NATURAL DISASTERS, ECONOMIC ACTIVITY, AND PROPERTY INSURANCE: EVIDENCE FROM WEEKLY U.S. STATE-LEVEL DATA

2025

BANCO DE ESPAÑA
Eurosistema

Documentos de Trabajo
N.º 2542

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(*) I am grateful to Christiane Baumeister, Pablo Burriel, Christoph Grosse Steffen, Juha Kilponen, Florens Odendahl, Evi Pappa, an anonymous referee, and the attendees at the IAAE Annual Conference, IPDC Annual Conference, EEA Congress, and an internal seminar at the Banco de España for their useful comments and suggestions. I am also very grateful to Christiane Baumeister, Danilo Leiva-León, and Eric Sims for sharing an updated vintage of the mixed-frequency dataset underlying the state-level weekly economic indicator used in this paper. I am thankful to Antonio Vega for his valuable research assistance.
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Documentos de Trabajo. N.º 2542

November 2025

https://doi.org/10.53479/41465

ISSN: 1579-8666 (online edition)

Abstract

We estimate the dynamic causal effects of natural disasters on economic activity using weekly U.S. state-level data over the last forty years. Focusing on large, plausibly unexpected events, we find a temporary decline in state activity that starts in the first week and dissipates within a year. The size and persistence of this decline are scaled with the initial severity and are primarily driven by disruptions to mobility, manufacturing sentiment, exports, household spending, and labor markets. Inflation shows a muted response. We further show that these geographically concentrated shocks rarely register at the national level, underscoring the importance of high-frequency, regional data for capturing the full dynamics of geographically concentrated shocks like natural disasters. Lastly, we show that property insurance materially shapes outcomes: states with higher property insurance coverage experience milder downturns and faster recoveries. Our findings indicate that access to property insurance plays a key role in cushioning local economies against the disruptive effects of natural disasters.

Keywords: climate change, natural disasters, local projections, economic activity, high-frequency data.

JEL classification: E23, F18, O44, Q54, Q56.

Resumen

Estimamos los efectos causales dinámicos de los desastres naturales sobre la actividad económica de Estados Unidos durante los últimos cuarenta años, utilizando los datos semanales desagregados por estados. Al identificar desastres de gran magnitud y posiblemente inesperados, observamos una caída temporal de la actividad económica estatal que comienza en la primera semana y desaparece en el plazo de un año. La magnitud y la persistencia de esta caída aumentan con la gravedad inicial y se deben principalmente a interrupciones en la movilidad, la confianza manufacturera, las exportaciones, el gasto de los hogares y el mercado laboral. No encontramos efectos sobre la inflación. Además, demostramos que el efecto de estos *shocks* rara vez se refleja a nivel nacional, lo que subraya la importancia de utilizar datos regionales de alta frecuencia para captar la dinámica completa de los *shocks* geográficamente concentrados, como los desastres naturales. Por último, mostramos que el seguro de propiedad influye de manera significativa en los resultados: los estados con una mayor proporción de hogares asegurados experimentan recesiones más suaves y recuperaciones más rápidas. Nuestros resultados indican que el acceso al seguro de propiedad desempeña un papel clave a la hora de amortiguar los efectos disruptivos de los desastres naturales sobre las economías locales.

Palabras clave: cambio climático, desastres naturales, proyecciones locales, actividad económica; alta frecuencia.

Códigos JEL: E23, F18, O44, Q54, Q56.

1 Introduction

The escalating climate emergency has pushed climate change to the forefront of international political and economic agendas. As global average temperatures continue to rise, natural disasters are projected to increase in both frequency and intensity over the coming century (IPCC, 2022). Consequently, accurately quantifying the economic impacts of these disasters has become a crucial priority for policymakers and central banks worldwide. Such assessments are essential for designing effective *ex-ante*, *in-situ*, and *ex-post* policy responses.[1]

This paper presents new evidence on the dynamic causal effects of natural disasters, using high-frequency economic data on economic activity from U.S. states spanning the past forty years. We leverage around 100,000 weekly observations across 50 states, combining economic data with detailed records of natural disasters to address two central questions. First, we quantify the economic consequences of natural disasters: How rapidly do they affect economic activity, and are these effects transitory or persistent? How do they influence key economic dimensions such as labor market outcomes, trade flows, expectations, new business formation, and household consumption? What role do they play in shaping inflation dynamics? Do natural disasters impact not only regional but also national economic activity? Second, we examine the extent to which property insurance mitigates the economic impact of disasters. Specifically, we assess how the prevalence of property insurance prior to a disaster influences the severity of its economic consequences.

Leveraging a weekly, state-level panel within a local-projection framework, we first estimate the average dynamic response of economic activity to these events. We find that disasters trigger an immediate deterioration in weekly conditions and a short-lived decline in aggregate performance. At the state level, economic activity falls immediately after a natural disaster and typically returns to its pre-disaster growth rate within 20–40 weeks. For most events, the effects dissipate within a year; severity, however, matters: both the magnitude and persistence of the response rise sharply with intensity. Disasters in the top 1% by fatalities generate shocks nearly ten times larger than the average event, with recovery taking about a year. To gauge scale, these shocks amount to roughly 25% of the average impact of the Global Financial Crisis across

[1] Recent bulletins from the ECB (ECB, 2025) and the BIS (Ehlers et al., 2025) underscore central banks' growing concern about the economic consequences of natural disasters. Moreover, the ECB's updated Monetary Policy Strategy assessment concludes that "within its mandate, the Governing Council is committed to ensuring that the Eurosystem fully takes into account the implications of climate change and nature degradation for monetary policy and central banking".

U.S. states, underscoring their sizable macroeconomic footprint.[2]

We further examine the specific channels through which natural disasters affect economic activity, using detailed disaggregated weekly and monthly economic data. Our results indicate that natural disasters negatively affect multiple dimensions of the economy: they temporarily disrupt regional labor markets, mobility, export flows, business formation, and manufacturing sentiment, yet cause a persistent decline in household spending. Although most effects are short-lived, the sustained drop in household spending suggests that heightened uncertainty following natural disasters prompts households to increase precautionary savings. Taken together, these results indicate that natural disasters negatively impact multiple dimensions of economic activity, helping to explain the broader decline in aggregate performance.

Turning to inflation, we find that, on average, effects on state-level inflation are muted. This suggests that natural disasters have characteristics of both negative supply and demand shocks, with reduced demand and rising supply-side costs largely offsetting each other, resulting in little net effect on inflation. However, in the case of the most severe disasters—those in the top 1% of fatalities in our sample—we observe a more pronounced inflationary response. These extreme events are followed by rising inflationary pressures, suggesting that negative supply shocks ultimately outweigh negative demand shocks. In sum, while typical natural disasters have little effect on inflation, the most catastrophic ones can cause a temporary but significant increase in state-level price dynamics.

