employment and wage data and weather data over the period 1996-2023. Our analysis takes place at the county level. This section provides an overview of the different data sources and the process for creating each variable.

2.1 Storm Events Database

The Storm Events Database (SED) is published by NOAA - National Weather Service (NWS) and is one of the primary repositories for details on extreme weather events in the United States. Initially, the SED documented details related to tornadoes, thunderstorms, wind, and hail events, but starting in 1996 the SED expanded significantly to include a comprehensive record of all types of extreme weather-related hazards that are capable of causing fatalities, injuries, property damage, and disruptions to commerce (National Weather Service, 2016).

The SED incorporates details related to a wide range of intense meteorological events, including but not limited to, thunderstorms, flash floods, floods, winter storms, hurricanes, droughts, wildfire events, and details of many other weather-related hazards. Each record contains detailed information about event start and end time and dates, geographic coordinates, detailed event and episode narratives, fatalities and property damage estimates in dollars.

The SED is primarily administered and verified by the NWS. However, the comprehensive nature of the SED data also relies on a diverse network of information sources beyond the NWS, including county, state and federal emergency management officials, local law enforcement officials, trained spotters, NWS damage surveys, newspaper clipping services, the insurance industry, and the general public (National Weather Service, 2016). This comprehensive approach therefore helps capture the full scope of extreme weather-related hazards that impact different geographies and communities within the U.S.

One of the advantages of using the SED for studying the economic impact of flooding in the U.S. is that the SED distinguishes between the nature of flooding based on onset patterns. The database differentiates between inland flash floods, which are characterized by sudden and rapid onsets and have a shorter duration (few hours)[4], and inland non-flash floods, which have a slower or more gradual onset, lasting for longer periods of time (can last for multiple days)[5]. We use the event start and end dates to count the number of days a county experienced flash and non-flash floods[6].

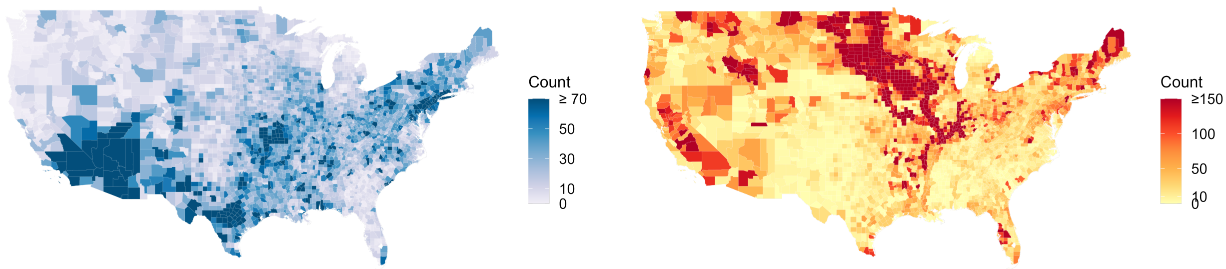
The other advantage of using the SED for identifying flash flood and flood exposure is that the data comprehensively documents a full spectrum of events, regardless of magnitude, spatial extent, or duration. This is unlike other databases such as the Dartmouth Flood Observatory (Brakenridge, 2025) or the FEMA Declared Federal Disasters Database (Federal Emergency Management Agency, 2025), which focus primarily on large-scale or federally declared events. Figure 1 shows that flash floods are more common in the southwest and northeast while slow-onset floods are more common along major rivers (e.g., the Mississippi and Missouri rivers). Almost all counties within the contiguous U.S. have experienced some flood days within the period of 1996-2023. There are numerous inland counties that are exposed to repeated flooding, particularly in the Mississippi Valley, Northeast, and Southwest regions.

[4]The SED classifies inland flash flooding as a "life-threatening, rapid rise of water into a normally dry area beginning within minutes to multiple hours of the causative event (e.g. intense rainfall, dam failure, ice jam)"(National Weather Service, 2016).

[5]In the SED, inland non-flash floods are documented as "Flood" under event type. The SED classifies inland non-flash floods as any "high flow, overflow, or inundation by water which cause damage. In general, this would mean the inundation of a normally dry area caused by an increased water level in an established watercourse, or ponding of water, that poses a threat to life or property." (National Weather Service, 2016). Additionally, low impact flooding such as "minor flooding in urban areas", "minor ponding of water during or after a heavy rain event or flood", "high stream levels due to steady or slowly rising/receding creeks/streams that do not pose a threat to life or property." (National Weather Service, 2016) – all are considered as non-flash inland flood events. An ongoing flood event may intensify into short-term flash flooding with intense rainfall resulting in sudden, rapid increase in flood waters. Conversely, flash flood events may transition into lower-intensity floods as sudden, violent water surges weaken. In such cases, the National Weather Service data preparers use their professional judgment to determine when an event ceases to be classified as flash flood and transitions to a flood classification (National Weather Service, 2016). This paper only considers the impacts of *inland* flash flooding, and *inland* non-flash flooding events. The SED also provides documentation of coastal flooding, defined as "those portions of coastal land zones (coastal county/parish) adjacent to the waters, bays, and estuaries of the oceans"; further detailed as "Flooding of coastal areas due to the vertical rise above normal water level caused by strong, persistent onshore wind, high astronomical tide, and/or low atmospheric pressure, resulting in damage, erosion, flooding, fatalities, or injuries." (National Weather Service, 2016). The data preparers determine coastal and inland areas where events are classified as Flash Flood or Flood- rather than Coastal Flooding (National Weather Service, 2016). To the extent that concurrent coastal flooding may influence our results- we include all other contemporaneous natural hazards as an additional control in our analysis.

[6]Between 1996 and 2006, for a subset of events, the Storm Events Database (SED) reports hazard exposure at the NWS Public Forecast Zone level rather than at the county level. We map these zones to counties using zone–county crosswalks (National Weather Service, 2025); however, for approximately 0.6% of all flood-related events, a reliable mapping cannot be established because the corresponding zone codes are no longer in use.

Figure 1: Count of Flash Flood or Non-Flash Flood Days by U.S. County (1996–2023)



(a) Flash floods

(b) Slow-onset / non-flash floods

2.2 Quarterly Census of Employment and Wages

Our sub-annual data on employment and wages come from the Quarterly Census of Employment (QCEW). The QCEW provides county-level employment data at both monthly and quarterly frequencies. It also provides the data disaggregated by industry. Employment is the count of filled temporary or permanent jobs, whether full or part time, by place of work[7]. The quarterly reports include each establishment's monthly employment levels for the pay period that includes the 12th of the month (Quarterly Census of Employment and Wages, 2025). The database is built using the federal and state unemployment insurance programs, and is supplemented with information from additional sources. The QCEW data are not estimates, and the Bureau of Labor Statistics (BLS) reports that the QCEW covers 95% of total U.S. employment (Autor et al., 2024; U.S. Bureau of Labor Statistics (BLS), 2023).

The QCEW reports data on total wages paid within a calendar quarter, i.e. quarterly wage bills, regardless of when the services were performed. Wages include total compensation paid, including bonuses, stock options, severance pay, profit distributions, the cash value of meals and lodging, tips and other gratuities, and, in some states, employer contributions to certain deferred compensation plans (such as 401(k) plans) (Quarterly Census of Employment and Wages, 2025).

2.3 Other Data Sources

GridMET- Precipitation and Temperature Data: Quarterly average daily precipitation and temperature for each county in a given quarter-year are used as control variables in the empirical analysis. GridMET provides daily high resolution (4km) surface meteorological data for the US from 1979 onward (Abatzoglou, 2013). We use daily precipitation and temperature data from 1996 to 2023 to align with our sample period of analysis. For our empirical analysis, the

[7]Temp agency workers used in construction or healthcare are classified in NAICS 56132. Independent contractors are not included in QCEW. Workers that travel or work away from the employer of record county are reported in the employer county.

daily gridded weather data are averaged at the county-quarter level. Specifically, we compute county-area–weighted daily precipitation and temperature using sub-cell coverage weights and then average these county-level daily values across all days within each quarter.

NOAA Coastal Shoreline County Classifications: The NOAA Coastal Shoreline County classification (NOAA Office for Coastal Management, 2025) identifies the coastal counties that are adjacent to open ocean, major estuaries, and the Great Lakes. Such counties, due to their proximity to water bodies, face significant vulnerability to coastal hazards. FEMA defines a coastal county as one that borders the open ocean or Great Lakes coasts, or, one that contains velocity zones (V-zones)[8] or coastal high hazard areas (NOAA Office for Coastal Management, 2025).

Bureau of Labor Statistics- Local Area Unemployment Statistics: The Bureau of Labor Statistics provides historical local area unemployment statistics. These estimates are derived from multiple sources which include the Current Population Survey, Current Employment Statistics survey, the Quarterly Census of Employment and Wages, various Census Bureau programs and unemployment insurance claims data from multiple state workforce agencies (U.S. Bureau of Labor Statistics, 2025). This data source provides monthly labor force and unemployment statistics dating back to 1990 at the county level, which includes the total number of people employed and unemployed and the not-seasonally adjusted unemployment rate. We use the monthly not-seasonally adjusted unemployment rate to obtain average quarterly unemployment rate. We use this as a measure of local labor market conditions prior to any flood exposure.

Small Area Income and Poverty Estimates (SAIPE) on Poverty and Median Household Income: The U.S. Census Bureau's SAIPE provides annual, model-based state and county estimates of poverty and median household income (U.S. Census Bureau, 2022). We use the data from 1997-2023, and the estimates for percent of people of all ages in poverty, as well as the median household income. These are estimates and not direct counts; they are produced by combining survey data with population estimates and administrative records (Bell et al., 2007).

The summary statistics of the employment, total wages, inland flash flood days, inland non-flash flood days, average precipitation and temperature are given in table A1. In our data, the average number of days flooded is 0.235 for flash floods and 0.626 for non-flash floods. Conditional on counties experiencing at least 1 flood day in a quarter, the number of days per quarter that a county experiences a flash flood or non-flash flood is 1.681 and 6.659 days, respectively.

