The (Macro)Economic Impact of Natural Disasters*

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Abstract

We estimate the dynamic causal effects of natural disasters using high-frequency data at the U.S. state level. Our findings indicate that natural disasters temporarily disrupt overall economic activity, with asymmetrical effects across various dimensions of economic performance. Natural disasters are followed by a temporary deterioration in regional labor markets, mobility, exports, business activity, and manufacturing sentiment, while exerting a persistent negative impact on household spending. Additionally, our findings reveal that while natural disasters cause significant economic disruptions at the regional level, their overall impact at the national level remains limited. We also provide historical patterns of natural disasters across time, location, and types since the twentieth century.

Key Words: Climate change; Natural Disasters; Local Projections; Economic Activity.
JEL Codes: E23, F18, O44, Q54, Q56.

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1 Introduction

The growing climate emergency has placed climate change at the forefront of the international political and economic agenda. As the Earth's average temperature continues to rise, the frequency and intensity of natural disasters—such as storms and heatwaves—are expected to increase over the next century (IPCC, 2022). Consequently, quantifying the economic impact of natural disasters has become a critical priority for policymakers and central banks worldwide, enabling them to design *ex-ante*, *in-situ*, and *ex-post* policies.[1]

While empirical evidence on the economic effects of temperature shocks has grown substantially in recent years (e.g., Dell et al., 2012, 2014; Kahn et al., 2021; Bilal and Känzig, 2024; Kim, 2024), less is known about the impacts of extreme climate-related events, such as natural disasters, on economic activity. What are the economic consequences of natural disasters? Do their effects on economic performance tend to be transitory or persistent? How do they influence labor market outcomes, mobility, exports, expectations, business activity, and household spending?

In this paper, we address these questions by presenting novel evidence on the dynamic causal effects of natural disasters, using high-frequency data at the U.S. state level.[2] Leveraging weekly regional panel data within a local projection framework, we analyze how economic activity responds in the aftermath of natural disasters. Our findings show that natural disasters temporarily disrupt weekly economic conditions, resulting in a short-term decline in overall economic performance.

At the state level, overall economic activity declines immediately following natural disasters but typically rebounds to its pre-disaster average within 20 weeks (approximately five months). This pattern is primarily driven by storms, whereas recovery from floods and wildfires takes significantly longer—often extending up to 40 weeks (around ten months). Moreover, while the economic impact of natural disasters generally dissipates within a year, the severity of this impact largely depends on the scale of the event. Notably, the most severe natural disasters—those in the top 1% in terms of fatalities—exert an economic shock nearly ten times greater than that of an average natural disaster.

[1] Recent bulletins from the ECB (ECB, 2025) and the BIS (Ehlers et al., 2025) underscore central banks' increasing concern about quantifying the impact of natural disasters.

[2] To track the dynamic negative effects of natural disasters, we use a recently developed indicator of U.S. state-level economic conditions by Baumeister et al. (2024). This weekly indicator provides a comprehensive measure of state-level economic performance, capturing various dimensions of economic activity, including mobility, labor market dynamics, real output, expectations, financial conditions, and household spending (e.g., credit and debit card transactions).

These findings suggest that while the economic effects of natural disasters are generally short-lived, recovery times and overall impact vary significantly depending on the disaster's magnitude and type, with floods and wildfires causing more prolonged economic disruptions than storms.

We also examine the effects of natural disasters on various aspects of economic activity using detailed, disaggregated weekly and monthly data on mobility, labor market outcomes, exports, manufacturing sentiment, business activity, and household spending. Our findings reveal that natural disasters have asymmetric impacts across different dimensions of economic activity. While they cause temporary disruptions in regional labor markets, mobility, business activity, exports, and manufacturing sentiment, they result in a persistent decline in household spending.

Do natural disasters negatively impact state-level economic conditions in a way that is visible nationwide? To address this question, we estimate the impact of an aggregate measure of natural disasters on U.S. weekly economic performance.[3] Our findings indicate that most natural disasters do not significantly affect U.S. weekly economic activity. Only the most severe events—those with fatalities in the top 1%—have a short-term negative impact at the national level. This result implies that although natural disasters have significant economic consequences at the state level, these effects rarely translate into measurable nationwide disruptions.

Finally, we complement our previous analyses by highlighting key patterns of natural disasters in the U.S. We show that natural disasters are unevenly distributed across time, location, and type, with several key insights emerging: (i) the frequency of natural disasters has risen sharply since the 1990s, (ii) storms and floods are the most common types of disasters affecting the U.S., and (iii) the Midwest has experienced relatively lower exposure to natural disasters compared to the Mid-East, with Texas standing out as the state most frequently affected.

The novelty of our approach lies in several key aspects of our dataset and empirical strategy. We argue that detailed, high-frequency, state-level data on natural disasters and economic outcomes is crucial for addressing key empirical challenges in identifying causal effects. By leveraging granular data on natural disasters across the U.S., we capture large-scale, plausibly unexpected events. Moreover, the use of high-frequency regional data helps mitigate concerns about underestimating economic effects due to national-level aggregation—consistent with our findings for the U.S. as a whole—or detecting small or negligible effects because post-disaster public and private responses partially or fully offset the economic impact of natural disasters.

Overall, our findings provide new insights into the increasing frequency of natural disasters

[3] Specifically, we use the U.S. Weekly Economic Conditions Index (ECI) constructed by Baumeister et al. (2024).

and their adverse effects on economic activity. These results emphasize the economic costs of climate change and serve as a warning about the potential consequences of extreme climate-related events.

Related Literature. Our paper contributes to two main strands of literature. First, it relates to studies that assess the economic impact of climate change. A growing body of research has focused on quantifying the effects of temperature-related local and global shocks (e.g., Dell et al., 2012, 2014; Kahn et al., 2021; Bilal and Rossi-Hansberg, 2023; Kim, 2024).[4] The general consensus is that rising temperatures negatively affect economic growth, though the magnitude of this impact varies across studies. For instance, Dell et al. (2012) finds that in developed countries, a 1°C rise in annual temperature reduces economic growth by 1.3 percentage points on average. Similarly, a recent study by Bilal and Känzig (2024) suggests that the macroeconomic damages from climate change may be significantly larger than previously estimated, with a 1°C increase in temperature potentially reducing global GDP by 12%.

In this paper, we build on existing empirical evidence by quantifying the economic impact of extreme climate-related events, such as natural disasters, and highlighting their temporary yet adverse effects on overall economic activity. Our findings indicate that natural disasters cause a short-term decline in regional labor markets, mobility, exports, and manufacturing sentiment, while having a lasting negative impact on household spending. Furthermore, we show that the most severe natural disasters can profoundly destabilize regional economic activity across all dimensions.

To the best of our knowledge, only a few studies have examined the macroeconomic impact of natural disasters (e.g., Noy, 2009; Fomby et al., 2013; Cavallo et al., 2013; Von Peter et al., 2024). These studies generally find that natural disasters have long-lasting effects on aggregate country-level economic activity, though the extent of the impact varies based on factors such as a country's level of economic development (Noy, 2009), the type of disaster (Fomby et al., 2013), its magnitude (Cavallo et al., 2013), and the presence of risk transfer mechanisms (Von Peter et al., 2024).[5] While these studies provide valuable insights into the national-level effects of natural disasters, they are limited by their reliance on cross-country comparisons and low-frequency

[4]Most of these studies rely on low-frequency annual data to assess the impact of temperature shocks on various aspects of economic activity, including economic growth. The only exception is Kim (2024), who uses quarterly data.

[5]For example, Von Peter et al. (2024) find that risk transfer mechanisms, such as insurance, can mitigate or even reverse the negative economic effects of natural disasters. Their analysis suggests that the observed negative impact on economic growth primarily arises from uninsured disasters.

data.[6]

In this paper, we demonstrate that regional high-frequency data is essential for accurately estimating the true impact of natural disasters on economic activity. Our findings indicate that the effects of natural disasters are evident at the regional level but not nationwide, and that the negative impact on overall economic activity largely dissipates within a year.[7] In addition, we provide novel evidence documenting, for the first time, how these disasters affect various dimensions of economic activity, including labor market outcomes, mobility, exports, household spending, business activity, and manufacturing sentiment.