Do natural disasters adversely affect state-level economic conditions in a way that is detectable at the national level? To answer this question, we estimate the impact of an aggregate measure of natural disasters on U.S. weekly economic activity. Our results show that, in general, natural disasters do not significantly affect national economic performance. This implies that, while such events can cause severe disruptions at the state or regional level, these shocks rarely cumulate into measurable nationwide downturns.[3] However, national effects are most evident in two settings: (i) when disasters strike the four most populous states, and (ii) when a single event simultaneously affects a large share of states. This finding points to an important policy implication: while natural disasters can significantly disrupt regional economies, their limited

[2]To capture the dynamic negative impacts of natural disasters, we rely on a recently developed indicator of state-level economic conditions by Baumeister et al. (2024). This weekly indicator offers a comprehensive measure of economic performance across states, incorporating various dimensions such as mobility, labor market dynamics, real output, firm and consumer expectations, financial conditions, and household spending (e.g., credit and debit card transactions).

[3]While our findings are based on U.S. data, smaller economies or developing countries may exhibit different aggregate responses to localized disasters.

average aggregate impact suggests that a nationwide policy responses—such as monetary policy— may not be appropiate. Instead, the evidence highlights targeted local interventions are better suited to mitigate the economic consequences of natural disasters at the regional level.

Does property insurance help mitigate the economic impact of natural disasters, and do regions with higher coverage recover more quickly? To address this question, we compile new data on property insurance coverage across U.S. states spanning several decades and estimate the differential effects of disaster severity on state-level economic conditions. Our empirical strategy exploits both cross-sectional and time-series variation in insurance coverage, combined with high-frequency, state-level measures of economic activity. We find that, for events with comparable initial impacts, states with above-median property insurance coverage in the week before the disaster experience significantly smaller declines in economic activity than less-insured states. Taken together, these results suggest that expanding access to property insurance plays a key role in cushioning local economies against the disruptive effects of natural disasters

Overall, our findings provide new insights into the rising frequency of natural disasters, their immediate adverse effects on economic activity, and the mitigating role of property insurance in reducing economic losses. These results highlight the economic costs associated with climate change and underscore the importance of climate adaptation—namely, broad access to property insurance.

Related Literature. Our paper contributes to two main strands of literature. First, it relates to studies that assess the economic impact of natural disasters (e.g., Noy, 2009; Fomby et al., 2013; Cavallo et al., 2013; Hsiang and Jina, 2014; Roth Tran and Wilson, 2020; Von Peter et al., 2024; Usman et al., 2025). 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; Roth Tran and Wilson, 2020), its magnitude (Cavallo et al., 2013; Roth Tran and Wilson, 2020), and the presence of risk transfer mechanisms (Von Peter et al., 2024).[4] 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]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.[5]

In this paper, we demonstrate that regional high-frequency data is essential for accurately estimating the true dynamic 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.[6] In addition, we provide novel evidence documenting, for the first time, how these disasters affect various dimensions of economic activity, including labor market outcomes, export flows, household spending, business formation and economic sentiment. Moreover, we show that such events typically do not affect inflation and that insurance coverage is a key factor in explaining the observed heterogeneity in post-disaster economic dynamics.

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 negative impact on multiple dimensions of economic activity—including overall economic activity, labor market outcomes, new business applications, and household spending—within the same week. While most of these effects dissipate within a year, the impact on household spending is notably more persistent. These findings highlight the value of disaggregated regional and high-frequency data in capturing the full dynamics of the temporary economic response to localized shocks such as natural disasters.

[5] This limitation is evident in work using annual data (e.g., Usman et al., 2025; Fomby et al., 2013). Usman et al. (2025), analyzing European NUTS-level regions, find no growth effect after floods. Fomby et al. (2013), using annual country-level data, report counterintuitive patterns, including positive associations between certain disasters and economic activity.

[6] Our findings align with those of Jacobson et al. (2022), Buda et al. (2023), and Baumeister et al. (2024). Jacobson et al. (2022) show that temporal aggregation bias plays a significant role in explaining the price puzzle often observed when estimating the effects of monetary policy shocks on inflation. Similarly, Buda et al. (2023) emphasize the value of high-frequency data in accurately capturing the impact of monetary policy shocks, while Baumeister et al. (2024) underscore the importance of weekly data in evaluating the effectiveness of the Paycheck Protection Program during the COVID-19 pandemic.

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. This section also examines which specific dimensions of economic activity are most significantly affected by disasters and provides additional evidence on their effects at the national level. Section 5 explores the role of property insurance in mitigating the severity of disasters. Finally, Section 6 presents additional robustness checks, and Section 7 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.[7] 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.[8]

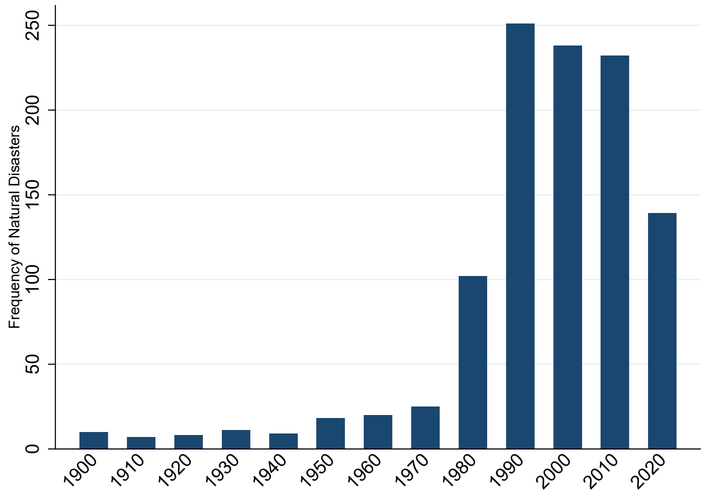
In this section, we analyze data on all natural disasters affecting the U.S. since 1900 and present key trends related to their frequency by decade, type, and state.

[7] 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.

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

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.

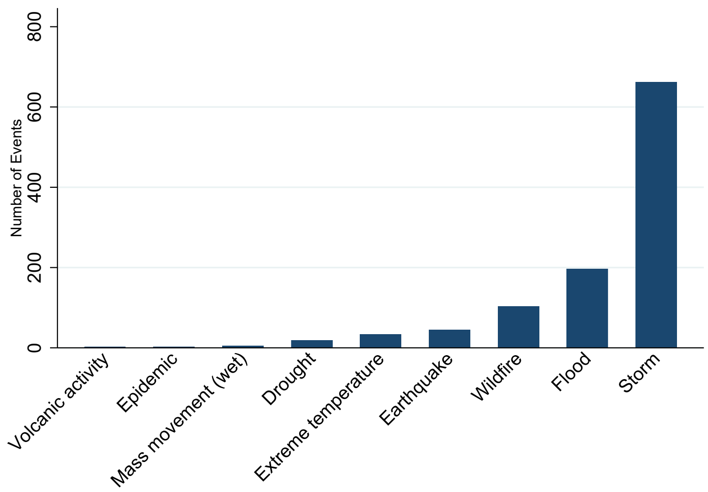
Figure 1: Frequency of natural disasters by decade.