3 Empirical Strategy

We are interested in how county-level private employment and total wages respond to contemporaneous exposure to flash and non-flash floods. We use a county-level fixed effects

[8] "V-zones are areas where wave heights more than 3 feet and/or high velocity water can cause structural damage in a 100-year flood, a flood with a 1-percent chance of occurring or being exceeded in a given year." (NOAA Office for Coastal Management, 2025)

estimation strategy to account for unobserved time-invariant confounders that may simultaneously affect both flood exposure and labor market outcomes, thereby using *within-county* variation in exposure to flash floods and floods over time. Specifically, we estimate the following baseline specification:

$$\begin{aligned}\log(Y_{cqt}) = \alpha + \beta_1 FlashFlood_{cqt} + \beta_2 NonFlashFlood_{cqt} + \\ + \beta_3 AvgPrec_{cqt} + \beta_4 AvgTemp_{cqt} + \lambda_c + \alpha_{sqt} + \epsilon_{cqt}\end{aligned} \tag{1}$$

Here $\log(Y_{cqt})$ is the logarithmic transformation of our outcomes of interest - private employment or total wages for county c in quarter q and year t. We also study the impact of flash floods and non-flash floods on sectoral and sub-sectoral level employment and wages, in which case our outcome variables of interest are the sector-specific employment and total wages. Our key explanatory variables of interest are $FlashFlood_{cqt}$ and $NonFlashFlood_{cqt}$ which measure the total number of flash flood and non-flash flood or slower onset flood days, respectively, experienced by county c, in quarter q and year t. To isolate the effect of flooding from broader weather patterns, we control for contemporaneous average precipitation- $AvgPrec_{cqt}$ and average temperature- $AvgTemp_{cqt}$ in a county c, in a given quarter q and year t. λ_c and α_{sqt} are county and state-quarter-year fixed effects. State-quarter-year fixed effects account for any state-specific policy changes, or regional economic shocks that affect all counties within a state, and state-specific seasonal employment patterns that vary across quarters and years (e.g., some states report 401k contributions). By including the state-quarter-year fixed effects we can ensure that the flash and non-flash flood estimates are not biased by broader state-level economic shocks or policy interventions that coincide with contemporaneous flood exposures. Standard errors are clustered at the county level.

The coefficients of interest are β_1 and β_2, which respectively measure the impact of a flash flood day and a slower onset/non-flash flood day on labor market outcomes. The identification strategy assumes – conditional on county, state-quarter-year fixed effects, and other controls such as average precipitation and temperature – the incidence of contemporaneous flash and non-flash floods is exogenous to our measures of labor market outcomes, i.e. employment and wages. In summary, we compare the same county across multiple different quarters over time, with and without exposure to flash floods and non-flash floods. As long as such flood events are unanticipated, $\hat{\beta}_1$ and $\hat{\beta}_2$ captures the causal effect of flash flood and non-flash flood exposure on local labor market outcomes.

4 Results

Our main findings reveal that flash floods generate significant sub-annual disruptions to the labor market, while slow-onset floods show minimal impacts. Specifically, we find that an additional day of flash flooding reduces private employment and total wages by 0.13% and 0.15% respectively (column (1) and (5) of table 1). In contrast, an additional non-flash flood or slower onset flood day has a somewhat smaller negative effect on employment and wages, the effect size is small and statistically insignificant (table 1). These results largely hold after controlling for any contemporaneous or concurring natural hazards[9] within a given county, in a given quarter-year (columns (2) and (6) of table 1). The nature of flooding matters in determining economic impacts. Flash floods, which are characterized by sudden, rapid and violent onset and with high-velocity flows, are found to have a statistically significant disruption to local labor market outcomes. Meanwhile, non-flash floods do not have a statistically negative labor market impact on average.

Our quarterly results provide evidence of sub-annual labor market shocks from flash flood exposure. Using aggregated annual data on employment and wages, both flash and non-flash flood exposure show negative but statistically insignificant effects on private employment and wages (columns (3), (4), and (7) and (8) of table 1). This finding aligns with the results in Jia et al. (2025), who find no significant employment effects from flood events, though their analysis focuses exclusively on large flood events.

In a separate specification, we estimate a model that includes lagged exposures for the previous three quarters, and find that lagged flash and non-flash floods have statistically insignificant effects on employment (figure 2). However, flash flood exposure in the past one-quarter has a negative and significant effect on total wages (figure 2), suggesting some persistence in lost wages.

Overall, these results reveal that flash floods generate sharp short-lived disruptions in local labor markets. Employment and total wages fall significantly in the contemporaneous quarter, reflecting immediate impacts either due to physical capital damages, workplace closures and interruptions, lower labor demand due to a fall in consumption demand, or labor supply disruptions. The effect of the one quarter lagged exposure on contemporaneous employment is negative but statistically insignificant, and by the second quarter lag, coefficient point estimates are close to zero and statistically insignificant. This dynamic pattern suggests adjustment of the labor market, returning employment and wages to their pre-shock levels. However, the recovery is restorative rather than expansionary, i.e. without overshooting prior levels. While prior research documents that some natural hazards, such as hurricanes and tornadoes, can raise wages through post-disaster improvements in local capital and productivity (Roth Tran and Wilson, 2025), this has not been found for flood hazards (Roth Tran and Wilson, 2025). This is possibly due to reluctance to undertake investments in improving local capital stock due to higher perceived probability of repeated flooding, thus, limiting the capital upgrading that drives long-run gains following other disaster types (Roth Tran and Wilson, 2025).

This short-lived adjustment process may help explain why the annual specifications detect no statistically significant labor market effects. Aggregating to the yearly level mechanically averages

[9]These would include natural hazards such as Heat, Thunderstorms, Frost/Freeze, Drought, Debris Flow, Avalanche and many other events, see National Weather Service (2016) for natural hazards recorded in the SED. Additionally, since recent evidence shows thunderstorms can also have negative labor market consequences (Coronese et al., 2025), we control specifically for contemporaneous thunderstorm days in a county (Table A7). Our results largely hold and are consistent with the results in table 1.

the negative contemporaneous shocks with other quarter observations that vary significantly due to other factors influencing labor markets. These sources of variability include macroeconomic fluctuations, policy shifts, and reporting noise, which could in turn obscure the impacts of relatively brief and geographically localized flood events. The absence of significant annual effects should not be therefore interpreted as evidence that floods leave labor market outcomes unaffected, rather, it reflects the consequence of temporal aggregation that masks the effects of transient but economically meaningful shocks. By exploiting quarterly variation, we uncover labor market disruptions that are obscured due to annual aggregation.

It is important to note that the drop in total wage bill here reflects a combined effect of employment reductions *and* potential decreases in hours worked. While QCEW data does not separately report hours, it is plausible that part-time or hourly workers experience reduced hours due to flood related disruptions. Recent literature using payroll records shows substantial sub-annual earnings volatility driven by firm-led labor demand fluctuations, that is more pronounced among labor dependent on hourly work (Ganong et al., 2025). Importantly, this volatility is largely masked in the annual aggregates (Ganong et al., 2025). In this context, our findings suggest that natural hazards such as flash floods represent an exogenous source of similar short-run earnings instability, further underscoring the importance of using a sub-annual temporal scale for understanding labor market impacts to localized shocks.

Table 1: Effect of Flash Flood and Non-Flash Flood Days on Total Private Employment and Wages

Dep. Vars.:	log(Emp.)				log(Tot.Wages)			
	Quarterly		Annual		Quarterly		Annual	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Flash Flood	-0.126**	-0.119**	-0.050	-0.044	-0.153**	-0.149**	-0.081	-0.078
	(0.053)	(0.053)	(0.049)	(0.049)	(0.065)	(0.065)	(0.062)	(0.062)
Non-Flash Flood	-0.008	0.0009	-0.0004	0.005	-0.008	-0.002	-0.002	0.0008
	(0.011)	(0.012)	(0.008)	(0.008)	(0.014)	(0.015)	(0.009)	(0.010)
Other Natural		-0.010**		-0.006***		-0.006		-0.003
Hazards		(0.004)		(0.002)		(0.006)		(0.003)
Observations	345,797	345,797	86,648	86,648	345,797	345,797	86,648	86,648
St×Qtr×Year FE	Yes	Yes			Yes	Yes		
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
St×Year FE			Yes	Yes			Yes	Yes

Notes: Controls include average precipitation and average temperature. All specifications include county and state×quarter×year fixed effects. All coefficients and standard errors have been multiplied by 100. Clustered (county-level) standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

We quantify total lost wages from flooding with a counterfactual exercise, using the combined effect of both flash and non-flash floods. Because the outcome variable is the log of the quarterly

Figure 2: Flood Effects on Employment and Total Wages: Contemporaneous and Lagged Flood Exposure