Second, we contribute to the broader literature that uses high-frequency data to study the rapid transmission of economic shocks across different sectors of the economy (Ganong and Noel, 2019; Andersen et al., 2022, 2023; Grigoli and Sandri, 2022; Buda et al., 2023; Chetty et al., 2024). This body of research leverages daily or weekly data to estimate how quickly various economic variables respond to shocks, such as changes in monetary policy, job losses, unemployment insurance (UI) benefits, or the COVID-19 pandemic. For example, Buda et al. (2023) investigates the transmission of monetary policy shocks and finds that sales, consumption, and employment react within one week. Similarly, Chetty et al. (2024) constructs a high-frequency database on spending, employment, and other outcomes, providing near real-time insights into the effects of the COVID-19 pandemic and related policy measures.

This paper builds on this approach by using high-frequency data to show that natural disasters have an immediate and negative impact on multiple economic dimensions—including overall activity, labor market outcomes, exports, manufacturing sentiment, and household spending—within the same week. While most of these effects fade within a year, household spending remains persistently affected.

Outline. The remainder of this paper is structured as follows: Section 2 describes the data and outlines historical patterns of natural disasters in the U.S. across time, regions, and disaster types. Section 3 introduces the empirical methodology and explains the identification strategy. Section 4 presents our baseline results on the effects of natural disasters on economic activity.

[6] This limitation is particularly evident in Fomby et al. (2013), whose findings—based on annual country-level data—yield some puzzling results, including evidence suggesting that certain natural disasters may have a positive impact on economic activity.

[7] Our findings are consistent with those of Jacobson et al. (2022) and Baumeister et al. (2024). Jacobson et al. (2022) demonstrate that temporal aggregation bias plays a significant role in explaining the price puzzle commonly observed when estimating the effects of monetary policy shocks on inflation. Similarly, Baumeister et al. (2024) highlights the importance of weekly data in accurately assessing the benefits of the Paycheck Protection Program during the COVID-19 pandemic.

This section also examines the heterogeneous impacts of natural disasters and provides additional evidence on their effects at the national level. Finally, Section 5 concludes.

2 Data and Historical Patterns of Natural Disasters

We use the EM-DAT database to identify state-level natural disasters in the U.S. The EM-DAT database, maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the Catholic University of Louvain, provides historical records of major disasters globally. It documents more than 26,000 mass disasters worldwide, covering events from 1900 to the present. The data is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutions, and press agencies.[8] The EM-DAT data is publicly accessible on CRED's website: www.cred.be.

CRED defines a disaster as a natural event that exceeds local response capacity and requires external assistance. The EM-DAT database records natural disasters when they meet at least one of the following criteria and are officially reported by authorities: (i) 10 or more fatalities, (ii) 100 or more people affected, (iii) a state of emergency declared, or (iv) a request for international assistance.

The database provides detailed information on each event, including the disaster type, location, start date (on a daily basis), and additional data such as the number of fatalities, injuries, people made homeless, and those affected, as well as estimated direct economic damages based on harm to infrastructure, property, and livelihoods.[9]

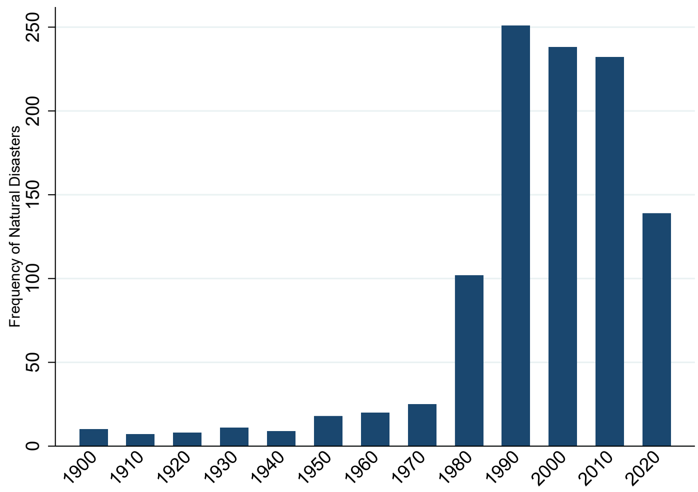
In this section, we analyze data on all natural disasters affecting the U.S. since 1900 and present key trends related to their frequency by decade, type, and state.

Frequency of natural disasters by decade. Figure 1 illustrates the number of natural disasters in the US by decade from 1900 to 2024. The data reveal a dramatic increase in the frequency of natural disasters since the 1990s. Notably, over 80% of all recorded natural disasters since 1900 have occurred within the past three to four decades. This significant observation underscores the sharp rise in disaster frequency in recent years, suggesting that these events may represent a critical adverse consequence of climate change.

[8] Disasters in the database are classified using the Disaster Loss Data (DATA) Peril Classification and Hazard Glossary developed by the Integrated Research on Disaster Risk (IRDR). This classification system standardizes disaster definitions and typologies across different databases.

[9] The reported damages in the database include only direct damages (e.g., destruction of infrastructure, crops, and housing).

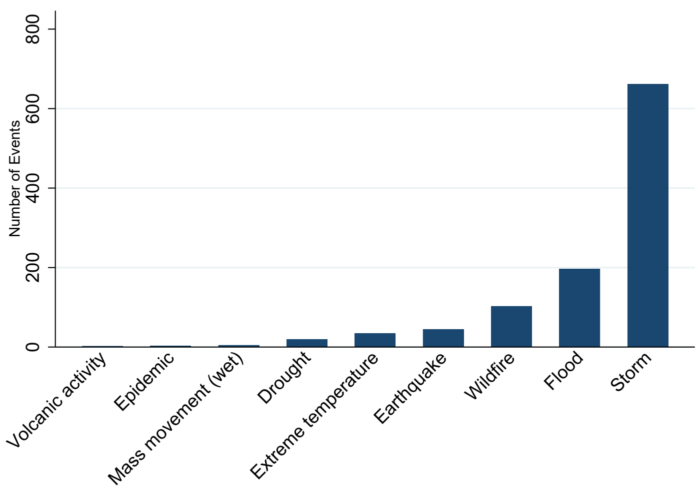
Figure 1: Frequency of natural disasters by decade.



Notes: This graph shows the number of natural disasters per decade. Sample 1900-2024

Frequency of natural disasters by type. Figure 2 presents the total number of events for each type of natural disaster from 1900 to 2024. The data reveal that storms and floods constitute the majority of disasters affecting US states. In contrast, wildfires, earthquakes, extreme temperature events, droughts, mass movements, epidemics, and volcanic activity account for only a small fraction of the total. Notably, storms and floods account for approximately 80% of all natural disasters in the U.S., while all other categories combined make up the remaining 20%.

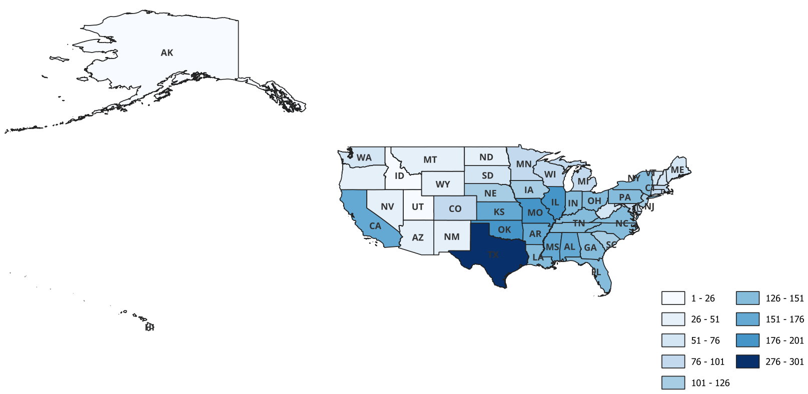
Figure 2: Frequency of natural disasters by type.



Notes: This graph shows the frequency of natural disasters by type. Sample 1900-2024.

Frequency of natural disasters by state. Figure 3 presents the geographical distribution of natural disasters across US states from 1900 to 2024.[10] Natural disasters in the US show a clear regional imbalance. The Mid-East consistently experiences more natural disasters than the Mid-West. Texas stands out as the most severely affected state, with almost 300 natural disasters recorded since the early 20th century. Missouri, Illinois, and Oklahoma also report significant activity, averaging around two disasters per year. On the West Coast, California ranks as the most frequently impacted state, with an average of nearly one disaster per year. In contrast, Louisiana and Alaska have been less exposed to natural disasters, recording fewer than 15 events over the past century.

Figure 3: Frequency of natural disasters by state.



Notes: This graph shows the spatial distribution of natural disasters across US states. Sample 1900-2024.

3 Empirical Methodology and Identification

In this section, we present our overarching empirical framework. We describe our empirical approach to estimating the dynamic effects of natural disasters on economic activity and explain how we identify unanticipated natural disasters to estimate the causal effects of these events.