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

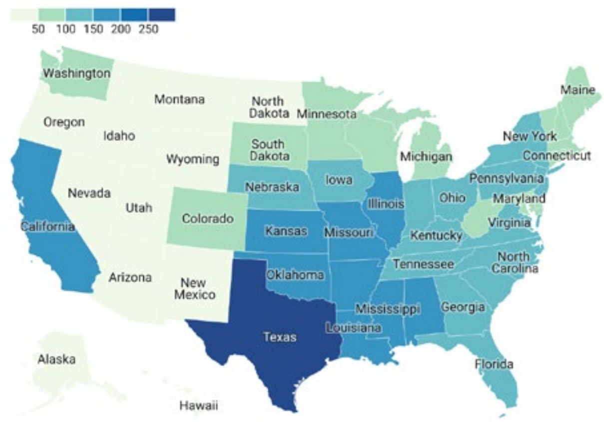
Frequency of natural disasters by type. Figure 2 presents the total number of events for each type of natural disaster from 1900 to 2024. The data reveal that storms and floods constitute the majority of disasters affecting US states. In contrast, wildfires, earthquakes, extreme temperature events, droughts, 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.

Figure 3: Frequency of natural disasters by state.



Notes: This graph shows the spatial distribution of natural disasters across US states. 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.[9] 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

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

contrast, Alaska and Utah have been less exposed to natural disasters, recording fewer than 20 events over the past century.

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.

3.1 Empirical Methodology

In this paper, we use high-frequency data to examine the economic consequences of natural disasters at the U.S. 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, firm expectations (such as new business applications), 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.[10] Figure A.2.1 presents the time-series evolution of the ECI across U.S. states, showing the 5th, median, and 95th percentiles. The figure demonstrates that the ECI effectively captures state-level economic fluctuations over the sample period.

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

[10]The state-level Economic Conditions Index (ECI) is scaled to match the average four-quarter growth rate of U.S. real GDP, facilitating a nationally consistent interpretation of state-level economic performance. Accordingly, the index serves as a real-time indicator of whether economic conditions in a given state are above or below the national historical trend. The ECI is normalized such that a value of zero corresponds to economic conditions in line with the long-run growth rate of U.S. real GDP.

$$
\begin{aligned}
ECI_{i,t+h} = \alpha_{i,h} + \beta_h \, \textit{Natural Disaster}_{i,t} + \sum_{l=1}^{4} \delta_{h,l} \, \textit{Natural Disaster}_{i,t-l} \, + \\
\theta_h \, \textit{Other Disaster}_{i,t} + \gamma_h \, \textit{Pandemic}_t + \sum_{l=1}^{4} \Gamma_{h,l} \, ECI_{i,t-l} + \varepsilon_{i,t+h}, \qquad (1)
\end{aligned}
$$

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. All specifications control for the potential persistence of past disasters by including lags of the main disaster indicator. Since we construct multiple disaster measures, as described in Section 3.2, we also include a dummy variable to account for other disasters not captured by the main indicator.[11] This approach controls for the effects of both concurrent and past disaster events on economic activity, allowing the estimated impacts to be interpreted as deviations in a state's weekly economic conditions following a disaster, relative to that same state's average non-disaster trajectory.

We further include a temporal pandemic dummy for the period between 2020w10 and 2020w31 to control for the sharp decline in economic activity following the outbreak of the COVID-19 pandemic.[12] The coefficient β_h traces the impulse response function (IRF) 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.[13] The maximum horizon considered is $h = 40$. For inference, we compute cluster-robust standard errors at the state level.[14]

3.2 Natural Disaster Indicator and Identification

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

[11] For example, as detailed below in Section 3.2, our baseline disaster measure includes all storms and floods with fatalities above the historical median. We therefore control for any other disaster—including non-storm or non-flood events, as well as storms or floods with fatalities below the median—that may occur concurrently in the same state and week.

[12] Our main results are robust to including week-of-year fixed effects to control for any residual seasonality.

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

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

Building the State-Level Natural Disaster Indicator. We construct our natural disaster indicator, $\textit{Natural Disaster}_{i,t}$, using data from the EM-DAT database. Specifically, we identify the timing (week) and location (state) of each disaster to create an indicator variable that reflects whether a natural disaster occurred in a given state during a particular week.[15] Based on empirical evidence from the previous section, we focus specifically on storms and floods, as these two disaster types collectively account for over 80% of all disasters impacting the U.S. This strategy ensures that our analysis concentrates on the most common and comparable natural disasters, while excluding disaster types with limited observations from our main disaster indicator. Additionally, when constructing our disaster indicator, we restrict our attention to events where the number of deaths exceeds the historical median, for two primary reasons.[16] First, this threshold allows us to capture the impact of significant natural disasters, filtering out minor events with negligible economic effects. Second, as discussed below, disasters with historically high death tolls are more likely to be unexpected—an essential condition for accurately identifying their causal effects. Using this definition, our baseline measure includes over 1,500 state-level natural disaster 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 and floods, the two most common natural disasters in the U.S. Third, we develop alternative measures of large-scale disasters by considering total direct damage, the number of affected states, and disaster intensity based on deaths relative to the affected state's population. These sensitivity analyses are discussed in detail in Section 6. Additionally, in Section 4, we present results not only for our baseline measure of natural disasters but also for alternative definitions: one including all disaster events without restrictions on fatalities, and another focusing exclusively on the most severe events, defined as those in the top 1% by fatalities.

Causality. Local projections, by themselves, do not solve the problem of identification.[17] The impulse response defined in Equation 1 represents a counterfactual difference in mean outcomes:

[15] We define our indicator as a dummy variable that equals one if at least one natural disaster occurs in a specific state within a given week. Notably, more than 95% of recorded natural disasters do not overlap with another event in the same state and week.

[16] In practice, our $\textit{Natural Disasteri}, t$ indicator is set to 1 when a storm or flood occurs in a given state and week, with the number of reported deaths exceeding 10.

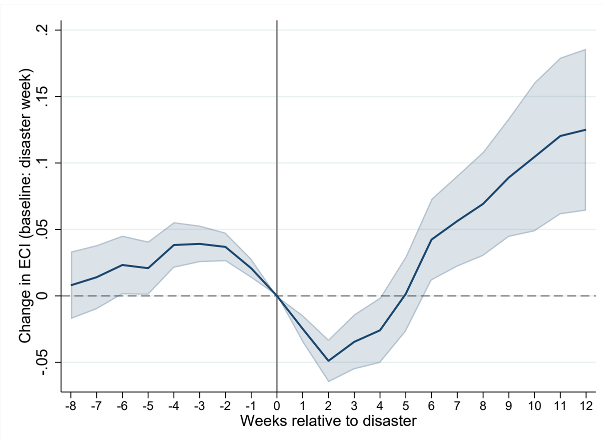
[17] We build on Jordà and Taylor (2024) to explain causality in our framework. We drop the cross-sectional state index i in the panel for ease of exposition.