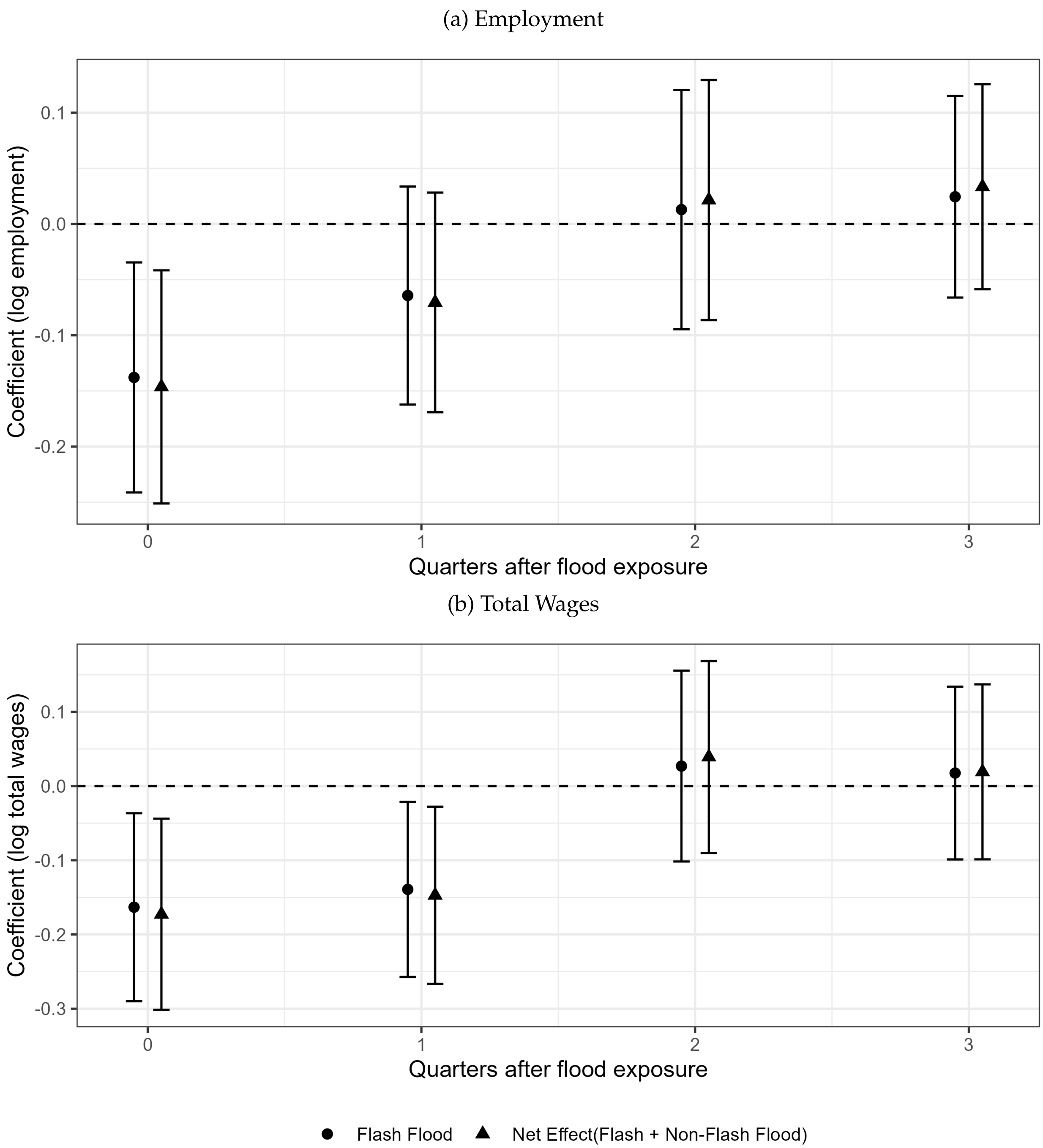
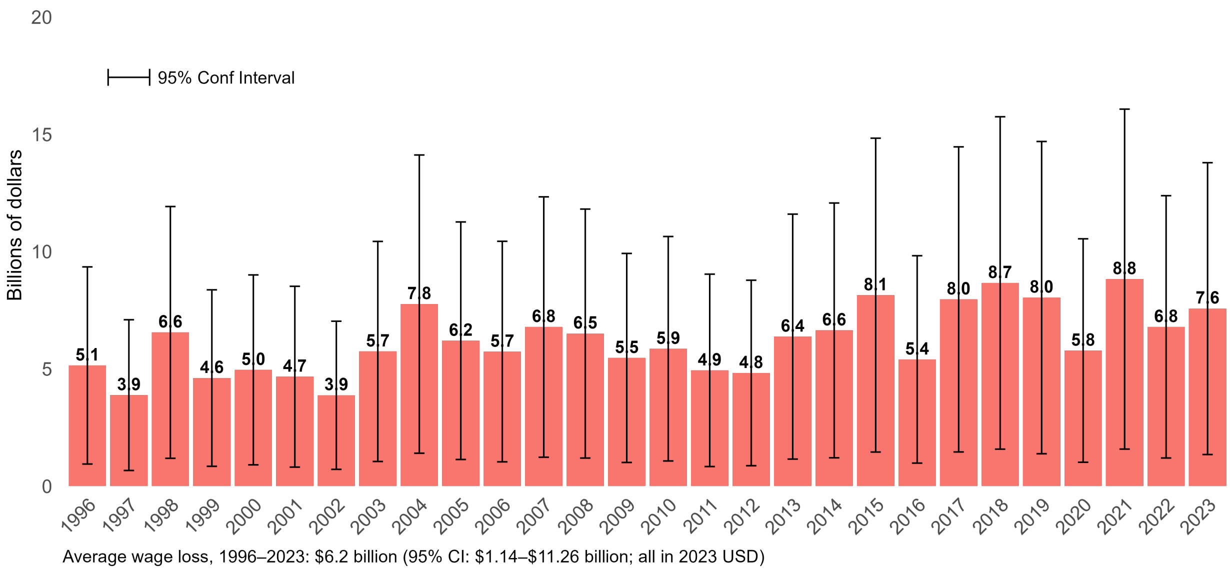


Figure 3: Annual Wage Losses due to Flash Floods and Non-Flash Floods Combined (Real, 2023$)



Notes: Here we use the estimates in column (5) of table 1 for Flash Flood and Non-Flash Flood and use the observed number of flash and non-flash flood days in each county-quarter to construct the counterfactual (hazard days set to zero) and sum the implied dollar losses to the year. The standard errors are computed using the delta method.

county wage bill, the coefficients are semi-elasticities. From the specification, we use the estimates β_1 and β_2 to compute $\beta_1 * FlashFloodDays + \beta_2 * NonFlashFloodDays$ and obtain the impact on the county-quarter wage bill, i.e., we use the estimates in column (5) of table 1 for Flash and Non-Flash Flood and use the observed number of flash and non-flash flood days in each county-quarter to construct the counterfactual (hazard days set to zero) and sum the implied dollar losses to the year (see figure 3). Averaging across years yields an average annual loss of about $6.2 billion (2023 dollars). Confidence intervals for the annual and average losses are obtained using the delta method. Since this exercise relies solely on contemporaneous coefficients and does not incorporate lagged effects from the previous quarters, the estimated dollar losses likely represent a lower bound estimate.

For the case of flash floods, our preferred estimate implies that one additional day of flash flooding in a quarter reduces the local wage bill by 0.15% (column (5) of table 1). Applying this effect to the observed exposure of flash floods in each county-quarter, we construct counterfactual wages with the hazard turned-off or under a no flash flood scenario, compute the implied losses, and then aggregate to the calendar year. Averaging across years in our estimation sample yields average annual wage losses of $5.9 billion, expressed in 2023 dollars (see figure A2).

5 Heterogeneity

Next, we examine heterogeneous effects of flood days across different dimensions such as economic sector, location (coastal versus inland counties), and by existing local labor market conditions. This approach identifies which industries and communities face the greatest vulnerability to flood-related labor market disruptions.

Sectoral and Sub-sectoral impacts: To better understand the channels through which flood events influence local labor markets, we move beyond aggregate outcomes and examine sectoral and sub-sectoral employment and wage responses. Sectors differ in exposure pathways, dependence on daily activity, and sensitivity to physical disruption. Sectors tied to physical capital and on-site activity (e.g. manufacturing and construction) are likely to face shutdowns when facilities are damaged, whereas consumer-facing service sectors may face mobility constraints and demand contraction (e.g. sectors such as leisure and hospitality, and retail trade).

Our sectoral analysis reveals that an additional day of flash flood reduces employment in goods-producing sectors by 0.27% (column (2) of table 2). The corresponding effect on service-providing sectors is a smaller reduction of 0.08% (column (3) of table 2), but this effect is not statistically significant. An additional flash flood day reduces total wages in goods-producing and service-providing sectors by 0.29% and 0.14% (columns (5) and (6) of table 2), respectively. Slow onset inland floods have small and statistically insignificant effects across both sectors, further reinforcing that high-velocity, sudden and rapid onset flash flooding causes more labor market disruption. The service sector experiences a significant decrease in wages per worker (see table 3) but not employment, suggesting that floods impact employment partially through a decrease in the number of hours worked.

We estimate the model with establishment counts as the dependent variable and find evidence that flash floods reduce goods-producing establishments (see table A3). This result suggests that damage to physical capital reduces employment in goods-producing firms.

We further examine sub-sectoral impacts in industries that face distinct vulnerability channels. We focus on trade, transportation and utilities (and retail trade within this), leisure and hospitality and construction because these industries are susceptible to flood impacts through distinct mechanisms. Sectors reliant on consumer mobility and day-to-day demand (retail, leisure and hospitality) experience meaningful reductions in employment and wage bills following flash floods (table A2). These effects are consistent with temporary constraints to access and mobility, reductions in consumption demand, and disruptions to foot traffic.

Interestingly, we find a negative and significant impacts of both flash floods and non-flash floods on construction sector employment and total wages (table A2). This suggests a broader physical exposure mechanism as even low-intensity flooding with gradual onset can disrupt labor activity in the construction sector through prolonged exposure to inundation and work delays. The construction sector's reliance on outdoor work sites makes it vulnerable to flooding that creates waterlogging, regardless of flood intensity or speed of onset.

Taken together, these findings indicate that the employment and wage effects of flooding

Table 2: Effect of Flash and Non-Flash Flood Days on Private Employment and Wages in Goods-Producing and Service-Providing Industries

Dep. Vars.:	log(Emp.)			log(Tot.Wages)		
	Total	Goods-Producing	Service-Providing	Total	Goods-Producing	Service-Providing
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Flash Flood	-0.126**	-0.272***	-0.075	-0.153**	-0.293***	-0.137**
	(0.053)	(0.092)	(0.050)	(0.065)	(0.104)	(0.060)
Non-Flash Flood	-0.008	-0.011	-0.007	-0.008	-0.014	-0.006
	(0.011)	(0.020)	(0.012)	(0.014)	(0.024)	(0.013)
Observations	345,797	343,489	344,445	345,797	343,489	344,445
St$\times$Qtr$\times$Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Controls include average precipitation and average temperature. All specifications include county and state$\times$quarter$\times$year fixed effects. All coefficients and standard errors have been multiplied by 100. Clustered (county- level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effect on Total Wages Per Worker

	log(Total Wages Per Worker)		
	Total	Goods-Producing	Service-Providing
	(1)	(2)	(3)
Variables			
Flash Flood	-0.027	-0.020	-0.062**
	(0.029)	(0.038)	(0.027)
Non-Flash Flood	-0.00007	-0.003	0.0003
	(0.006)	(0.009)	(0.005)
Observations	345,797	343,489	344,445
St$\times$Qtr$\times$Year FE	Yes	Yes	Yes
FIPS FE	Yes	Yes	Yes

Notes: Controls include average precipitation and average temperature. All specifications include county and state$\times$quarter$\times$year fixed effects. All coefficients and standard errors have been multiplied by 100. Clustered (county- level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

operate primarily through labor-demand fluctuations rather than the channels of labor-supply shocks. Labor demand is most likely affected due to physical capital damages, lower consumption demand due to lower foot traffic and mobility constraints. Although supply side factors such as disruptions to labor mobility to workplaces itself cannot be dismissed, recent evidence shows that mortality impacts from similar inland flash flooding and non-flash flooding are concentrated on senior populations (above 65 years old) rather than prime-age workers (Chu et al., 2025).