[10]Given the lower frequency of disasters before the 1980s, we note that the map looks very similar in our effective sample starting in 1987.

3.1 Empirical Methology

In this paper, we use high-frequency data to examine the economic consequences of natural disasters at the US state level. We estimate the dynamic effects of natural disasters on economic activity in two steps. First, we estimate the dynamic aggregate effects of these disasters by analyzing their economic impact on a measure that captures overall weekly state-level economic performance. Second, we explore the potential heterogeneous effects of natural disasters on economic activity using detailed, disaggregated weekly and monthly data on mobility, labor market outcomes, exports, manufacturing sentiment, business activity, and household metrics, such as credit card spending.

We use data from Baumeister et al. (2024), who introduces a novel indicator featuring a Weekly Economic Conditions Index (ECI) for US states, constructed using a mixed-frequency dynamic factor model. The ECI captures various aspects of state-level economic performance, including mobility, labor market activity, real output, expectations, financial conditions, and household metrics, with each category comprising multiple input series. We use this indicator as our main outcome to track the dynamic negative effects of natural disasters on economic activity.

We analyze how economic activity response to a natural disaster by estimating the following local projections (Jordà, 2005):

$$\Delta^h y_{i,t+h} = \alpha_{i,h} + \beta_h \, \textit{Natural Disaster}_{i,t} + \sum_{l=1}^{4} \Gamma_{h,l} \Delta y_{i,t-l} + \varepsilon_{i,t+h}, \tag{1}$$

where $\alpha_{i,h}$ represents the state fixed effects, $h = 0, 1, 2, 3, \ldots, 40$, and $\textit{Natural Disaster}_{i,t}$ is an indicator that turns on if a natural disaster occurs in state i during week t. We include lags of the dependent variable to control for economic activity prior to the natural disaster at the state level.[11] The coefficient β_h traces the impulse response functions (IRFs) of the Weekly Economic Conditions Index (ECI) at horizon h following a natural disaster realization. We estimate the model using weekly data from 1987w14 to 2024w39.[12] The maximum horizon considered is $h = 40$. For inference, we compute cluster-robust standard errors at the state level.[13]

[11] We also include a temporal pandemic dummy between 2020w10 and 2020w31.

[12] The selection of this sample is determined by the availability of the Weekly Economic Conditions Index (ECI).

[13] See Jordà and Taylor (2024) for a comprehensive discussion on inference in the local projection (LP) framework.

3.2 Natural Disaster Indicator and Identification

In this section, we detail the construction of the *Natural Disaster*$_{i,t}$ indicator and outline our approach for identifying the causal effects of natural disasters on economic activity.

Building the State-Level Natural Disaster Indicator. We construct our natural disaster indicator, *Natural Disaster*$_{i,t}$, using data from the EM-DAT database. Specifically, we identify the week and location of each disaster to create an indicator variable that marks whether a natural disaster occurs in a given state during a specific week.[14] Building on the empirical evidence from the previous section, we focus on storms and floods, which together account for over 80% of all disasters impacting the US. This approach emphasizes including the most common and comparable disasters while excluding rare events from our main disaster indicator, thereby reducing the risk of outlier-driven distortions in our estimates. Moreover, when constructing our natural disaster indicator, we focus on events where the number of deaths exceeds the historical median for two key reasons.[15] First, this approach allows us to capture the impact of major natural disasters while excluding minor events with little to no economic effect. Second, as explained below, disasters with historically high death tolls are more likely to be unexpected—a key factor for identifying the causal effects of natural disasters. As a result, our baseline measure of natural disasters includes 1,524 state-level events.

We perform several robustness checks to ensure our results are not driven by these choices. First, we create a natural disaster indicator that encompasses all disaster types beyond storms and floods. Second, we separately analyze storms, floods, and wildfires—the three most common natural disasters in the U.S. Third, we develop alternative measures of large-scale disasters by considering total direct damage and the number of affected states. These sensitivity analyses are discussed in detail in Section 4.2.

Additionally, in our main analyses, we present results not only for our baseline measure of natural disasters but also for all disasters—without restrictions on fatalities—and for the most severe events, defined as those in the top 1% of fatalities.

[14] We define our indicator as a dummy variable activated when at least one natural disaster occurs in a specific state during a given week. Notably, more than 95% of natural disasters do not overlap with multiple disasters in the same state and week.

[15] In practice, our *Natural Disaster*$_{i,t}$ indicator is set to 1 when, in a given week and state, a storm or flood occurs, and the number of reported deaths exceeds 10.

Causality. Local projections, by themselves, do not solve the problem of identification.[16] The impulse response defined in Equation 2 represents a counterfactual difference in mean outcomes:

$$R_{sy}(h,\delta) \equiv \mathbb{E}[y_{t+h}|s_t = s_0 + \delta; \mathbf{x}_t] - \mathbb{E}[y_{t+h}|s_t = s_0; \mathbf{x}_t], \quad h = 0, 1, \ldots, H,$$

where $s_t \in 0, 1$ and $s_t = \textit{Natural Disaster}_t$ in our framework. The key to identification is to establish how interventions in s_t are determined. In particular, identification requires that the variation in s_t is as good as random so that disasters are uncorrelated with the residuals in Equation 2. While there is no reason to believe that natural disasters can be systematically correlated with other omitted factors affecting state-level economic activity, we argue that the use of high-frequency state-level data is crucial to address some empirical challenges in identifying the causal effects of natural disasters.

Predictability of Natural Disasters. One important concern is that some natural disasters may be partially or fully anticipated. The predictability of natural disasters implies that economic agents can react in anticipation of forthcoming natural disasters. Therefore, the specification of Equation 2 would suffer from downward bias, as anticipated natural disasters may have a very different effect from non-anticipated ones.[17] To address this concern, Panel (a) plots the time-series evolution of economic conditions during the four weeks preceding natural disasters, using data from all recorded disasters in our sample. If natural disasters were truly random and unpredictable, we would expect to observe a wide range of economic trajectories prior to their occurrence. In some instances, a disaster would strike when economic conditions—measured by our weekly economic indicator—are historically strong, in others when conditions are weak, and most commonly when conditions are close to historical norms.

This is precisely what Panel (a) of Figure 4 illustrates: we observe a variety of economic trajectories prior to natural disasters, with most disasters occurring during normal periods when weekly economic conditions are slightly below, slightly above, or near zero.[18] Furthermore, the series exhibits a symmetric pattern, suggesting that disasters are equally likely to occur during periods of both highly favorable and unfavorable economic conditions. If anticipation were a

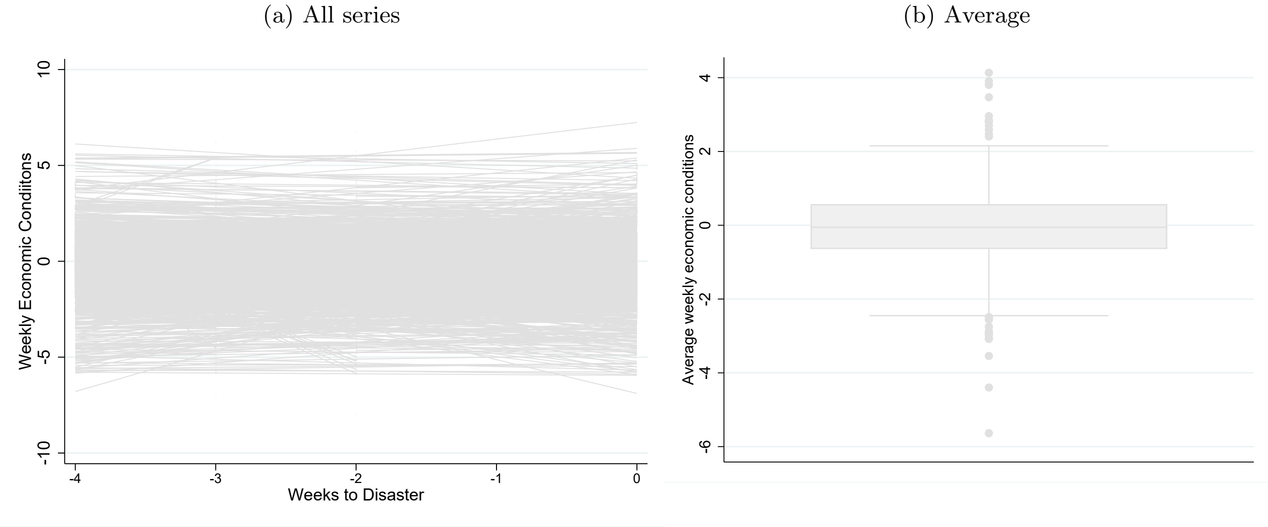
[16] We build on Jordà and Taylor (2024) to explain causality in our framework. For simplicity, we omit the subscript i, denoting different states, given the panel structure of our data.