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

where, in our framework, $s_t \in \{0, 1\}$, $s_t = \textit{Natural Disaster}_t$, and y_{t+h} denotes the h-period-ahead ECI. 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 1. 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 full dynamics of unexpected natural disasters.

Predictability of Natural Disasters. An important consideration is that some natural disasters may be partially or fully anticipated. When disasters are predictable, economic agents often adjust their behavior in advance—for instance, by delaying investment decisions, stockpiling goods, or evacuating. As a result, the economic impacts observed in Equation 1 may capture only part of the overall effect, since some adjustments occur before the event takes place. Consequently, anticipated natural disasters may have distinctly different economic effects than unanticipated ones.[18]

Figure 4: Weekly Economic Conditions Before and After Natural Disasters



Notes: The figure plots an event study of weekly economic conditions (ECI) around the onset of natural disasters (week $t = 0$). For each event, the ECI is normalized to zero at $t = 0$, and the series shows the change in ECI relative to that baseline for weeks $t \in [-8, 12]$. The solid line reports the cross-event mean change at each relative week; the shaded region shows pointwise 95% confidence intervals. Weeks in the COVID-19 period (2020w10–2020w31) are excluded.

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

To assess potential anticipation, Figure 4 traces weekly economic conditions from eight weeks before through twelve weeks after the disaster, relative to the event week ($t = 0$). For each event–state pair, we normalize the Economic Conditions Index (ECI) to zero at $t = 0$ and plot the average path before and after the shock. The figure shows that weekly economic conditions are systematically higher throughout the eight weeks preceding the disaster than in the event week. Moreover, economic conditions in the week immediately prior to the disaster ($t = -1$) are comparable to the average over weeks -8 to -2. The clear break at $t = 0$ and the subsequent decline in the ECI are therefore consistent with disasters arriving as unanticipated shocks, followed by a short-run deterioration that gradually reverts toward baseline. To further guard against anticipatory dynamics, our baseline specification restricts attention to natural disasters with historically high death tolls, which are less likely to be anticipated.

State-level, high-frequency data. Another key consideration is spatial and temporal aggregation.. Most existing studies rely on country-level data, which can underestimate the true effects of natural disasters because shocks are geographically concentrated: economic activity in unaffected regions often remains stable, partially offsetting losses in affected areas—especially when disasters strike regions that account for a small share of national output. Consistent with this concern, Section 4.4 shows that estimates using aggregate U.S. data reveal no discernible effect on overall activity when disasters occur anywhere in the country, and that negative effects appear only when a disaster strikes one of the four largest states or when many states are affected simultaneously.

A second concern is temporal aggregation. In Section 4, we show that most disasters have short-lived effects on economic conditions—roughly 5–6 months. Aggregating to annual frequency, therefore, mixes the initial decline with the later rebound and can hide the underlying dynamics. We therefore use weekly, state-level data to isolate affected regions and to track the immediate drop and short-run recovery within the year.

4 Empirical Results

In this section, we begin by estimating the dynamic causal effects of natural disasters on U.S. state-level economic activity using high-frequency data. Next, we investigate the disaggregated impacts of these disasters by analyzing their effects across multiple dimensions of economic performance. Additionally, we provide estimates of how natural disasters influence inflation at the state level.

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.

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. At the peak, state-level economic activity falls by just over 0.1 percentage points relative to the historical national average growth rate. Importantly, these dynamics are in *growth rates*: the economy returns to its pre-disaster *average growth rate* within 20–25 weeks (about 5–6 months) after the shock. In Appendix Figure B.1, we report the *approximated cumulative change in levels* (constructed from the cumulative sum of weekly growth rates) and show that the level of economic activity recovers to its pre-disaster path in about 52 weeks or one year.[19] This evidence indicates that natural disasters have a temporary negative impact on economic conditions, with effects that dissipate 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 an indicator that captures all storms and floods occurring in a given state and week, 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 somehow 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 exceeding the median fatality threshold. Following severe natural disasters, state-level economic activity is 1 percentage points below the national historical long-run economic growth. To provide a sense of scale, the peak decline in average

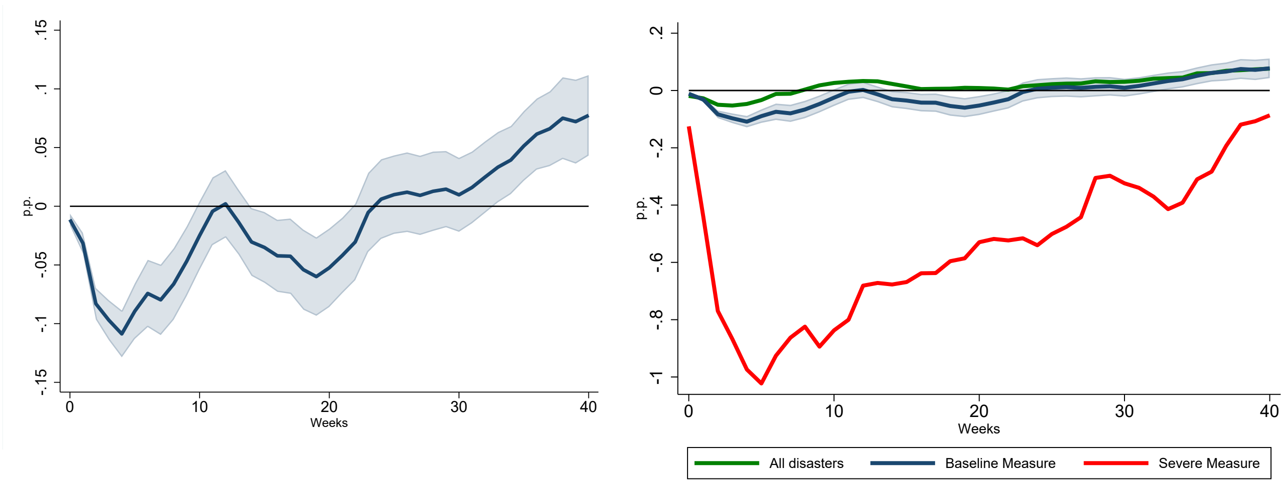
[19]The weekly economic conditions index (ECI) is scaled to a growth-rate unit (comparable to a four-quarter GDP growth rate). Following Baumeister et al. (2024), we define the dependent variable as the *cumulative sum of weekly growth rates*, $\sum_{q=0}^{h} \mathrm{ECI}_{i,t+q}$. This accumulates growth over the window $[t, t+h]$, providing a linear approximation to the cumulative change in log levels.

weekly economic activity across U.S. states during the aftermath of the Global Financial Crisis was around 4 percentage points relative to national historical economic growth. Therefore, a severe natural disaster shock amounts to roughly 25% of the average economic impact of the Global Financial Crisis across U.S. states.[20]

This result indicates that while the adverse effects of natural disasters on aggregate economic performance are typically short-lived, their magnitude varies substantially with disaster severity. Consistent with this, the impulse responses in Panel (a) of Figure 5 show a negative but transitory impact for most events. Our findings also illustrate the value of high-frequency indicators for studying these shocks: because the estimated downturn persists for roughly 20–30 weeks, analyses based on lower-frequency outcome measures could easily miss much of the negative effect.[21]

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 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. In Panel (b), all disasters measure includes all storms and floods without any restriction on the number of fatalities. The baseline measure includes all storms and floods with fatalities above the median, while the severe measure includes all storms and floods with fatalities in the top 1%. The sample period is 1987w14–2024w39. The shaded area denotes the 68% confidence interval, based on state-level clustered standard errors.