Heterogeneous Effect by Coastal County: The existing literature largely focuses on the impacts and economic costs of flooding in coastal areas or coastal cities (Hallegatte et al., 2013; Strauss et al., 2015; Desmet et al., 2015, 2018), with comparatively less emphasis on *inland* flooding. Some recent literature does study the economic impacts of large federally declared floods for the contiguous U.S. (Jia et al., 2025; Erda, 2024), but does not distinguish the impacts across inland and coastal counties. Coastal shoreline counties may experience greater vulnerability to flood-related disruptions than inland counties for multiple reasons. Coastal counties are far more densely populated and economically concentrated. The population density in coastal shoreline counties is over six times greater than inland counties (NOAA, 2013), and so a given disruption can affect more workers, establishments and infrastructure. Finally, disruptions could be more likely as it can be compounded over multiple repeated natural hazards such as storm surge, high tides and sea level rise which potentially lead to larger damages and result in a prolonged impact. Specifically, we examine the heterogeneous effects of inland flooding (flash and non-flash) across geographically inland and coastal counties; we do not examine the impacts of coastal flooding events.

Flooding in inland counties is not rare or negligible. As shown in figure 1, there are numerous inland counties in the U.S. that experience flood events over multiple days on average during a given year. Moreover, figure A1 shows that while the intensity of exposure (average days of flooding) is broadly similar across inland and coastal counties, the scale of exposure differs substantially as more inland counties experience flooding, exposing a large population residing in these counties. This makes the coastal-inland county comparison empirically meaningful for understanding the heterogeneous labor-market effects of flooding.

We identify the location-based heterogeneity by interacting our flash flood and non-flash flood days exposure measure with a coastal county indicator based on the NOAA Coastal Shoreline County classification (NOAA Office for Coastal Management, 2025). Our indicator variable takes a value of 1 if the county is a coastal shoreline county, and 0 otherwise.

We find that an additional day of flash flooding reduces employment and wages in inland counties by 0.11% and 0.13%, while the corresponding effect on employment and wages for coastal counties is larger, at 0.25% and 0.37% respectively. While the point estimates suggest larger coastal effects, the difference in effect size between inland and coastal counties is statistically insignificant (table 4).

Using these estimates in column (2) of table 4, we further quantify total wage losses due to flash and non-flash floods, by inland and coastal counties. We construct counterfactual county-quarter wage bills with flood exposures set to zero and aggregate to calendar years. Figure A3 reports the resulting annual losses by coastal versus inland counties. On average over the sample, coastal counties lose roughly $7 billion per year (in 2023 dollars), while inland counties lose about $2.9

Table 4: Heterogeneous Effect by Inland-Coastal Counties

Dependent Variables:	log(Emp.) (1)	log(Tot. Wages) (2)
Variables		
Flash Flood	-0.111**	-0.129*
	(0.056)	(0.069)
Non-Flash Flood	-0.005	-0.006
	(0.012)	(0.015)
Flash Flood X Coastal	-0.143	-0.238
	(0.124)	(0.159)
Non-Flash Flood X Coastal	-0.041	-0.037
	(0.025)	(0.035)
Net Effect- Flash Flood in Coastal Counties	-0.254**	-0.366**
	(0.117)	(0.148)
Net Effect- Non-Flash Flood in Coastal Counties	-0.046**	-0.043
	(0.022)	(0.033)
Observations	345,797	345,797
St×Qtr×Year FE	Yes	Yes
County FE	Yes	Yes

Notes: Indicator variable- Coastal takes 1 if the county is a coastal shoreline county, and 0 otherwise. Controls include average precipitation and average temperature. All specifications include county and state×quarter×year fixed effects. All coefficients and standard errors have been multiplied by 100. Clustered (county- level) standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

billion per year (in 2023 dollars, statistically significant at 10% level of significance)[10]. Average annual losses in wages in inland counties are therefore about 41% of the quantified losses in coastal counties.

Heterogeneous Effect by Local Labor Market Conditions: Finally, we test how existing local labor market conditions moderate the impacts of flooding. We measure local labor market strength with a time-variant proxy of labor market slack, defined by the county-level unemployment rates in the preceding quarter relative to the national distribution. Specifically, we classify a county as high-slack if its unemployment rate in the past quarter exceeds the 90th percentile of the national distribution in the same year-quarter. We use the past quarter unemployment rate to identify high or low slack counties to capture the most recent labor market conditions and because the contemporaneous unemployment rate can interact endogenously with contemporaneous flood

[10]The confidence intervals are obtained based on the delta-method with county-clustered standard errors.

exposures. In the appendix, we test for robustness to cumulative flood exposure.

Low slack counties are closer to full employment levels, and have stronger underlying demand conditions than in high slack counties. In contrast, high-slack counties are operating below full employment, with weaker labor demand, lower vacancy creation, and reduced private-sector absorption capacity (Shimer, 2005; Imbens and Lynch, 1993). Within the search and matching framework, job finding depends on labor market tightness and empirically high unemployment coincides with lower vacancy creation (Shimer, 2005). Existing evidence also suggests re-employment probabilities for workers are lower in high unemployment areas, thus possibly making flood induced separations harder and costlier to reverse in high-slack places (Imbens and Lynch, 1993). On the other hand, additional evidence also suggests that vacancy yields (hires per vacancy) decline with labor market tightness and that firms adjust through costly instruments in the form of recruitment intensities, screening, and compensations (Davis et al., 2013), thus, implying replacement costs are higher in tight labor markets which strengthens the incentives to hoard labor rather than separate during transitory shocks. Consequently, upon experiencing contemporaneous flooding, high slack counties could face greater vulnerability to economic and labor market disruptions, whereas low-slack counties are better positioned to buffer the shock through retention or faster reallocation.

Our indicator variable takes a value of 1 if in the past quarter the unemployment rate in the county was above the 90th percentile of the national distribution over the same quarter-year, and 0 otherwise. Using this definition, figure A4 maps the spatial distribution of counties ever classified as high-slack during our sample period, shading them by the unemployment rate at the time they crossed the threshold[11]. High-slack counties appear across both inland and coastal regions, with many counties in parts of the midwest, the rural south, the southwest, and certain west coast areas; many of these also experience flash flood and non-flash flood hazards.

Our results provide evidence that there is a differential impact for both flash and non-flash floods between high slack and low slack counties. An additional flash flood day reduces employment and wages by 0.41% and 0.59% respectively in high-slack counties (columns (1) and (2) of table 5), while the effect for flash flooding in low slack counties indicates a smaller drop in employment and wages by 0.10% and 0.12% respectively (columns (1) and (2) of table 5). Importantly, these differences are statistically significant (columns (1) and (2) of table 5), confirming that stronger labor markets buffer against severe flood shocks.

We observe similar patterns for lower intensity, slower onset flooding. An additional day of non-flash floods reduces employment and wages by 0.097% and 0.12% respectively in high-slack counties (columns (1) and (2) of table 5), while the effects in low-slack counties are close to zero and statistically insignificant. Importantly, even in this case, the difference in effect size between

[11]For counties classified as high-slack in multiple quarters, the map reports the maximum unemployment rate observed across all high-slack episodes for that county during the sample period, as it is not feasible to display each episode separately.

high and low-slack counties is statistically significant, suggesting a differential effect even for non-flash or slower onset flood events. This is likely because high slack counties have weaker adjustment capacity, and with lower re-employment probabilities, even slow onset non-flash floods can negatively impact employment and total wages.

Table 5: Heterogeneous Effect by High-Low Slack Counties (Alternate Definitions)

Dependent Variables:	log(Emp.) (1)	log(Tot.Wages) (2)	log(Emp.) (3)	log(Tot.Wages) (4)	log(Emp.) (5)	log(Tot.Wages) (6)
Variables						
Flash Flood	-0.102*	-0.116*	-0.099*	-0.115*	-0.106**	-0.128*
	(0.053)	(0.064)	(0.053)	(0.065)	(0.054)	(0.066)
Non-Flash Flood	-0.001	-0.0002	-0.0002	0.0003	0.0008	0.001
	(0.012)	(0.015)	(0.012)	(0.015)	(0.012)	(0.015)
Flash Flood × High Slack	-0.308*	-0.474*				
(=1 if Past Qtr. Unemp. > 90th perc.)	(0.177)	(0.246)				
Non-Flash Flood × High Slack	-0.096*	-0.115**				
(=1 if Past Qtr. Unemp. > 90th perc.)	(0.051)	(0.054)				
Flash Flood × High Slack			-0.761***	-1.08***		
(=1 if *all* Past 4 Qtrs. Unemp. > 90th perc.)			(0.250)	(0.356)		
Non-Flash Flood × High Slack			-0.209***	-0.224***		
(=1 if *all* Past 4 Qtrs. Unemp. > 90th perc.)			(0.068)	(0.074)		
Flash Flood × High Slack					-0.864**	-1.06**
(=1 if *all* Past 8 Qtrs. Unemp. > 90th perc.)					(0.338)	(0.480)
Non-Flash Flood × High Slack					-0.303***	-0.322***
(=1 if *all* Past 8 Qtrs. Unemp. > 90th perc.)					(0.073)	(0.089)
Net Effect- Flash Flood in	-0.410**	-0.590**				
High Slack Counties	(0.179)	(0.248)				
Net Effect- Flash Flood in			-0.860***	-1.196***		
High Slack Counties			(0.251)	(0.357)		
Net Effect- Flash Flood in					-0.971***	-1.193**
High Slack Counties					(0.334)	(0.477)
Net Effect- Non-Flash Flood in	-0.097**	-0.115**				
High-Slack Counties	(0.048)	(0.051)				
Net Effect- Non-Flash Flood in			-0.209***	-0.224***		
High-Slack Counties			(0.066)	(0.071)		
Net Effect- Non-Flash Flood in					-0.302***	-0.321***
High-Slack Counties					(0.071)	(0.086)
Observations	345,776	345,776	345,797	345,797	345,797	345,797
St×Qtr×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In columns (1) and (2) the High Slack indicator variable takes value 1 if in the past quarter the unemployment rate in the county was above the 90th percentile of the national distribution over the same quarter-year, and 0 otherwise. Alternatively for columns (3) and (4), counties are classified as high-slack if unemployment exceeded 90th percentile in each of the past four quarters, and finally in columns (5) and (6) counties are classified as high-slack if unemployment exceeded 90th percentile in each of the past eight quarters. Controls include average precipitation and average temperature. All specifications include county and state×quarter×year fixed effects. All coefficients and standard errors have been multiplied by 100. Clustered (county- level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We also test this heterogeneous effect using alternate definitions of persistent slack- counties, classified as high-slack if unemployment exceeded the 90th percentile in *each* of the past four quarters (columns 3-4 of table 5), or *each* of the past eight quarters (columns 5-6 of table 5). These measures proxy persistently weak economic conditions in recent quarters, and chronic labor-market weakness. This is possibly a more robust measure of local economic strength as it relies on identifying slack over an extended time period unlike the previous measure which relies on the unemployment rate only in the past quarter. In columns 3-6 of table 5 we find larger negative effects of both flash and non-flash floods on employment and wages for high-slack counties compared to columns 1-2 of table 5, thus suggesting persistent slack has a larger impact. These results reinforce that underlying labor-market strength plays an important role in shaping flood vulnerability.