[17] In particular, if a natural disaster is anticipated, it is expected to have a smaller, temporary effect on economic activity.

[18] The Weekly Economic Conditions Index (ECI) from Baumeister et al. (2024) has a mean close to zero by state across the entire sample.

factor, we would expect to see a systematic decline in economic conditions in the weeks leading up to disasters. However, the lack of such a pattern indicates that disaster anticipation is not a significant concern in our sample.[19]

Figure 4: Weekly Economic Conditions Before Natural Disasters



Notes: Panel (a) illustrates the time-series evolution of economic conditions during the four weeks preceding natural disasters, using data from all recorded natural disasters. Panel (b) presents the distribution of average economic conditions over the same four-week period. The box-and-whisker plot highlights the median (the central line within the box), the 25th and 75th percentiles (the lower and upper box boundaries), and the lowest and highest adjacent values of the pre-disaster weekly economic conditions, respectively.

Panel (b) of Figure 4 reinforces this finding by showing the average weekly economic conditions during the four weeks leading up to disasters across all events in our sample. Consistent with Panel (a), most disasters cluster around zero, with similar outliers appearing on both the positive and negative ends. To further ensure that our analysis excludes anticipated disasters, our baseline specification focuses on natural disasters with historically high death tolls, capturing events that are more likely to be unexpected.

State-Level Data. Another important issue is the level of data aggregation. Most studies on natural disasters rely on panel data from aggregate economies, which presents a significant limitation. Natural disasters typically impact only one or a few states within the US, meaning that using aggregate country-level data can underestimate their effects. This occurs because economic activity in unaffected regions may remain stable, offsetting the negative impact of the

[19] We also conduct a formal test to determine whether economic conditions are systematically different in the week leading up to large, unexpected natural disasters, and we find no evidence to reject the null hypothesis at the conventional 5% significance level.

disaster. The problem is particularly pronounced when disasters affect regions that contribute only a small share of the country's total economic activity. In this paper, we address this limitation by using state-level data, allowing us to accurately identify the regions impacted by each disaster.[20] Consistent with this, in section 4.4, we estimate the dynamic effects of natural disasters using aggregate US economic data and find smaller, statistically insignificant effects.

High-Frequency Data. Another concern is that public and private authorities may partially or fully offset the economic impact of natural disasters in their aftermath. Specifically, insurance payouts, family transfers, and government support to affected households and businesses are expected to be systematically correlated with natural disasters, often in the same direction.[21] Although such offsetting typically occurs with a lag, the existing literature on natural disasters has largely relied on annual data, increasing the likelihood of underestimating or detecting no effects due to this limitation.[22] To address this issue, in this paper, we exploit high-frequency data. By using weekly data, we demonstrate that natural disasters have an immediate impact on economic activity, with the effects dissipating within a year. This finding highlights the limitations of studies that rely on lower-frequency data, which fail to fully capture the real short-term effects of such events.

4 Empirical Results

In this section, armed with our unexpected natural disasters and the empirical framework presented in Section 3, we present results summarizing the causal links between natural disasters and US state-level economic activity. In the second step, we investigate the disaggregate effects of natural disasters on economic activity by exploring their impact on different dimensions of the economy.

[20] Although county- or metropolitan-level data would provide an advantage, high-frequency data at these levels is extremely limited. As we explain in detail in this section, high-frequency data is crucial for accurately estimating the causal effects of natural disasters. State-level data offers a practical balance, allowing for sufficient disaggregation to capture the real effects of natural disasters while ensuring the availability of high-frequency information.

[21] For example, several studies have shown that in developing economies, remittances systematically increase after natural disasters (e.g., Yang, 2008; Beaton et al., 2017; Bettin and Zazzaro, 2018; Babii et al., 2022).

[22] Furthermore, the use of lower-frequency data makes the estimated effects highly sensitive to the timing of the disaster. Events occurring early in the year may be offset by economic responses in subsequent months, leading to underestimated or muted effects.

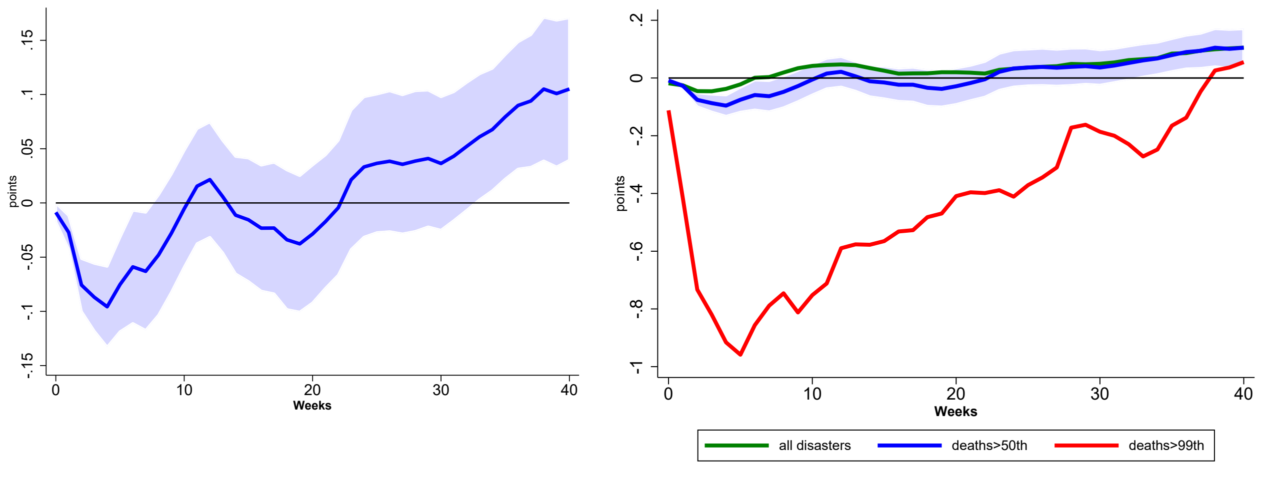
4.1 Effects of Natural Disasters on Aggregate Economic Activity

Figure 5 displays the impulse responses of economic activity—measured by the weekly economic indicator—following a natural disaster across various horizons h. The responses are tracked for up to 40 weeks after the disaster.

Figure 5: Dynamic Response of Economic Activity to a Natural Disaster

(a) Baseline Measure of Natural Disasters

(b) Measure of Natural Disasters by Severity



Notes: Estimated cumulative changes in the Weekly Indicator Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 2, ..., 40$, following a natural disaster. In panel (a) natural disasters include all storms and floods with the number of reported deaths above the median. The sample period is 1987w14–2024w39. The shaded area denotes the 68% confidence interval, based on state-level clustered standard errors.

Panel (a) of Figure 5 presents results based on our baseline measure of natural disasters. It shows that natural disasters are followed by a decline in overall weekly economic conditions, with the peak impact occurring 4 to 5 weeks, or roughly 1 month, after the event. Importantly, the effects on economic performance are short-lived, with the economy returning to its pre-disaster average within 20 weeks, or about 5 months, after the shock. This evidence indicates that natural disasters have a temporary negative impact on economic conditions, with the effects fully dissipating within a year.

Panel (b) of Figure 5 extends our baseline analysis from Panel (a) by incorporating two additional measures of natural disasters. First, we construct a natural disaster indicator based on the number of reported storms and floods per week and state, without restricting it to high-fatality events. This indicator captures all storms and floods, regardless of severity. Second, we develop an extreme natural disaster indicator for the most severe events, defined as those in the top 1% of fatalities. For all disasters, we find that the economic impact is smaller, with recovery occurring within 10 weeks. This result is expected, as the indicator includes disasters with minimal fatalities, suggesting that many of the captured events are relatively minor. In contrast, the results for the most severe disasters are striking—natural disasters in the top 1% of fatalities cause economic disruptions over ten times greater than those observed in our baseline measure, which includes disasters with fatalities above the median.

This result highlights that while the negative impact of natural disasters on overall economic performance is generally short-lived, the magnitude of the impact depends on the severity of the disaster. Our findings, therefore, contrast with those of other studies that report long-term declines in output growth based on country-level annual data (e.g., Cavallo et al., 2013; Von Peter et al., 2024).[23]

These differences underscore the advantages of using state-level high-frequency data rather than country-level low-frequency data, which allows for a more precise assessment of both the magnitude and persistence of natural disasters' economic effects. This aligns with Jacobson et al. (2022) and Baumeister et al. (2024), who demonstrate that temporal aggregation bias is a key factor in explaining the price puzzle commonly observed when estimating the effects of monetary policy shocks on inflation (Jacobson et al., 2022) and in accurately assessing the benefits of the Paycheck Protection Program following the COVID-19 pandemic (Baumeister et al., 2024).