This point aligns with findings by Jacobson et al. (2022) and Baumeister et al. (2024), who

[20] Estimating a local projection with state fixed effects and using a dummy variable for 2008w1 to capture the economics dynamics following the GFC shock yields an average peak decline in the ECI in the range of 3.5–4%.

[21] Our findings thus differ from studies that identify long-term declines in output growth based on annual, country-level data (e.g., Cavallo et al., 2013; Von Peter et al., 2024). For example, Cavallo et al. (2013) found that GDP per capita in affected countries is, on average, 10% lower ten years after a disaster. Similarly, Von Peter et al. (2024) reported that major disasters initially reduce growth by 1 to 2 percentage points and cumulatively result in an output loss of 2% to 4% of GDP, in addition to immediate damage to property and infrastructure.

demonstrate that temporal aggregation bias can explain puzzles such as the counterintuitive inflation responses following monetary policy shocks (Jacobson et al., 2022) and difficulties in accurately assessing the benefits of the Paycheck Protection Program after the COVID-19 pandemic (Baumeister et al., 2024). Our results also align with Buda et al. (2023), who demonstrates that impulse responses to monetary policy shocks differ substantially depending on whether high-frequency (daily or weekly) data or aggregated quarterly data are used—further underscoring the importance of data frequency in shaping economic interpretations and implications.

While the impulse response functions based on the weekly economic index offer valuable insights into the overall impact of natural disasters at the state level, the composite nature of the index limits our ability to disentangle the effects across specific economic dimensions. To overcome this limitation and build on the preceding analysis, Section 4.2 explicitly estimates the effects of natural disasters across a range of key economic outcomes. This disaggregated approach allows us to identify which dimensions of the economy—such as mobility, labor markets, exports, expectations, new business applications, and household credit and debit card spending—are most affected.

4.2 Disaggregate Effects of Natural Disasters

Thus far, we have established that natural disasters cause a temporary decline in overall economic activity. In this section, we identify which specific dimensions of economic activity are most significantly affected and investigate the mechanisms underlying these effects. To do so, we analyze detailed economic indicators that capture various dimensions of economic performance, including regional labor markets, mobility, exports, new business applications, manufacturing sentiment, and household spending via data available at weekly or monthly intervals. Additionally, we utilize state-level price data to estimate the impact of natural disasters on inflation.[22]

To assess the impact of natural disasters on different aspects of economic activity, we re-estimate equation 1 using the weekly and monthly outcomes described above.[23] Panels (a)–(f)

[22]These variables capture different dimensions of regional economic activity. For instance, we use mobility indicators to proxy for disruptions in weekly routines and economic activity; unemployment insurance claims to capture labor market conditions; export data on manufacturing and non-manufacturing commodities to reflect external demand and production linkages; and measures of manufacturing sentiment to gauge business expectations, confidence, and current production. In addition, we consider new business applications as a forward-looking indicator of firm confidence in future economic activity and as a proxy for investment in new productive capacity, while household-level metrics, such as credit card spending, provide insight into consumption patterns and demand-side dynamics.

[23]For monthly outcomes, we sum weekly values within each month to construct the monthly index and include year–month fixed effects to absorb common shocks across states. The baseline disaster indicator equals one if a state experiences at least one disaster during the month; results are nearly identical if we instead use the

of Figure 6 illustrate the average weekly dynamics of card spending, initial jobless claims, new business applications, and mobility following natural disasters.[24] For insurance claims and new 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)–(b) of Figure 6, initial jobless claims show no immediate response but rise by about 1.5% roughly five weeks after a disaster, then gradually return to pre-disaster levels by around 30 weeks. Extreme disasters have far larger effects: claims surge by around 60% within ten weeks and then recede toward historical levels over the next about 20 weeks, indicating severe short-run labor-market disruption. These patterns imply sizable labor-market effects, with severe events driving dramatic spikes in short-term unemployment.

Panels (c) and (d) of Figure 6 illustrate how the trajectory of firm expectations, as measured by new business applications, varies with disaster severity. After typical disasters, applications experience minimal disruption and exceed historical levels between weeks 8 and 30; after severe disasters, they fall by around 30% within ten weeks and remain depressed—about 40% below average even after 40 weeks—underscoring a prolonged hit to business expectations. Consistent with our main results on weekly economic activity, severe events (fatalities in the top 1%) have markedly larger effects.

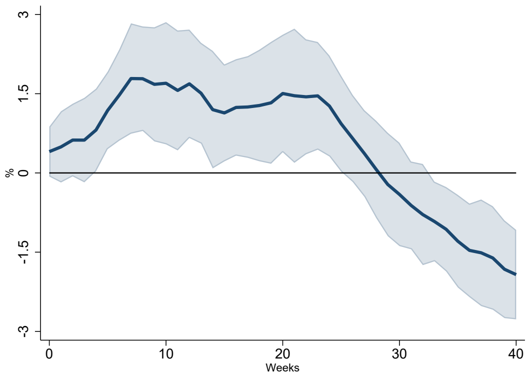
Measures of mobility gained prominence during the pandemic as a means of tracking economic activity. Consistent with aggregate dynamics, panel (e) shows mobility dropping 15–20% within ten weeks and recovering to its historical trend by around 35 weeks (about eight months), mirroring the path of weekly activity. In contrast to the temporary nature of mobility disruptions, panel (f) indicates a more persistent effect on household consumption—proxied by credit and debit card transactions. Spending declines by more than 2% within 20 weeks and remains lower thereafter; even after 40 weeks it is about 1.5% below its historical average. This pattern suggests that, while broader activity rebounds, the impact on household spending—and thus consumption—is more persistent, likely reflecting increased financial caution in the aftermath.

state–month count of disasters.

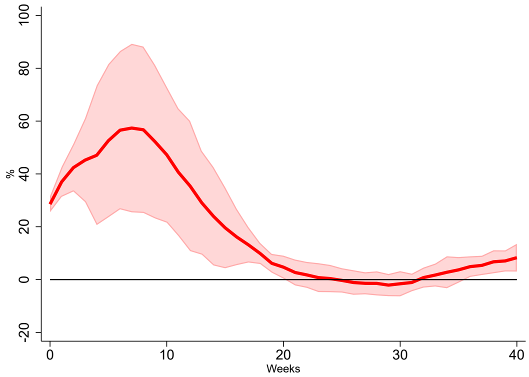
[24] Initial jobless claims are filed by individuals who have lost their jobs to determine their eligibility for unemployment insurance benefits.