A potential concern with our slack-based heterogeneity design is that the high-slack classification relies on lagged unemployment rates. If previous flood exposures elevated unemployment in affected counties, then our high-slack indicator could partially reflect persistent effects of earlier flood shocks rather than underlying labor-market conditions or labor-market strength. In this case, the interaction between current flood exposure and the high-slack indicator might conflate genuine heterogeneity with the mechanical persistence from past disasters. To mitigate such concerns, we further control for cumulative flood exposures in past quarters. The results are reported in table A4. The estimated coefficients remain very similar to those in table 5, though we observe some modest attenuation in effect size after controlling for cumulative flood exposure, suggesting some possible role of past shocks contributing to the slack classification without altering the overall patterns of heterogeneity. Finally, even after accounting for cumulative past flood exposure, high slack may still proxy for other time-varying local vulnerabilities (e.g., sectoral composition, fiscal capacity, credit constraints, or infrastructure conditions) that can influence baseline flood risk, damages, and the local capacity to recover from flood hazards.

Additionally, as a descriptive check, we examine whether counties classified as high-slack are more likely coastal counties. For each county, we calculate the share of sample quarters in which it is classified as high-slack under each slack definition, and then compare mean values between coastal and inland counties using simple difference-in-means test. Table A5 shows no systematic evidence that coastal counties are more frequently classified as high-slack. If anything, under one of the more persistent slack definitions, high-slack status is more prevalent in inland counties. This suggests that our slack-based heterogeneity is not simply capturing coastal versus inland heterogeneity.

Overall, the heterogeneous effects align with the labor market literature suggesting low-slack economies operating closer to full employment are more resilient and potentially have greater absorptive capacity to reallocate displaced workers following disruptions. High slack counties on the other hand, face weaker economic conditions in the form of lower job-finding rates, reduced vacancy creation and diminished labor demand (Imbens and Lynch, 1993; Shimer, 2005). Therefore, additional flood induced disruptions generate disproportionately larger labor market impacts. Existing evidence shows that fiscal stimulus and interventions have stronger effects when unemployment is high and private-sector absorption capacity is limited. Our results suggest that targeted post-disaster federal aid may be most valuable in high-slack counties, where flood induced disruptions generate disproportionate labor market impacts.

Finally, we examine heterogeneous effects using alternate measures of economic vulnerability, i.e., county level poverty rates and median household income from 1997-2023. We classify counties as high-poverty rate if the previous year exceeds the 90th percentile of the national distribution, and as low-median-income if the median household income falls below the 10th percentile[12]. Both measures are time-varying to capture recent relative economic conditions at the county level.

Table A6 shows that flash floods and non-flash floods have a larger negative effect in economically vulnerable counties. Low-median income counties experience significantly larger wage losses from both flash floods (net effect -0.76%) and non-flash floods (-0.13%), as well as significantly larger employment losses from non-flash floods. High poverty counties exhibit significantly larger employment losses from non-flash floods (-0.077%). While the pattern of larger negative effects in vulnerable counties hold across both measures and flood types, some interaction terms are imprecisely estimated and not statistically significant. All specifications include controls for cumulative flash and non-flash flood exposure over the past eight quarters. These patterns reinforce that underlying economic conditions amplify flood vulnerability, consistent with our slack-based heterogeneity findings.

6 Robustness

We also explore the robustness of our results to a range of alternative specifications. This includes models estimated at the commuting zone level, allowing for spatially correlated errors, controlling for extreme precipitation, considering flood severity, and placebo analysis.

Flooding events may overlap with other severe weather phenomena that may independently affect local labor markets. To address this identification concern we already control for all other co-occurring natural hazards documented in SED, occurring within a county, in a given quarter-year (see table 1 and table A7).

Previous literature documents labor market related dynamics at the CZ level (Autor et al., 2013, 2024; U.S. Department of Agriculture, Economic Research Service, 2025) because labor markets often span multiple counties due to commuting flows and supply-demand linkages. Counties, on the other hand, could be seen as administrative boundaries, and may not correspond to the

[12]High Poverty is a time-varying classification based on whether a county's poverty rate in the previous year is above the 90th percentile of the national county-level poverty distribution in the given year (=1), the indicator variable takes value 0 otherwise. Low Median Income is also a time-varying indicator based on whether a county's median household income in the previous year is below the 10th percentile of the national county-level median income distribution in that given year (=1), the indicator variable takes value 0 otherwise. Due to inconsistent county coding for Connecticut in 2022–2023 in the poverty and income related data source (SAIPE), we assign Connecticut counties to 0 for both indicators. This is assumed because Connecticut counties are never classified as high-poverty or low-income in earlier years of the same data.

functional geography within which labor market adjustments occur. To ensure our results are not driven by the choice of spatial unit, we conduct similar analysis at the CZ-level. We obtained the county to commuting zone, and commuting zone to census division crosswalk files from Autor and Dorn (2013). We find largely similar and consistent results, reported in table A8, supporting the robustness of our results.

A potential concern in county-level analyses of natural hazards is that spatially correlated shocks across nearby counties can lead to downward-biased standard errors and spurious statistical significance if not accounted for. To address this, we re-estimate our baseline specification by allowing for spatial clustering based on spatially robust Conley standard errors (Conley, 1999) with varying cutoffs at 25 km, 50 km, 75 km and 100 km, this allows for spatial correlation across nearby counties. Our results are robust and statistically significant after allowing for this spatial correction (table A9).

We also control for the contemporaneous rainfall anomalies by including the number of days a county experiences rainfall exceeding 1 inch, 50 mm, 75 mm or 100mm in a given quarter. Table A10 shows that while the flash flood coefficients attenuate slightly as we control for increasingly severe rainfall thresholds, the negative effect on both employment and total wages remains in a similar range and is statistically significant across specifications.

Table A11 examines whether the baseline average effects are not simply driven by counties experiencing high-intensity flooding (large reported damages) or by counties experiencing periods of Presidentially declared flood disasters. To proxy for high intensity floods we use the NOAA Storm Events Database (SED) to compute total reported flood damages in each county–year–quarter, defined as the sum of reported property and crop damages. We then construct a High Damage Reported indicator that takes the value 1 if a county's reported damages in a given year-quarter exceeded the 90th percentile of the positive-damages distribution over 1996–2023 (i.e., conditional on damages being strictly greater than zero), and 0 otherwise.

Using this classification, we do not find that the effects are concentrated only in high-damage county-quarters. Columns (1) and (2) of table A11 show the impacts of an additional flash flood day on employment and wages in county-quarters with no or low reported damages are similar in magnitude to the baseline estimates in table 1, and the differences across high- and no-or-low-damage periods are not statistically significant.

Next, we use the FEMA Presidential Disaster Declarations database to identify flood-related emergency declarations. The FEMA Declared Emergency indicator is set to 1 for county-year-quarters that overlap with a Presidentially declared flood disaster period, and 0 otherwise. The results in columns (3)-(4) of table A11 show that additional flash flood days *outside* of Presidentially declared periods also reduce employment and wages. However, the net effect of an additional flash flood day during a Presidentially declared flood disaster is larger (more negative) for both employment and total wages, and this difference is statistically significant relative to non-declared periods.

Overall, these findings support the interpretation that the baseline labor-market impacts of flash flooding are not an artifact of the extreme, high-damage flooding events. Instead, adverse labor market impacts are visible even in quarters with no or lower reported damages and outside federally declared emergencies, while major FEMA declared emergencies appear to intensify the quarterly impacts on employment and wages.

Finally, to ensure that our estimated effects are not driven by spurious correlation, we conduct a within-county placebo analysis. In this, we shuffle flood exposure within each county over time, which preserves the distribution of flash flood exposure within a county while breaking the link between the true timing of flooding and labor market outcomes. We estimate our baseline specification 1000 times on these placebo exposures and construct the distribution of coefficients using the random exposure timing. Our observed estimates lie far in the tails of the placebo distributions (see figure A5) indicating that the effects we observe do not arise by chance. We also conduct a within state-quarter-year placebo, shuffling flash flood exposures across counties within the same state-quarter-year. This preserves the temporal distribution of flash floods while breaking the spatial link between exposure and outcomes. Our observed estimates again lie at the tails of the placebo distribution (see figure A6), confirming the observed effects are not spurious.

7 Conclusion

In this paper, we revisit and examine the labor market impacts of flood hazards. Our findings provide new evidence on the sub-annual labor market impact of flash and non-flash flood exposure, revealing dynamics that complement and extend existing research. While past literature documented productivity shocks from large flood events with evidence of no contemporaneous change in annual employment (Jia et al., 2025), our sub-annual analysis uncovers significant labor market disruptions at the quarterly level that are not observable over a longer temporal window (i.e., at the annual level), with the sub-annual impacts not made up in future quarters. Past literature documents productivity shocks from large events, while we show that even moderate sized flash floods have short term labor market consequences. These patterns are important to uncover as they matter for documenting losses in economic welfare and for improving rapid policy responses to such weather-related hazards.

In our analyses, we distinguish between the nature of flood events, documenting the impact of inland flash floods which have a more sudden and rapid onset, versus inland non-flash floods which have a more gradual onset yet last longer. This distinction is empirically important as the nature of flooding could determine the differential patterns of economic disruption. We also include floods that range in severity and do not make a distinction in terms of spatial scope and duration, or federal declaration status, providing a more comprehensive assessment of flood impacts than studies that have focused solely on large-federally declared disaster events (e.g., Kocornik-Mina et al., 2020; Jia et al., 2025; Roth Tran and Wilson, 2025). These results suggest that disaster responses may need to consider short-run labor market impacts even for floods that do not rise to the level of a declared emergency.