While the impulse response functions of the weekly economic index provide valuable insights into the effects of natural disasters on state-level economic performance, the composite nature of the index makes it difficult to measure the precise magnitude of the impact. To address this limitation, Section 4.3 quantifies the effects of natural disasters across key economic dimensions, including mobility, labor market outcomes, exports, expectations, business applications, and household credit and debit card spending.

4.2 Robustness Analyses

Heterogeneity. Our baseline results rely on a single natural disaster indicator that combines both storms and floods. However, these disaster types may have distinct effects on economic activity. To examine this heterogeneity, we construct separate indicators for storms and floods. Additionally, we create an indicator for wildfires, the third most common natural disaster in the

[23] For instance, Cavallo et al. (2013) found that 10 years after a disaster, the GDP per capita of affected countries is, on average, 10% lower than at the time of the disaster. Similarly, Von Peter et al. (2024) reported that major disasters initially reduce growth by 1 to 2 percentage points and, over time, result in an output loss of 2% to 4% of GDP, in addition to the immediate damage to property and infrastructure.

U.S. We then re-estimate our baseline regression, as specified in Equation 2, for each disaster type. The results are presented in Appendix B.

Since storms account for the majority of the variation in our baseline natural disaster measure, the results for storms largely mirror those shown in Figure 5. Following a storm, weekly economic conditions decline and take approximately 20 weeks to recover to their pre-disaster average. In contrast, floods appear to have a more prolonged impact on economic performance, requiring about 40 weeks—twice as long as storms—for conditions to return to their pre-disaster average.[24] Wildfires, meanwhile, have a larger impact on overall economic performance compared to both storms and floods, with the peak effect occurring approximately 30 weeks after the disaster. As with floods, it takes around 40 weeks for economic conditions to return to their pre-disaster average.

All Types of Natural Disasters. We also construct an aggregate natural disaster indicator that includes all types of disasters. Specifically, in this exercise, the indicator takes a positive value for a given week and state if any of the following disasters occur: volcanic activity, epidemic, mass movement, drought, extreme temperature, earthquake, wildfire, flood, or storm, with reported deaths exceeding the median. We then incorporate this aggregate series into our baseline regression, presented in Equation 2. The results, shown in Appendix B, reveal that the effects of including all types of disasters are nearly identical to our baseline results, which focus solely on storms and floods. This finding broadens the empirical evidence on the aggregate effects of natural disasters, confirming that such events negatively impact overall state-level economic performance.

Alternative Measure of Large Natural Disasters. To construct our baseline natural disaster indicator, we use the number of reported deaths as a proxy for large, unexpected natural disasters. In this sensitivity check, we explore two alternative metrics for measuring large disasters. First, we use the number of affected states to capture the disaster's magnitude and construct an indicator that is activated only when the number of affected states exceeds the median. Second, we apply the same approach using reported direct estimated damage. These additional analyses are presented in Appendix B.

Overall, we find that the effects of large natural disasters are consistent with our baseline

[24]Floods are less common in the baseline measure, resulting in wider standard error bands in the estimated impulse responses.

results shown in Figure 5. However, while the trajectory of state-level economic conditions following large natural disasters—measured by the number of affected states—is nearly identical to that of the baseline indicator, the economy appears to recover more quickly, within 10 weeks, when large disasters are measured by the reported total direct damage.

Placebo Exercise. One might wonder whether the results we observe could arise randomly. To address this, Figure B.1 presents the impulse responses from a placebo test in which we randomly reshuffle the timing of natural disasters. Specifically, we assign the week of the natural disaster indicator by drawing from a uniform distribution and estimate the impulse responses using 500 replications.[25] We then plot the median of the point estimates at each forecast horizon, along with the 5th–95th percentile band of the impulse responses across simulations.

As expected, the results show a muted effect of natural disasters on weekly economic activity, indicating that our main findings are not the result of random chance.[26]

COVID-19 pandemic. Our empirical analysis thus far has been based on the full sample period for which the weekly economic indicator is available. However, there may be concerns that including post-pandemic data could influence the results. In our baseline specification, we account for the expected decline in average economic activity following the pandemic outbreak by incorporating a temporal dummy for the period from March to July 2020. As part of this robustness check, we re-estimate our regression, presented in Equation 2, using only data prior to March 2020. When excluding post-pandemic data, we find results that are consistent with our baseline estimates.

4.3 Disaggregate Effects of Natural Disasters

So far, we have shown that natural disasters have a causal, temporary negative impact on overall economic activity. In this section, we examine which specific dimensions of economic activity are most affected and explore the mechanisms behind these effects. To do this, we estimate the post-disaster dynamics of various variables used to construct the weekly economic index from Baumeister et al. (2024). Our analysis focuses on key dimensions of economic activity, including

[25] In each iteration, we randomly set the probability of a natural disaster to 1.5%, consistent with the actual probability of natural disasters in our sample.

[26] Additionally, this placebo test enhances confidence in the Weekly Economic Indicator (ECI) as an outcome measure, as it rules out concerns that the observed results are purely random or driven by the specific methodology used to construct the index.

mobility, labor market outcomes, exports, expectations, business activity, and household credit and debit card spending. These measures are available on either a weekly or monthly basis.

To track the impact of natural disasters on various dimensions of economic activity, we estimate local projections following the specification in Equation 2, where the dependent variable $\Delta^h y_{i,t+h}$ represents the h-period-ahead change in the selected outcome variables.[27]

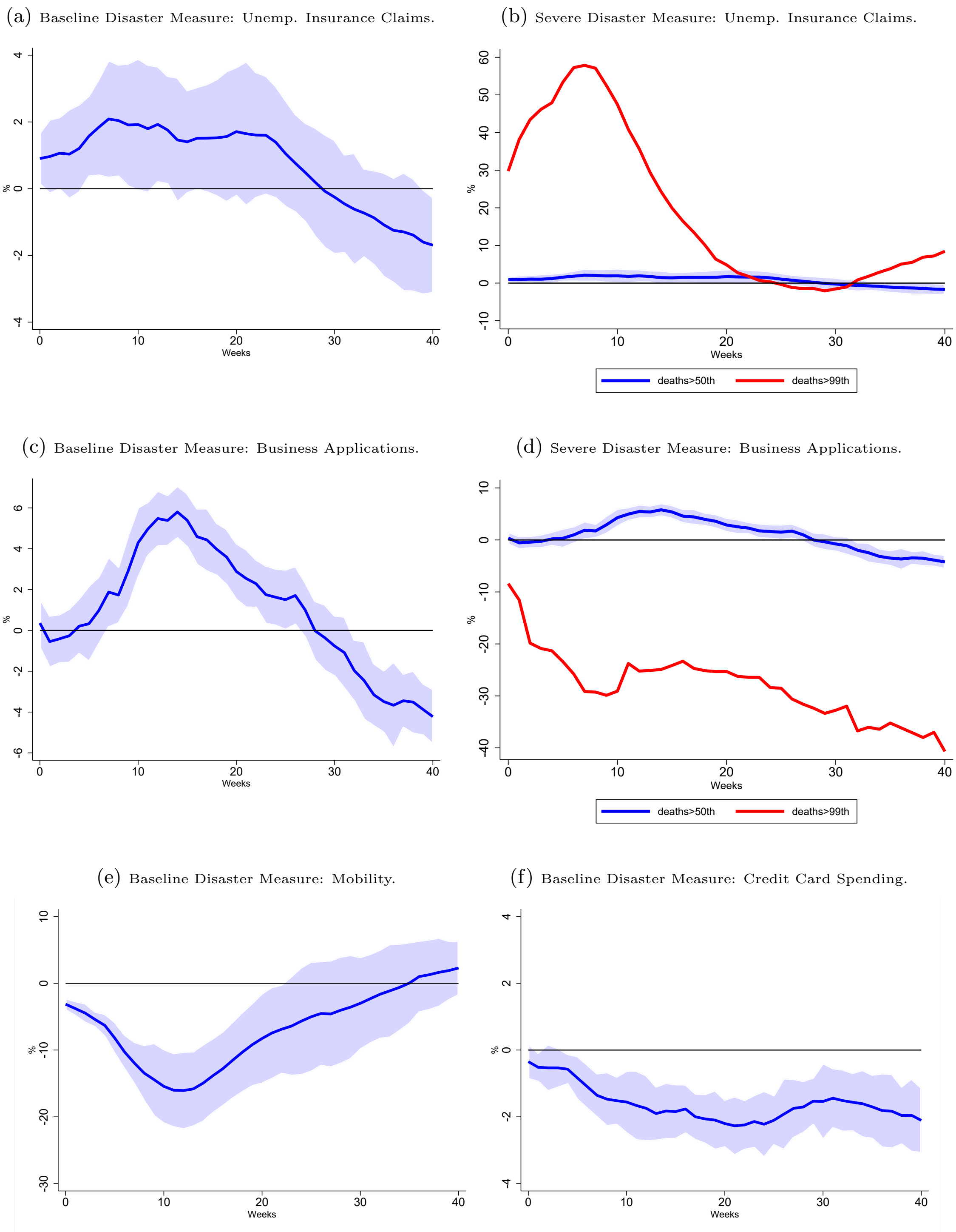
Panels (a)–(f) of Figure 6 illustrate the average weekly dynamics of card spending, initial jobless claims, business applications, and mobility following natural disasters. For insurance claims and business applications, we analyze the effects of natural disasters based on two severity levels: our baseline indicator (fatalities above the median) and the most severe disasters (fatalities in the top 1%). However, for credit card spending and mobility, we only report results for the baseline indicator, as the short time span of these series means they do not overlap with any extreme disasters in our sample.