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

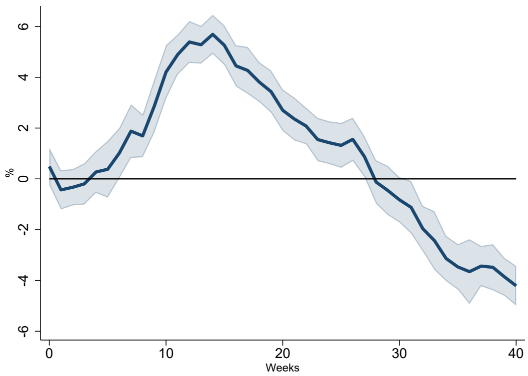
(a) **Unemp. Insurance Claims**. Baseline Disaster Measure.



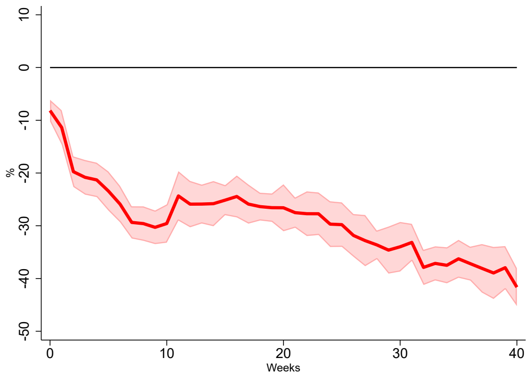
(b) **Unemp. Insurance Claims**. Severe Disaster Measure.



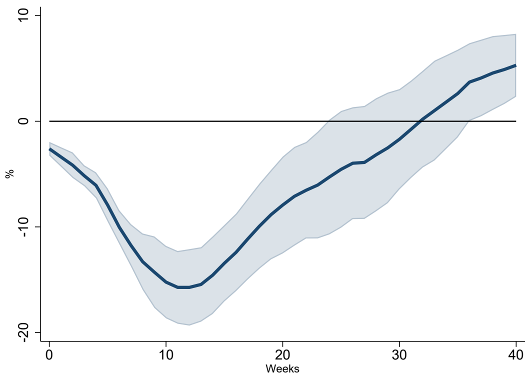
(c) **New Business Applications**. Baseline Disaster Measure.



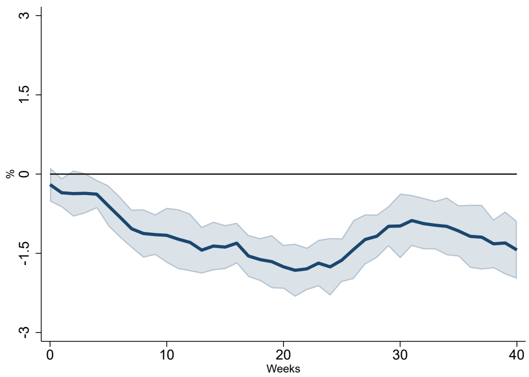
(d) **New Business Applications**. Severe Disaster Measure.



(e) **Mobility**. Baseline Disaster Measure.



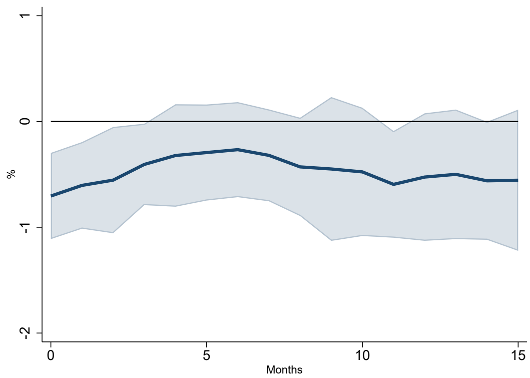
(f) **Credit Card Spending**. Baseline Disaster Measure.



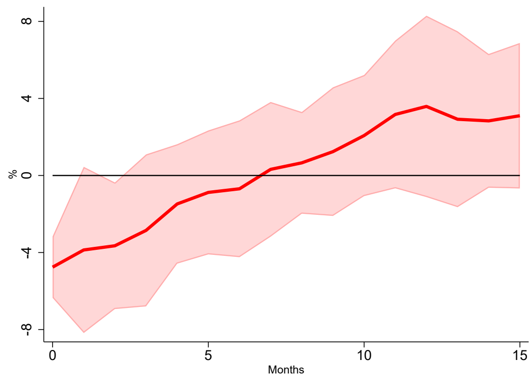
Notes: Estimated cumulative changes in selected outcomes following a natural disaster. Horizons $h = 1, 2, \ldots, 40$. The baseline natural disaster indicator includes all storms and floods with the number of reported deaths above the median. The severe natural disaster indicator includes all storms and floods with the number of reported deaths in the top 1%. The sample periods vary by outcome: 1987w14–2024w39 for initial jobless claims, 2006w5–2024w39 for new 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.

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

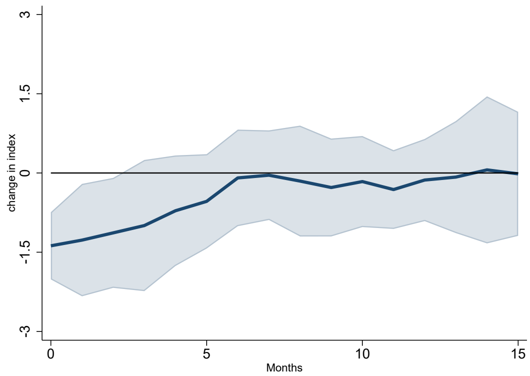
(a) **Exports**. Baseline Disaster Measure.



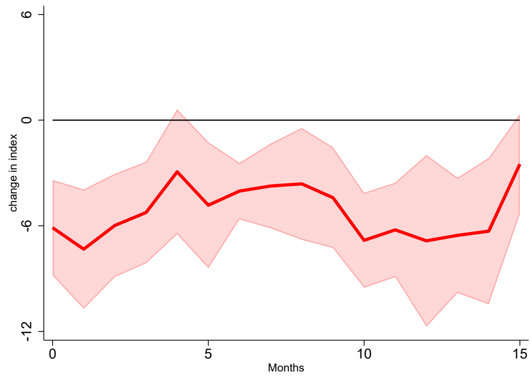
(b) **Exports**. Severe Disaster Measure.



(c) **Manufacturing Sentiment**. Baseline Disaster Measure.



(d) **Manufacturing Sentiment**. Severe Disaster Measure.



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 severe natural disaster indicator includes all storms and floods with the number of reported deaths in the top 1%. The sample periods vary by outcome: 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.

Panels (a)–(d) of Figure 7 report monthly responses. Exports of manufactured and non-manufactured commodities fall by around 1% in the disaster month and show no clear recovery even after 15 months, with statistically significant effects concentrated in the initial months. Extreme disasters generate an initial drop around five times as large as in typical disasters but the effect is shorter-lived, with exports returning to trend within six months. This contrast highlights a disproportionately large yet less persistent export response to severe events and suggests meaningful trade disruptions, consistent with reduced external demand and local supply-chain frictions.