We also uncover heterogeneous effects by geographic location (coastal versus inland counties) and by local labor market strength. Specifically, we show that although the effect size of non-flash flood and flash flooding in coastal counties is larger, the difference is statistically insignificant and inland counties also suffer a negative effect of flash flooding on employment and wages. Importantly, we also find that recent pre-flood labor market conditions can shape labor market vulnerability to floods. High labor market slack counties (counties with past-quarter unemployment rates above the 90th percentile of the national distribution) experience a larger negative impact of both flash flooding and non-flash flooding on labor market outcomes than low-slack counties. This finding suggests that flooding can worsen already struggling local economies, highlighting the need for targeted policy interventions based on local economic conditions. It also suggests that investments that create favorable employment conditions can enhance labor market resilience to floods.

Despite its contributions, our study has some limitations which could be addressed in future research. While using the SED data has advantages in terms of its comprehensive coverage, it lacks details related to the exact spatial extent and severity of inundation. Additionally, we assign flood events to the entire county, whereas events could be spatially localized, impacting a relatively small area, and affecting only local populations and establishments. In this regard, future research could leverage high-resolution satellite data to precisely map inundation extent and link flood exposure to specific populations and establishments, providing more accurate estimates of economic losses. Additionally, incorporating real-time mobility and spending data could capture short-term loss in economic welfare as well as immediate behavioral and adaptive responses that our quarterly analysis may miss. Such analysis could further document the mechanisms through which floods disrupt local economies and inform more effective policy responses.

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7.1 Appendix: Figures and Tables

Table A1: Summary Statistics

Dependent Variables:	Mean (1)	SD (2)	Sample (3)
Variables-Quarterly			
Employment	35653	130663	345797
log(Employment)	8.879	1.677	345,797
Total Wage (in million USD)	423.6	2,116.9	345,797
log(Total Wages)	17.854	1.837	345,797
Flash Floods	0.235	0.759	345,797
Flash Floods (*Conditional on Flash Flood* > 0)	1.681	1.304	48,247
Non-Flash Floods	0.626	4.199	345,797
Non-Flash Floods (*Conditional on Non-Flash Flood* > 0)	6.659	12.142	32,505
Quarterly Average Daily Precipitation (mm)	2.814	1.614	345,797
Quarterly Average Daily Temperature (C)	12.87	9.058	345,797
Other Natural Hazards	9.089	18.919	345, 797
Other Natural Hazards (*Conditional on Other Natural Hazards* > 0)	11.192	20.426	280,834
Variables-Annual			
Employment	35576	130497	86,648
log(Employment)	8.872	1.684	86,648
Total Wage (in million USD)	1,690.5	8,394.9	86,648
log(Total Wages)	19.233	1.846	86,648
Flash Floods	0.937	1.700	86,648
Conditional on Flash Flood > 0	2.274	1.994	35,707
Non-Flash Floods	2.502	11.176	86,648
Conditional on Non-Flash Flood > 0	9.356	20.073	23,173
Annual Average Daily Precipitation (mm)	2.812	1.147	86,648
Annual Average Daily Temperature (C)	12.86	4.581	86,648

Figure A1: Flash and Non-Flash Flood Exposure in Coastal and Inland Counties

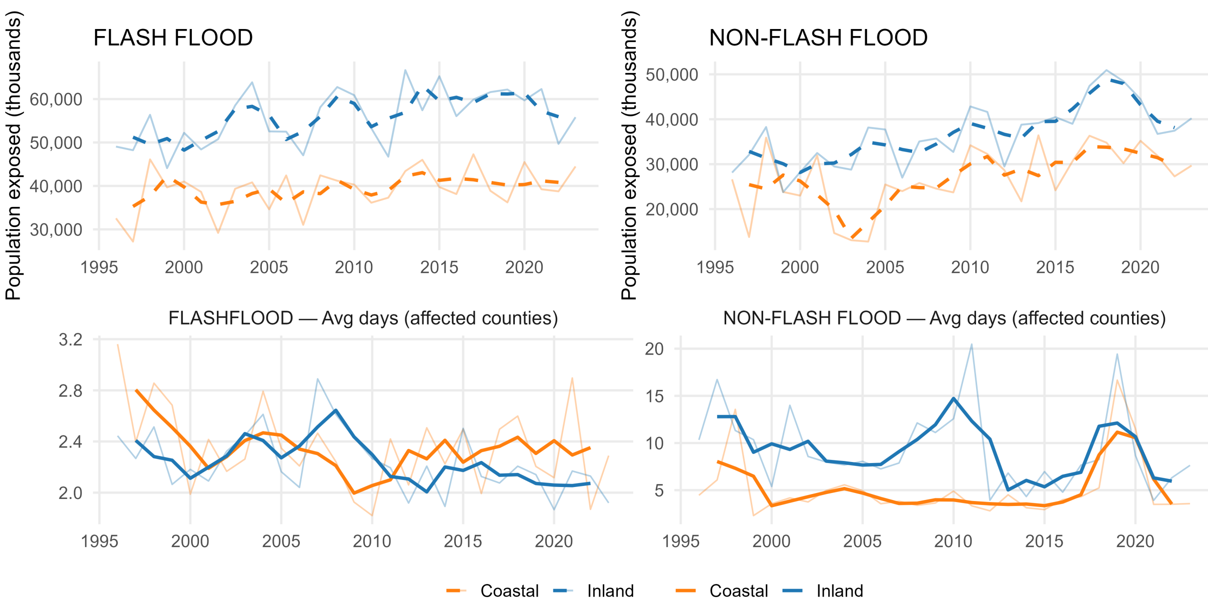
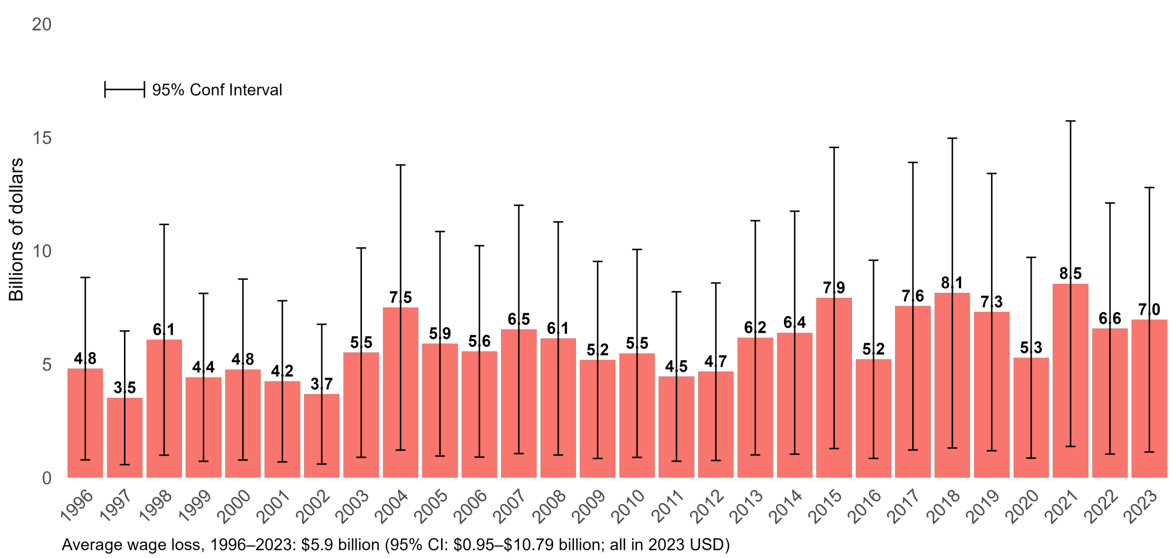


Figure A2: Annual Wage Losses due to Flash Flooding (Real 2023$)



Notes: To calculate the total wage losses, we use our preferred estimate of one additional day of flash flood in a quarter reducing local wage bill by 0.15% (column (5) of table 1). We use this to construct counterfactual wages with the hazard turned-off or under no-flash flood scenario, compute the implied losses and then aggregate to the calendar year. The standard errors are computed using the delta method.

Table A2: Effect of Flash and Non-Flash Floods Days on Private Employment and Wages in Specific Industries

Dep. Vars.:	log(Emp.)				log(Tot.Wages)			
	Trade, Transpt. Utilities	Retail	Leisure & Hospitality	Construction	Trade, Transpt. Utilities	Retail	Leisure & Hospitality	Construction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Flash Flood	-0.106*	-0.124**	-0.159**	-0.225**	-0.114	-0.126**	-0.246***	-0.441***
	(0.056)	(0.050)	(0.073)	(0.098)	(0.070)	(0.058)	(0.087)	(0.125)
Non-Flash Flood	-0.012	-0.007	-0.023	-0.053**	-0.010	-0.005	-0.033	-0.068**
	(0.019)	(0.014)	(0.020)	(0.025)	(0.020)	(0.016)	(0.025)	(0.030)
Observations	346,157	340,503	337,409	305,721	346,157	340,503	337,409	305,721
St×Qtr×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

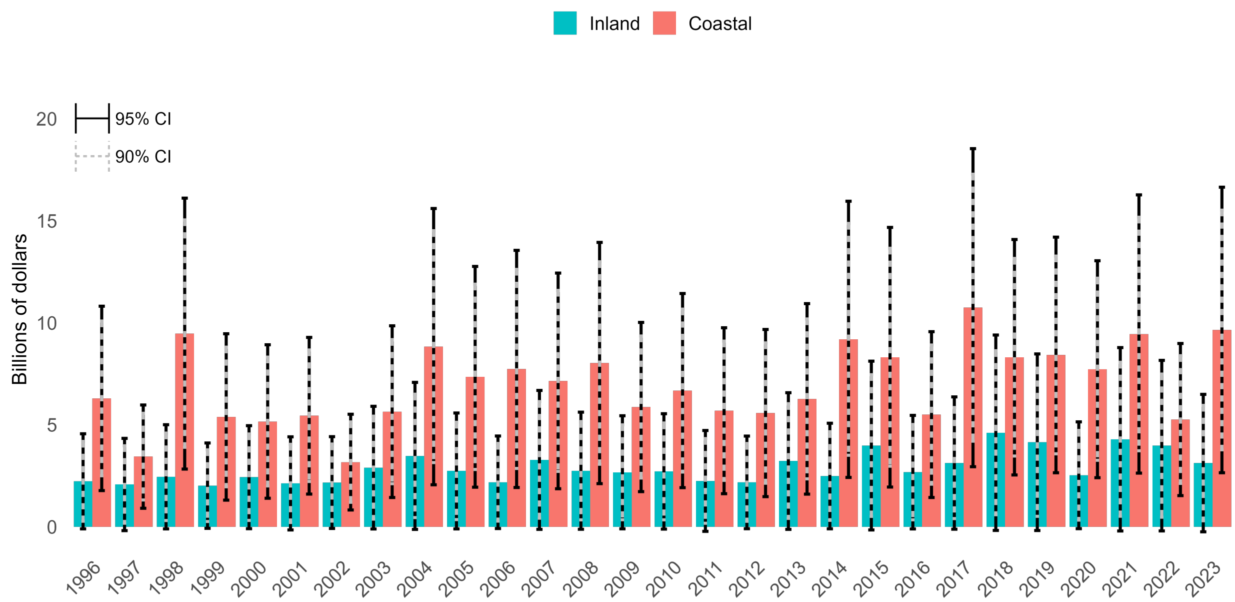
Notes: Controls include average precipitation and average temperature. All specifications include county and state×quarter×year fixed effects. All coefficients and standard errors have been multiplied by 100. Clustered (county- level) standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: Effect of Flash Flood and Non-Flash Flood Days on Establishments