Focusing on Panels (a) and (b) of Figure 6, initial jobless claims show no immediate response but begin to rise approximately five weeks after a natural disaster, increasing by around 2%. This effect is relatively persistent, with claims gradually returning to pre-disaster levels after about 30 weeks. However, the impact of extreme natural disasters is substantially larger in comparison—causing jobless claims to increase sharply by approximately 60% within ten weeks, a magnitude far exceeding that of our baseline measure. While claims eventually decline to historical levels over the following 20 weeks, the sheer scale of the initial increase highlights the severe economic consequences of extreme disasters.

Panels (c) and (d) of Figure 6 illustrate how the trajectory of business applications varies with disaster severity. Following typical natural disasters, business applications experience minimal disruption and even rise above historical levels between 8 and 30 weeks after the event. However, in the aftermath of severe disasters, the pattern is markedly different—business applications drop significantly by approximately 30% within 10 weeks and remain well below their historical average, declining by 40% even after 40 weeks (or 10 months). This persistent downturn underscores the severe and prolonged economic impact of the most severe disasters on business expectations.

[27] As in our main analysis presented in Equation 2, we include lags of the weekly economic conditions to control for pre-existing economic activity at the state level. When the selected outcome variable is available at a monthly frequency, we aggregate the weekly index to a monthly level and include time-fixed effects to account for time-varying shocks affecting all states simultaneously.

Figure 6: Dynamic Response of Labor Market, Business Applications, Household Spending, and Mobility to Natural Disasters



(a) Baseline Disaster Measure: Unemp. Insurance Claims.

(b) Severe Disaster Measure: Unemp. Insurance Claims.

(c) Baseline Disaster Measure: Business Applications.

(d) Severe Disaster Measure: Business Applications.

(e) Baseline Disaster Measure: Mobility.

(f) Baseline Disaster Measure: Credit Card Spending.

Notes: Estimated cumulative changes in selected outcomes following a natural disaster. Horizons $h = 1, 2, \ldots, 40$. The baseline natural disaster indicator includes all storms and floods with the number of reported deaths above the median. The sample periods are as follows: 1987w14–2024w39 for initial jobless claims, 2006w5-2024w39 for business applications, 2020w9–2024w31 for credit and debit card spending, and 2020w9–2022w21 for mobility. Impulse response functions (IRFs) have been smoothed using a 4-week rolling-window moving average applied to the response coefficients. The shaded area represents the 68% confidence interval, based on state-level clustered standard errors.

The trajectory of unemployment claims and business applications following natural disasters aligns with our main findings on weekly economic activity. While natural disasters negatively affect various dimensions of economic activity, severe natural disasters—those with fatalities in the top 1%—have a markedly more severe impact.

Turning to mobility and household expenditure, Panels (e) and (f) of Figure 6 depict the evolution of both indicators following natural disasters. Mobility declines sharply, falling by approximately 20% within 10 weeks of a disaster. However, it gradually recovers, returning to its historical trend within 35 weeks (approximately 8 months).

Natural disasters appear to have a more prolonged negative impact on household spending, as measured by credit and debit card transactions, compared to other economic indicators. Household spending steadily declines by more than 2% within 20 weeks of a disaster and remains at this lower level in the weeks that follow. Even after 40 weeks, spending remains 2% below its historical average. This suggests that while the broader economic disruptions caused by natural disasters may be temporary, their impact on household spending is more persistent, likely reflecting increased financial caution among households in the aftermath of such events.

Panels (a)–(e) of Figure 7 depict the impact of natural disasters on manufacturing sentiment and exports. As in previous analyses, we examine the evolution of these variables using both our baseline measure and the severe disaster indicator.

Exports experience a prolonged decline following natural disasters, decreasing by about 1% in the month of the disaster and showing no signs of recovery even 15 months later. However, the point estimates indicate a high degree of uncertainty, with statistical significance observed only in the first two months. In contrast, extreme natural disasters lead to a far more severe initial shock, with exports dropping by approximately five times the magnitude of typical disasters. Despite this sharp decline, the effect is less persistent, as exports recover to their historical trend within six months. This stark difference highlights the disproportionately large but relatively short-lived impact of severe disasters on trade.

Manufacturing sentiment experiences a significant and prolonged decline following a disaster, with full recovery taking up to 15 months. However, the exhibit a high degree of uncertainty, as reflected in the wider confidence intervals, suggesting that the effects are statistically distinguishable from zero only in the first months. The impact is substantially more severe in the case of high-fatality natural disasters, as shown in Panel (d) of Figure 7. In these instances, manufacturing sentiment declines by approximately six times the magnitude observed after a typical disaster and remains persistently low, showing signs of recovery only after 40 weeks. This stark contrast underscores the disproportionate disruption caused by severe disasters.

Figure 7: Dynamic Response of Exports and Manufacturing Sentiment to Natural Disasters

Notes: Estimated cumulative changes in selected outcomes following a natural disaster. Horizons $h = 1, 2, \ldots, 15$. The baseline natural disaster indicator includes all storms and floods with the number of reported deaths above the median. The sample periods are as follows: 1987m4–2024m8 for manufacturing sentiment, and 1995m8–2024m8 for exports. Impulse response functions (IRFs) have been smoothed using a 2-month rolling-window moving average applied to the response coefficients. The shaded area represents the 68% confidence interval, based on state-level clustered standard errors.

Overall, this section highlights that while the broader economic effects of natural disasters generally dissipate within a year, the severity of their impact largely depends on the scale of the event. In particular, severe natural disasters—those in the top 1% in terms of fatalities—cause a significantly greater economic disruption than typical disasters. Moreover, while natural disasters tend to have a temporary impact on labor markets, business activity, mobility, and manufacturing sentiment—aligning with their short-term effects on overall economic performance—their impact on household spending is notably more prolonged and persistent.

4.4 The impact of natural disasters on the US

In Subsection 4.1, we examined the effects of natural disasters on economic activity using state-level data. A natural follow-up question is whether these disasters have a measurable impact on overall U.S. economic activity. To investigate this, we construct a weekly national natural disaster indicator, which is activated whenever at least one disaster occurs anywhere in the country. We construct two indicators—one based on total fatalities exceeding the median and another for severe disasters, defined as those with total fatalities above the 99th percentile. We then use these indicators to assess the impact of natural disasters on national economic activity.[28]

In particular, we estimate the following local projections:

$$\Delta^h y_{t+h} = \alpha_h + \beta_h \, \textit{Natural Disaster}_t + \sum_{l=1}^{4} \Gamma_{h,l} \Delta y_{t-l} + \varepsilon_{t+h}. \tag{2}$$

Here, $\Delta^h y_{t+h}$ represents the h-period-ahead change in the Weekly Economic Condition Index (ECI) for the U.S. as a whole, while *Natural Disaster*$_t$ is a dummy variable activated when at least one natural disaster occurs in the U.S in week t.

Panels (a) and (b) of Figure 8 present the main results, indicating that natural disasters have minimal impact on overall U.S. economic activity. For our baseline measure of natural disasters, there is a slight decline in activity—consistent in timing with the results from state-level panel fixed-effects regressions—but the effect is smaller and remains statistically insignificant across all time horizons.