Manufacturing sentiment—a measure of firm activity and expectations (production, capacity utilization, new orders, employment, and hours worked)—declines after natural disasters and recovers only slowly, with full normalization taking up to 15 months.[25] Effects are imprecisely estimated beyond the early months and are statistically significant mainly at the outset. High-fatality events (panel (d)) produce declines around six times larger than typical disasters; sentiment remains depressed and begins to recover only after around 40 weeks. This contrast underscores the large and persistent impact of severe disasters on manufacturing expectations and activity.

4.3 Effects on Inflation

In this section, we estimate the impact of natural disasters on inflation using state-level inflation data. Theoretically, the effect of natural disasters on inflation is ambiguous, as supply shocks, demand fluctuations, and policy responses can all influence prices in different directions. On the supply side, natural disasters can destroy physical capital, lead to losses of human life and human capital, and disrupt supply chains — all of which tend to put upward pressure on inflation. On the demand side, however, they may weaken consumer and business confidence, reduce investment, and dampen external demand, potentially exerting downward pressure on prices. Accordingly, the net effect of natural disasters on inflation ultimately depends on whether supply-side pressures or demand-side forces prevail.

To examine the effects of natural disasters on inflation at the state level, we use data from Hazell et al. (2022), which provides state-level quarterly inflation rates for subcategories of the Consumer Price Index excluding shelter, covering the period from 1978 to 2017.[26] To capture the short-run dynamics of inflation following natural disasters, we interpolate the quarterly data to a monthly frequency.[27]

Panel (a) of Figure 8 highlights the contrasting effects of most natural disasters on economic

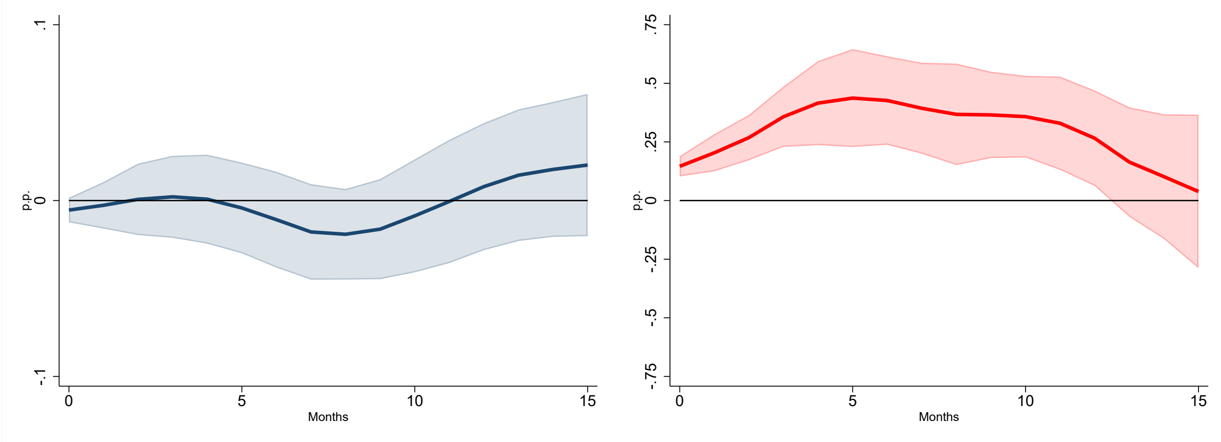
[25]Manufacturing sentiment is constructed using a combination of survey-based indicators, including the Production Index, Capacity Utilization, New Orders, Employment, and Hours Worked.

[26]Hazell et al. (2022) provides inflation rates for twenty-nine out of the fifty U.S. states. Unfortunately, high-frequency price data are not available at the state level, which limits our ability to capture the immediate inflation dynamics in the same way we do for economic activity. Nevertheless, we believe it is still valuable to estimate the effects of natural disasters on prices. As discussed above, the theoretical implications of such shocks for inflation are ambiguous—depending on whether demand or supply channels dominate—and the results have important consequences for monetary policy design. Moreover, it is well established that prices exhibit nominal rigidities and take time to adjust to shocks (see, e.g., Buda et al., 2023). For instance, Buda et al. (2023) shows that output and consumption respond to monetary policy shocks almost immediately—within the same day—while consumer prices react more slowly, with effects peaking only after a longer delay. As a result, any inflationary effects of natural disasters may unfold more gradually over time, further justifying the inclusion of price responses in our empirical analysis despite the lower frequency of available data.

[27]We convert the quarterly inflation data from Hazell et al. (2022) into a monthly series using linear interpolation. We also estimate the effects using the original quarterly inflation measures and find very similar results. Thus, the interpolation method does not affect our main findings regarding inflation.

Figure 8: Dynamic Response of Inflation Rate to Natural Disasters

(a) **Inflation Rate**. Baseline Disaster Measure. (b) **Inflation Rate**. Severe Disaster Measure.



Notes: Estimated changes in inflation rate 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 severe natural disaster indicator includes all storms and floods with the number of reported deaths in the top 1%. The sample period is 1989m3–2017m12. 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.

activity and inflation. While disasters–measured by our baseline indicator– trigger a sharp decline across multiple dimensions of economic activity, their effects on inflation are muted. Inflation falls slightly after a disaster, but the change is small and not statistically significant, suggesting little to no overall effect on prices. This muted inflation response, in contrast to the strong contraction in activity, implies that natural disasters resemble a combination of negative demand and supply shocks: they reduce output without generating significant inflationary or deflationary pressures. This price stability aligns with our disaggregated results, which show that disasters suppress demand by lowering household spending and investment, while also disrupting supply through impaired supply chains and production constraints—e.g., manufacturing sentiment declines noticeably after natural disasters. These opposing forces largely offset each other, leading to minimal net changes in prices.

By contrast, the most severe disasters—those in the top 1% in terms of fatalities—do have an impact on inflation, as shown in Panel (b) of Figure 8. Following such events, inflation rises and remains above its typical path for over a year, with a sizable magnitude. These dynamics suggest that negative supply shocks ultimately dominate the economic response to severe disasters. Overall, while typical disasters have little effect on inflation, the most catastrophic events lead to a temporary but noticeable increase in state-level price dynamics.

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, new business applications, 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. Furthermore, most natural disasters have minimal effects on inflation, suggesting they primarily operate through a combination of negative demand and supply shocks that dampen economic activity without substantially altering price dynamics. Only the most extreme events produce a temporary, yet measurable, impact on inflation.