	Log(Establishments)		
	Total	Goods-Producing	Service-Providing
	(1)	(2)	(3)
Flash Flood	0.0001	-0.075*	0.002
	(0.040)	(0.045)	(0.043)
Non-Flash Flood	0.006	0.015	0.005
	(0.007)	(0.012)	(0.008)
Observations	345,797	343,489	344,445
St×Qtr×Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes

Notes: Controls include average precipitation and average temperature. All specifications include county and state×quarter×year fixed effects. All coefficients and standard errors have been multiplied by 100. Clustered (county- level) standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure A3: Annual wage losses due to Flash Floods + Non-Flash Floods, by Inland and Coastal counties (Real, $ 2023)



Notes: Here we use the flash and non-flash flood estimates in column (2) of table 4 and use the observed number of flash and non-flash flood days in each county-quarter and by inland and coastal counties to construct the counterfactual (hazard days set to zero) and sum the implied dollar losses to the year. The standard errors are computed using the delta method.

Figure A4: High-Slack Counties based on Past Quarter Unemployment Rate

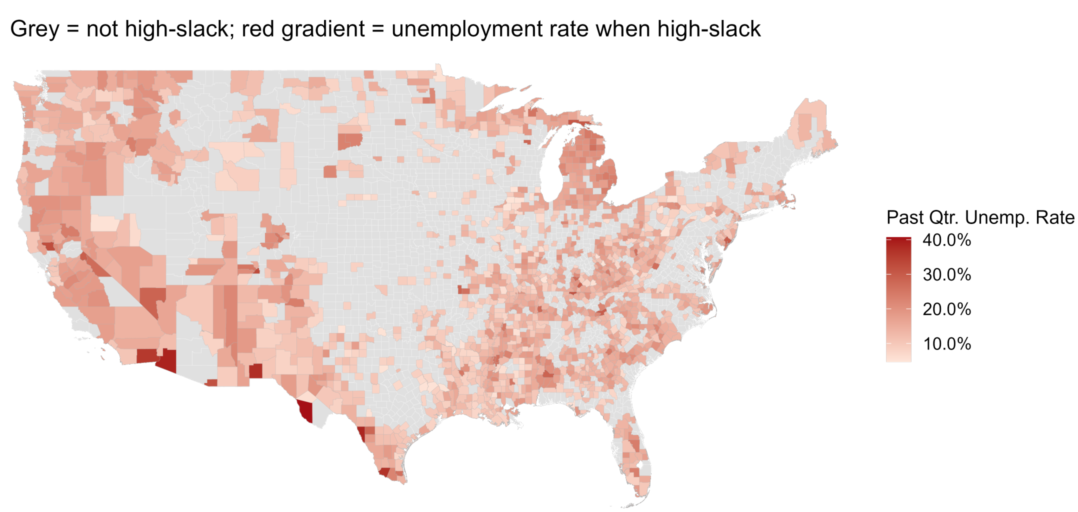


Table A4: Heterogeneous Effect by High-Low Slack Counties

Dependent Variables:	log(Emp.)	log(Tot.Wages)	log(Emp.)	log(Tot.Wages)	log(Emp.)	log(Tot.Wages)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Flash Flood	-0.111**	-0.126**	-0.107**	-0.116*	-0.119**	-0.138**
	(0.052)	(0.063)	(0.049)	(0.059)	(0.048)	(0.059)
Non-Flash Flood	0.0004	0.001	-0.004	-0.004	0.004	0.005
	(0.010)	(0.012)	(0.008)	(0.010)	(0.009)	(0.011)
Flash Flood × High Slack	-0.285	-0.445*				
(=1 if Past Qtr. Unemp. > 90th perc.)	(0.176)	(0.244)				
Non-Flash Flood × High Slack	-0.095*	-0.112**				
(=1 if Past Qtr. Unemp. > 90th perc.)	(0.051)	(0.054)				
Flash Flood × High Slack			-0.738***	-1.07***		
(=1 if *all* Past 4 Qtrs. Unemp. > 90th perc.)			(0.244)	(0.343)		
Non-Flash Flood × High Slack			-0.189***	-0.199***		
(=1 if *all* Past 4 Qtrs. Unemp. > 90th perc.)			(0.067)	(0.072)		
Flash Flood × High Slack					-0.848***	-1.02**
(=1 if *all* Past 8 Qtrs. Unemp. > 90th perc.)					(0.325)	(0.451)
Non-Flash Flood × High Slack					-0.285***	-0.307***
(=1 if *all* Past 8 Qtrs. Unemp. > 90th perc.)					(0.071)	(0.087)
$FlashFlood_{t-1}$	✓	✓				
$Non-FlashFlood_{t-1}$	✓	✓				
Cumulative Flash Floods- Past 4 Qtrs.			✓	✓		
Cumulative Non-Flash Floods- Past 4 Qtrs.			✓	✓		
Cumulative Flash Floods- Past 8 Qtrs.					✓	✓
Cumulative Non-Flash Floods- Past 8 Qtrs.					✓	✓
Net Effect- Flash Flood in High Slack Counties	-0.396**	-0.571**				
	(0.177)	(0.244)				
Net Effect- Flash Flood in High Slack Counties			-0.844***	-1.188***		
			(0.244)	(0.343)		
Net Effect- Flash Flood in High Slack Counties					-0.967***	-1.161***
					(0.321)	(0.448)
Net Effect- Non-Flash Flood in High Slack Counties	-0.095**	-0.111**				
	(0.048)	(0.051)				
Net Effect- Non-Flash Flood in High Slack Counties			-0.192***	-0.204***		
			(0.064)	(0.069)		
Net Effect- Non-Flash Flood in High Slack Counties					-0.281***	-0.302***
					(0.069)	(0.084)
Observations	342,678	342,678	333,405	333,405	321,013	321,013
St×Qtr×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In columns (1) and (2) the High Slack indicator variable takes value 1 if in the past quarter the unemployment rate in the county was above the 90th percentile of the national distribution over the same quarter-year, and 0 otherwise. Alternatively for columns (3) and (4), counties are classified as high-slack if unemployment exceeded 90th percentile in each of the past four quarters, and finally in columns (5) and (6) counties are classified as high-slack if unemployment exceeded 90th percentile in each of the past eight quarters. Controls include average precipitation and average temperature. Additionally, we control for past quarter flash floods and non-flash floods in columns (1) and (2), cumulative flash flood and non-flash flood exposures in past-4 quarters in columns (3) and (4) and cumulative flash flood and non-flash flood exposures in past-8 quarters in columns (5) and (6). All specifications include county and state×quarter×year fixed effects. All coefficients and standard errors have been multiplied by 100. Clustered (county- level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Coastal vs. Inland: Differences in Share of Quarters with High-Slack Status

Variable	Mean (Inland)	Mean (Coastal)	Diff	p-value	Sig.
Past qtr. unemployment above 90th percentile	0.10	0.11	0.01	0.372	
Past 4 qtrs. unemployment above 90th percentile	0.05	0.04	-0.01	0.125	
Past 8 qtrs. unemployment above 90th percentile	0.04	0.02	-0.01	0.040	**

Notes: Entries are means of county-level indicators. Each county value is the fraction of quarters in the panel for which the high-slack indicator equals 1. p-values are from two-sample t-tests comparing coastal to inland counties. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Table A6: Heterogeneous Effect by High-Low Poverty and Median Income

Dependent Variables: Model:	log(Emp.) (1)	log(Tot.Wages) (2)	log(Emp.) (3)	log(Tot.Wages) (4)
Variables				
Flash Flood	-0.131***	-0.121**	-0.119**	-0.106*
	(0.049)	(0.059)	(0.049)	(0.059)
Non-Flash Flood	0.003	0.003	0.003	0.006
	(0.008)	(0.010)	(0.008)	(0.010)
Flash Flood × High Poverty	-0.065	-0.438		
	(0.192)	(0.300)		
Non-Flash Flood × High Poverty	-0.080**	-0.080		
	(0.038)	(0.055)		
Flash Flood × Low Median Income			-0.221	-0.656**
			(0.207)	(0.316)
Non-Flash Flood × Low Median Income			-0.104**	-0.135**
			(0.042)	(0.053)
Cumulative Flash Flood- Past 8 Qtrs.	✓	✓	✓	✓
Cumulative Non-Flash Flood- Past 8 Qtrs.	✓	✓	✓	✓
Net Effect - Flash Flood in	-0.196	-0.559*		
High Poverty Counties	(0.185)	(0.291)		
Net Effect - Non-Flash Flood in	-0.077**	-0.078		
High Poverty Counties	(0.036)	(0.053)		
Net Effect - Flash Flood in			-0.340*	-0.761**
Low Median-Income Counties			(0.200)	(0.306)
Net Effect - Non-Flash Flood in			-0.101**	-0.129***
Low Median-Income Counties			(0.040)	(0.050)
Observations	320,941	320,941	320,941	320,941
St×Qtr×Year FE	Yes	Yes	Yes	Yes
FIPS FE	Yes	Yes	Yes	Yes

Notes: High Poverty is a time-varying classification (indicator variable=1) based on whether a county's poverty rate (including all ages) in the *previous year* is above the 90th percentile of the national county-level poverty distribution in that year, the indicator variable takes value 0 otherwise. Similarly, Low Median Income is a time-varying classification (indicator variable=1) based on whether a county's median household income in the *previous year* is below the 10th percentile of the national county-level median income distribution in that year, the indicator variable takes value 0 otherwise. Controls include average precipitation and average temperature. All specifications include county and state×quarter×year fixed effects. Additionally, we control for cumulative flash flood and non-flash flood exposure in the past-8 quarters. All coefficients and standard errors have been multiplied by 100. Clustered (county- level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Effect of Flash Flood and Non-Flash Flood Days on Total Private Employment and Wages