Only the most extreme events—those with fatalities in the top 1%—appear to have a short-term negative impact on national economic activity. Following such disasters, U.S. weekly economic activity declines for approximately two months (eight weeks) before stabilizing. However, the magnitude of this effect is about five times lower than the one observed for severe disasters in our state-level regressions.

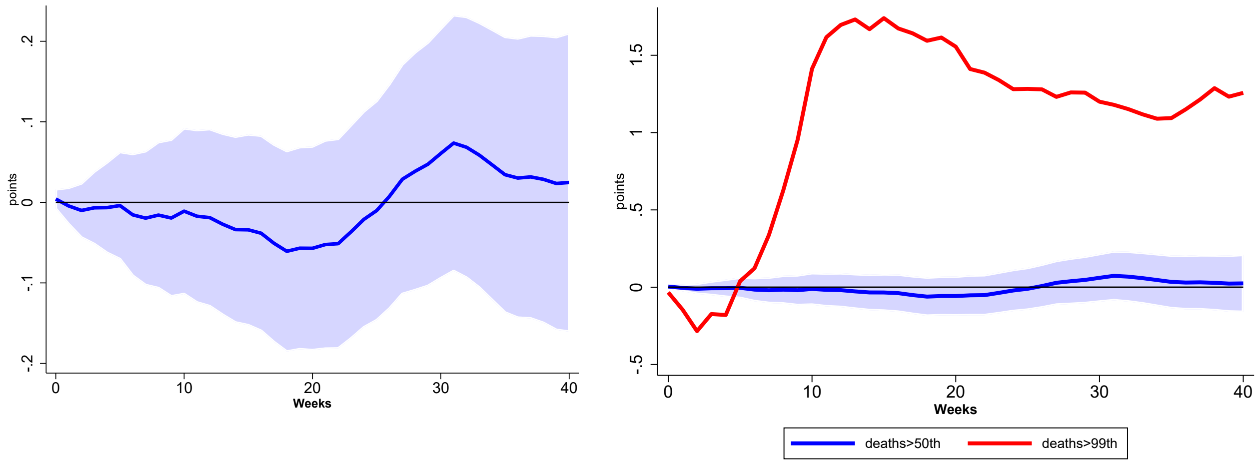
Overall, while natural disasters significantly disrupt economic activity at the state level in the short to medium term, this effect is not consistently observed at the national level. This finding underscores the advantage of using state-level data, which captures localized economic disruptions more effectively than aggregate country-level data.

[28] We also create an alternative U.S. natural disaster indicator based on the total number of disasters occurring in a given week and confirm our main finding that natural disasters have no significant impact on the U.S. economy as a whole.

Figure 8: Dynamic Response of US Economic Activity to a Natural Disaster

(a) Baseline Measure of Natural Disasters

(b) Measure of Natural Disasters by Severity



Notes: Estimated cumulative changes in the Weekly Indicator Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 2, ..., 40$, following a natural disaster. In panel (a) natural disasters include all storms and floods with the number of reported deaths above the median. The sample period is 1987w14–2024w39. The shaded area denotes the 68% confidence interval, based on robust standard errors.

5 Conclusion

What are the causal effects of natural disasters on economic activity? This paper explores this question by leveraging high-frequency data on overall economic activity and a comprehensive dataset of natural disasters across U.S. states. We focus on large, plausibly unexpected natural disasters and find that these events lead to a temporary decline in state-level economic activity, with effects fully dissipating within a year.

This decline is largely driven by short-term disruptions in mobility, manufacturing sentiment, and the labor market. However, household spending faces a more prolonged impact, staying significantly below its historical average even a year after the disaster. Additionally, we document key stylized facts about natural disasters in the U.S. throughout the twentieth century, highlighting a sharp increase in their frequency in recent decades.

Overall, our findings provide novel evidence on the increasing frequency of natural disasters and their negative impact on economic activity. These results underscore the economic costs of climate change and serve as a warning about the expected consequences of extreme climate-related events. By shedding light on these impacts, our study helps inform policymakers and central banks worldwide in developing proactive and adaptive strategies to prevent and mitigate the adverse effects of such disasters.

References

Andersen, A. L., E. T. Hansen, N. Johannesen, and A. Sheridan (2022): "Consumer responses to the COVID-19 crisis: Evidence from bank account transaction data," *The Scandinavian Journal of Economics*, 124, 905–929.

Andersen, A. L., A. S. Jensen, N. Johannesen, C. T. Kreiner, S. Leth-Petersen, and A. Sheridan (2023): "How do households respond to job loss? lessons from multiple high-frequency datasets," *American Economic Journal: Applied Economics*, 15, 1–29.

Babii, A., M. A. Carare, D. Vasilyev, and M. Y. Yakhshilikov (2022): *Evolution of remittances to CAPDR countries and Mexico during the COVID-19 pandemic*, International Monetary Fund.

Baumeister, C., D. Leiva-León, and E. Sims (2024): "Tracking weekly state-level economic conditions," *Review of Economics and Statistics*, 106, 483–504.

Beaton, M. K., M. S. Cerovic, M. Galdamez, M. Hadzi-Vaskov, F. Loyola, Z. Koczan, M. B. Lissovolik, M. J. K. Martijn, M. Y. Ustyugova, and J. Wong (2017): *Migration and remittances in Latin America and the Caribbean: engines of growth and macroeconomic stabilizers?*, International Monetary Fund.

Bettin, G. and A. Zazzaro (2018): "The impact of natural disasters on remittances to low-and middle-income countries," *The Journal of Development Studies*, 54, 481–500.

Bilal, A. and D. R. Känzig (2024): "The Macroeconomic Impact of Climate Change: Global vs. Local Temperature," Tech. rep., National Bureau of Economic Research.

Bilal, A. and E. Rossi-Hansberg (2023): "Anticipating climate change across the united states," Tech. rep., National Bureau of Economic Research.

Buda, G., V. M. Carvalho, G. Corsetti, J. B. Duarte, S. Hansen, Á. Ortiz, T. Rodrigo, and J. V. Rodríguez Mora (2023): "Short and variable lags," *Robert Schuman Centre for Advanced Studies Research Paper*.

Cavallo, E., S. Galiani, I. Noy, and J. Pantano (2013): "Catastrophic natural disasters and economic growth," *Review of Economics and Statistics*, 95, 1549–1561.

Chetty, R., J. N. Friedman, and M. Stepner (2024): "The economic impacts of COVID-19: Evidence from a new public database built using private sector data," *The Quarterly Journal of Economics*, 139, 829–889.

Dell, M., B. F. Jones, and B. A. Olken (2012): "Temperature shocks and economic growth: Evidence from the last half century," *American Economic Journal: Macroeconomics*, 4, 66–95.

——— (2014): "What do we learn from the weather? The new climate-economy literature," *Journal of Economic literature*, 52, 740–798.

ECB (2025): "The economic impact of floods," *ECB Economic Bulletin, Issue 1/2025.*

Ehlers, T., J. Frost, C. Madeira, and I. Shim (2025): "BIS Bulletin," .

Fomby, T., Y. Ikeda, and N. V. Loayza (2013): "The growth aftermath of natural disasters," *Journal of applied econometrics*, 28, 412–434.

Ganong, P. and P. Noel (2019): "Consumer spending during unemployment: Positive and normative implications," *American economic review*, 109, 2383–2424.

Grigoli, M. F. and M. D. Sandri (2022): *Monetary policy and credit card spending*, International Monetary Fund.

Jacobson, M., C. Matthes, and T. B. Walker (2022): "Inflation Measured Every Day Keeps Adverse Responses Away: Temporal Aggregation and Monetary Policy Transmission," .

Jordà, Ò. (2005): "Estimation and inference of impulse responses by local projections," *American economic review*, 95, 161–182.

Jordà, Ò. and A. M. Taylor (2024): "Local projections," *Journal of Economic Literature (forthcoming).*

Kahn, M. E., K. Mohaddes, R. N. Ng, M. H. Pesaran, M. Raissi, and J.-C. Yang (2021): "Long-term macroeconomic effects of climate change: A cross-country analysis," *Energy Economics*, 104, 105624.

Kim, H. S. (2024): "Heterogeneity in the Economic Impact of Temperature Shocks Across US States," .

Noy, I. (2009): "The macroeconomic consequences of disasters," *Journal of Development economics*, 88, 221–231.

Von Peter, G., S. von Dahlen, and S. Saxena (2024): "Unmitigated disasters? Risk sharing and macroeconomic recovery in a large international panel," *Journal of International Economics*, 149, 103920.

Yang, D. (2008): "Coping with disaster: The impact of hurricanes on international financial flows, 1970-2002," *The BE Journal of Economic Analysis & Policy*, 8.

Appendix

A Data Sources and Summary Statistics

A.1 Data Sources

Table A.1.1: Selected Variables and Data Sources

Variables	Frequency	Data Source
Weekly Economic Index (ECI)	Weekly	Baumeister et al. (2024)
Credit and debit card spending	Weekly	AS
Business applications	Weekly	FRED
Initial unemployment insurance claims	Weekly	FRED
Cellphone mobility index	Weekly	Apple
Real exports of goods	Monthly	FRED
Business Tendency Survey for Manufacturing	Monthly	FRED

A.2 Summary Statistics

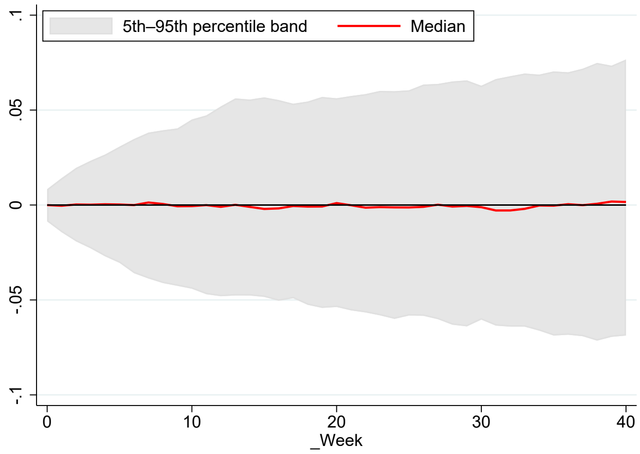
Table A.2.1: Summary Statistics

Variables	Mean	Std. Dev.	Min	Max
Total Damage ('000 US$)	2871123	8347558	170	1.25e+08
Number Affected States	12.02486	10.28306	1	50
Total Deaths	42.81203	144.5728	1	6000
No. Injured	105.1766	288.1053	1	7000
No. Affected	882450.8	7938792	9	8.50e+07
No. Homeless	7276.706	22430.74	12	250000
Total Affected People	528562.8	6150731	1	8.50e+07

Source: Authors' estimates using the EM-DAT database.

B Sensitivity Checks

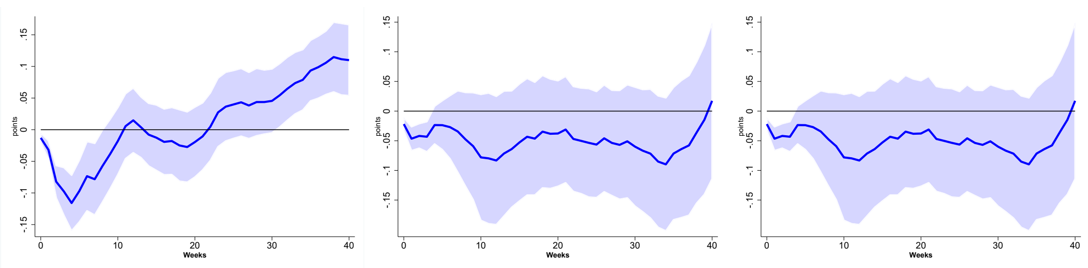
Figure B.1: IRFs from Random Natural Disasters



Notes: The figure illustrates the impulse responses from a placebo test in which the occurrence of natural disasters is randomly reshuffled. In each iteration, the week of the natural disaster indicator is drawn from a uniform distribution, with the probability of a natural disaster randomly set to 1.5%—consistent with the probability observed in our sample—and the impulse responses are estimated using 500 replications. The plot shows the median point estimates of the impulse responses at each forecast horizon, with shaded areas representing the 5th–95th percentile band across simulations.

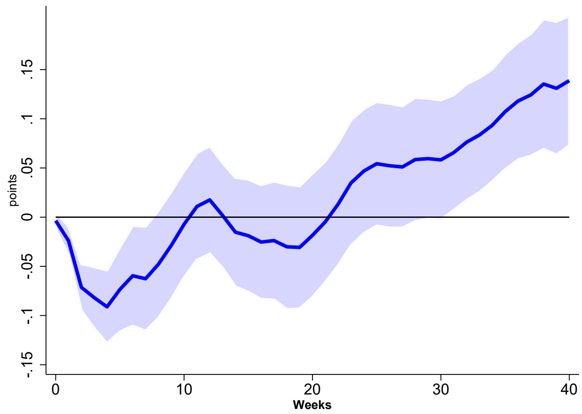
Figure B.2: Heterogeneity

(a) Storms (b) Floods (c) Wildfires



Notes: Estimated cumulative changes in the Weekly Indicator Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 2, ..., 40$, following a natural disaster. Panel (a) includes all storms with reported deaths above the median. Panel (b) includes all floods with reported deaths above the median. Panel (c) includes all wildfires with reported deaths above the median. The sample period is 1987w14–2024w39. The shaded area denotes the 68% confidence interval, based on state-level clustered standard errors.

Figure B.3: All types of natural disasters

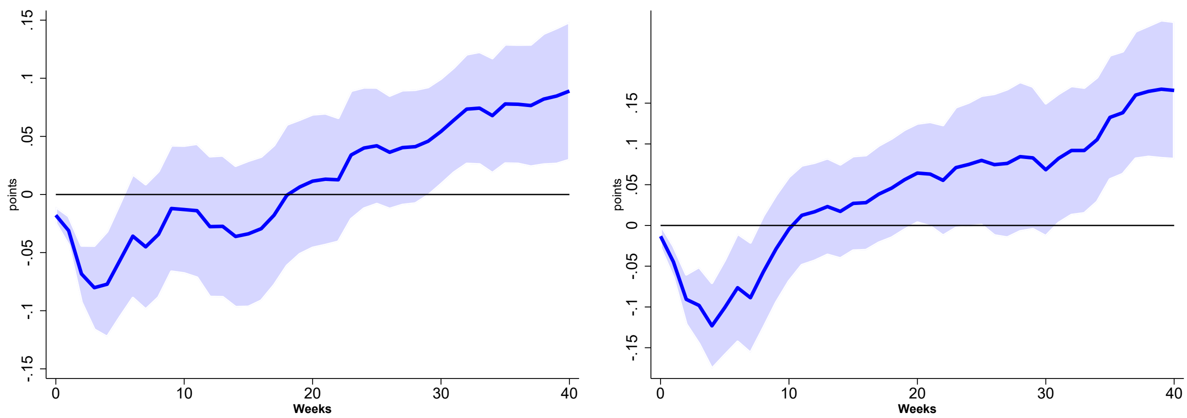


Notes: Estimated cumulative changes in the Weekly Indicator Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 2, ..., 40$, following a natural disaster. Natural disasters include all types of disasters with the number of reported deaths above the median. The sample period is 1987w14–2024w39. The shaded area denotes the 68% confidence interval, based on state-level clustered standard errors.

Figure B.4: Impact of Large Natural Disasters

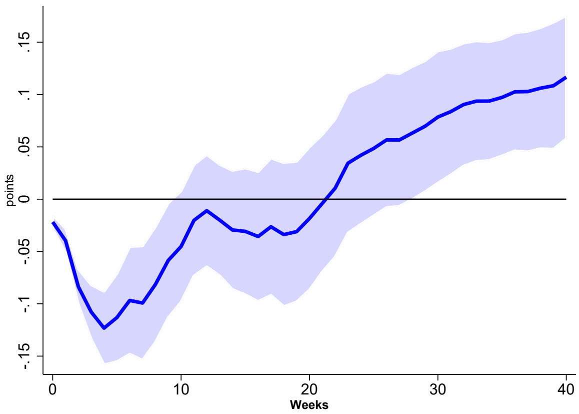
(a) By Number of Affected States

(b) By Total Damage



Notes: Estimated cumulative changes in the Weekly Indicator Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 2, ..., 40$, following a natural disaster. Panel (a) includes storms and floods for which the number of affected states is above the median, while panel (b) includes those where the reported total cost exceeds the median. The sample period is 1987w14–2024w39. The shaded area denotes the 68% confidence interval, based on state-level clustered standard errors.

Figure B.5: Subsample: Excluding post-Pandemic Data



Notes: Estimated cumulative changes in the Weekly Indicator Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 2, ..., 40$, following a natural disaster. Natural disasters include all storms and floods with the number of reported deaths above the median. The sample period is 1987w14–2020w10. The shaded area denotes the 68% confidence interval, based on state-level clustered standard errors.