Dependent Variables:	log(Emp.) (1)	log(Total Wages) (2)
Flash Flood	-0.116**	-0.140**
	(0.053)	(0.065)
Non-Flash Flood	-0.008	-0.008
	(0.011)	(0.014)
Thunderstorm	-0.066	-0.085
	(0.044)	(0.052)
Observations	345,797	345,797
St×Qtr×Year FE	Yes	Yes
County FE	Yes	Yes

Notes: Controls include average precipitation and average temperature. All specifications include county and state×quarter×year fixed effects. All coefficients and standard errors have been multiplied by 100. Clustered (county- level) standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A8: Effect of Flash Flood and Non-Flash Flood Days on Total Private Employment and Wages (Commuting-Zone (CZ) level analysis)

Dependent Variables:	log(Emp.) (1)	log(Total Wages) (2)
Flash Flood	-0.142***	-0.225***
	(0.040)	(0.052)
Flood	-0.0006	0.002
	(0.010)	(0.014)
Observations	80,740	80,740
Commuting-Zone (CZ) FE	Yes	Yes
Census Division×Qtr×Year FE	Yes	Yes

Notes: Controls include average precipitation and average temperature. All specifications include commuting-zone and census-division×quarter×year fixed effects. All coefficients and standard errors have been multiplied by 100. Clustered (CZ- level) standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A9: Effect of Flash Flood and Non-Flash Flood Days on Total Private Employment and Wages (with Spatially robust Conley Standard Errors)

Dependent Variables:	log(Emp.) 25 km (1)	log(Emp.) 50 km (2)	log(Emp.) 75 km (3)	log(Emp.) 100 km (4)	log(Tot. Wages) 25 km (5)	log(Tot. Wages) 50 km (6)	log(Tot. Wages) 75 km (7)	log(Tot. Wages) 100 km (8)
Flash Flood	-0.126**	-0.126**	-0.126**	-0.126*	-0.153**	-0.153**	-0.153**	-0.153*
	(0.053)	(0.058)	(0.064)	(0.070)	(0.065)	(0.070)	(0.078)	(0.085)
Non-Flash Flood	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008
	(0.012)	(0.011)	(0.013)	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)
Observations	345,797	345,797	345,797	345,797	345,797	345,797	345,797	345,797
St×Qtr×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FIPS FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Controls include average precipitation and average temperature. All specifications include county and state×quarter×year fixed effects. All coefficients and standard errors have been multiplied by 100. Spatially robust Conley standard errors in parentheses. Columns (1) and (5) use a spatial cutoff of 25 km, (2) and (6) use 50 km, (3) and (7) use 75 km and (4) and (8) use 100 km cutoff. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Controlling for Rainfall Anomalies

Dependent Variables:	log(Emp.) (1)	log(Emp.) (2)	log(Emp.) (3)	log(Emp.) (4)	log(Tot. Wages) (5)	log(Tot. Wages) (6)	log(Tot. Wages) (7)	log(Tot. Wages) (8)
Variables								
Flash Flood	-0.127**	-0.128**	-0.125**	-0.122**	-0.154**	-0.153**	-0.151**	-0.147**
	(0.053)	(0.053)	(0.054)	(0.053)	(0.065)	(0.066)	(0.066)	(0.066)
Non-Flash Flood	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008
	(0.011)	(0.011)	(0.011)	(0.011)	(0.014)	(0.014)	(0.014)	(0.014)
#Days $\geq$ 1-inch Rain	✓				✓			
#Days $\geq$ 50mm Rain		✓				✓		
#Days $\geq$ 75mm Rain			✓				✓	
#Days $\geq$ 100mm Rain				✓				✓
Observations	345,797	345,797	345,797	345,797	345,797	345,797	345,797	345,797
St×Qtr×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FIPS FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Other controls include average precipitation and average temperature. All specifications include county and state×quarter×year fixed effects. All coefficients and standard errors have been multiplied by 100. Clustered (county- level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A11: Heterogeneous Effect by High Damage Reported Quarters & FEMA Declared Emergency Quarters

Dependent Variables:	log(Emp.) (1)	log(Tot.Wages) (2)	log(Emp.) (3)	log(Tot.Wages) (4)
Variables				
Flash Flood	-0.136**	-0.151**	-0.108**	-0.120*
	(0.055)	(0.068)	(0.053)	(0.066)
Non-Flash Flood	-0.008	-0.008	-0.010	-0.012
	(0.012)	(0.015)	(0.014)	(0.017)
Flash Flood × High Damage Reported	0.079	-0.015		
(*=1 if Reported Damages> 90th perc.*)	(0.068)	(0.086)		
Non-Flash Flood × High Damage Reported	-0.0002	0.0009		
(*=1 if Reported Damages> 90th perc.*)	(0.016)	(0.019)		
Flash Flood × FEMA Declared Emergency			-0.243**	-0.436***
(*=1 if a Qtr. in FEMA Declared Flood Disaster*)			(0.121)	(0.148)
Non-Flash Flood × FEMA Declared Emergency			0.012	0.018
(*=1 if a Qtr. in FEMA Declared Flood Disaster*)			(0.020)	(0.024)
Net Effect - Flash Flood in	-0.057	-0.166*		
High Damage Reported	(0.074)	(0.091)		
Net Effect - Non-Flash Flood in	-0.008	-0.007		
High Damage Reported	(0.016)	(0.019)		
Net Effect- Flash Flood in			-0.351***	-0.556***
FEMA Declared Emergency			(0.128)	(0.154)
Net Effect- Non-Flash Flood in			0.001	0.006
FEMA Declared Emergency			(0.015)	(0.019)
Observations	345,797	345,797	345,797	345,797
St×Qtr×Year FE	Yes	Yes	Yes	Yes
FIPS FE	Yes	Yes	Yes	Yes

Notes: High-Damage Reported indicator takes value 1 if a county's reported damages in a given year-quarter exceeded 90th percentile of the positive-damages distribution over 1996-2023, and 0 otherwise. FEMA Declared Emergency indicator is set to 1 for county-year-quarters that overlap with a FEMA or Presidentially declared flood disaster period, and 0 otherwise. Controls include average precipitation and average temperature. All specifications include county and state×quarter×year fixed effects. All coefficients and standard errors have been multiplied by 100. Clustered (county- level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure A5: Placebo Analysis- Within County

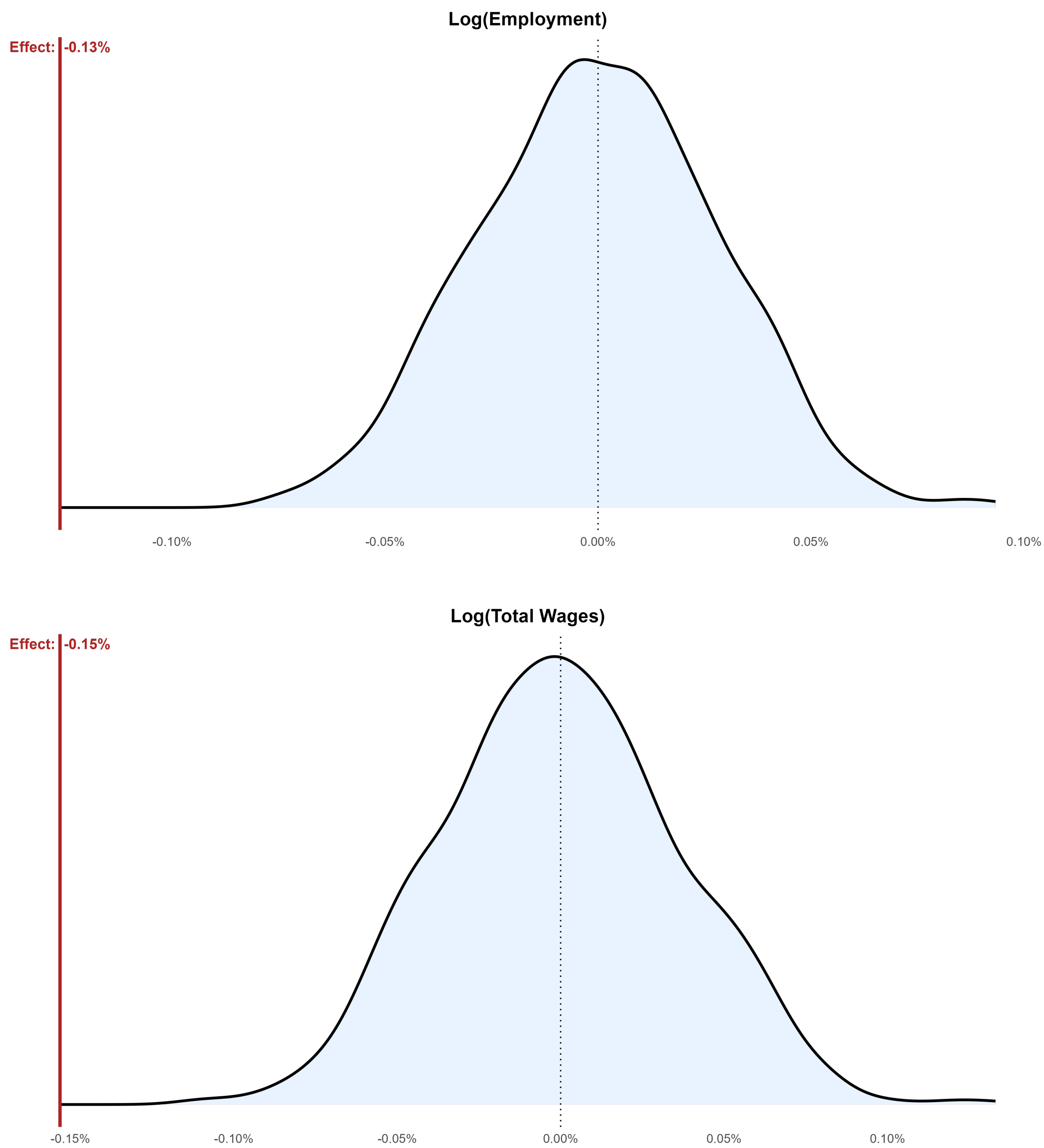


Figure A6: Placebo Analysis- Within State-Quarter-Year