4.4 The impact of natural disasters on the US

In Subsection 4.1, we examined the effects of natural disasters on state-level economic activity. As a natural follow-up, we ask whether these events also have measurable effects on aggregate U.S. performance. To test this, we construct weekly national disaster indicators. Our baseline indicator equals one in any week with at least one disaster anywhere in the country. We also consider (i) an indicator that turns on only when a disaster occurs in one of the four most populous states—California, Texas, Florida, or New York—and (ii) an indicator that turns on when a single event affects a large majority of states simultaneously. We then estimate separate regressions using each indicator to assess the impact of natural disasters on national economic activity.[28]

In particular, we estimate the following local projections:

$$\begin{aligned} ECI^{US}_{t+h} = {} & \alpha_h + \beta_h \, Natural\ Disaster^{US}_t + \sum_{l=1}^{4} \delta_{h,l} \, Natural\ Disaster^{US}_{t-l} + \\ & \theta_h \, Other\ Disaster^{US}_t + \gamma_h \, Pandemic^{US}_t + \sum_{l=1}^{4} \Gamma_{h,l} \, ECI^{US}_{t-l} + \varepsilon_{t+h}, \end{aligned} \tag{2}$$

Here, $ECI^{US}_{i,t+h}$ represents the h-period-ahead weekly economic conditions for the U.S. as a whole, while $Natural\ Disaster^{US}_{i,t}$ is a dummy variable activated when at least one natural

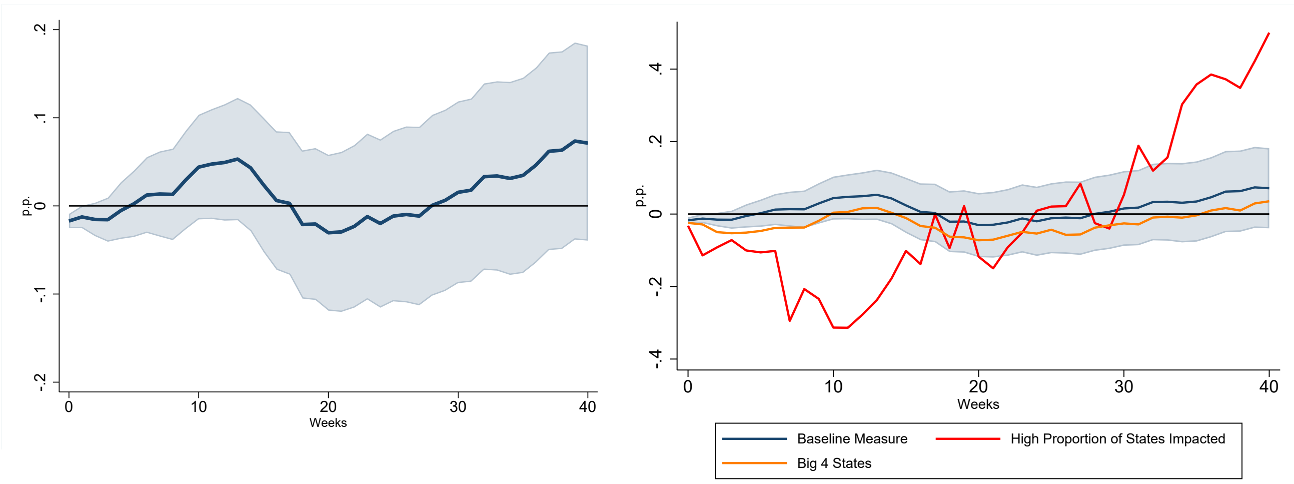
[28]We also construct a count-based national measure—the number of disasters per week—and reach the same conclusion that natural disasters do not significantly affect aggregate U.S. activity.

disaster occurs in the U.S in week t.[29]

Figure 9: Dynamic Response of US Economic Activity to a Natural Disaster

(a) Baseline Measure

(b) Other Measures of Natural Disasters



Notes: Estimated changes in the Weekly Economic Conditions Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 2, \ldots, 40$ following a natural disaster. Panel (a) includes all storms and floods for which the number of reported deaths exceeds the median. Panel (b) uses three measures: the baseline includes all storms and floods with fatalities above the median; the "Big Four States" measure includes storms and floods with above-median fatalities striking one of the four most populous states (California, Texas, Florida, or New York); and the "high proportion of states" measure includes only events with above-median fatalities that affected more than 70% of states. The sample period is 1987w14–2024w39. The shaded area denotes the 68% confidence interval, based on robust standard errors.

Panels (a) and (b) of Figure 9 summarize our main results: most natural disasters have little to no effect on aggregate U.S. economic activity. In Panel (a), using the baseline indicator, the estimated responses are small and statistically insignificant at all horizons.[30] This muted aggregate response likely reflects the fact that the median disaster affects around 15% of the states (see Table A.2.1), while economic activity in the remaining states remains largely stable, offsetting localized disruptions. Panel (b) considers two broader cases: (i) disasters striking one of the four most populous states (California, Texas, Florida, or New York), and (ii) disasters affecting more than 70% of states simultaneously. In the first case, national activity declines and remains depressed for nearly a year; in the second, we observe a more pronounced decline lasting roughly 10–15 weeks, followed by a recovery and modest rebound.

Overall, our analysis shows that while natural disasters significantly disrupt economic activity

[29] Since our baseline disaster indicator includes storms and floods that result in fatalities above the median, we identify qualifying events by aggregating the number of deaths caused by all such disasters occurring within the same week.

[30] With the exception of the first few weeks, during which the responses are statistically significant but economically small.

at the state level in the short to medium term, these localized shocks do not systematically translate into measurable effects at the national level. This finding underscores the value of using state-level data, which more precisely captures localized economic disruptions than previous studies that primarily relied on aggregated national data.

5 The Role of Private Insurance

Thus far, we have documented the average effects of natural disasters on individual U.S. states and on the national economy. In this section, we present novel evidence on the critical role of property insurance in mitigating the economic impact of such events.

Our focus on property insurance is motivated by recent empirical findings from Von Peter et al. (2024), who, using cross-country comparisons and low-frequency annual data, show that natural disasters have large and persistent negative effects on output—effects primarily driven by uninsured losses. We complement this evidence by exploiting both time-series and cross-sectional variation in property insurance coverage across U.S. states. Using high-frequency, state-level data on economic activity, we test whether insurance coverage shapes the trajectory of post-disaster outcomes.

To that end, we compile new data on property insurance coverage across U.S. states from 1993 to 2021. Specifically, we use data from the National Association of Insurance Commissioners (NAIC), based on the report House Years by Policy Form by State for Owner-Occupied Homeowners, which provides annual state-level information on insured properties.[31]

We extract the number of insured house years at an annual frequency between 1993 and 2021.[32] To align with the broader sample period of our analysis, we extend the series by assuming that values from 1993 apply to the years 1987–1992, and that values from 2021 apply to the years 2022–2024. This choice is motivated by the high persistence of property insurance coverage within a given state over time.[33] In addition, we collect state-level data on population

[31]This report covers homeowners dwelling, fire, and tenant insurance, and contains a summary of market distribution and average cost by policy form. It also includes insurance-specific information for each state regarding the number of homeowners policies written, the amount of insurance, and average premiums. The report reflects the latest available year of data and is updated annually.

[32]In our analysis, we focus exclusively on owner-occupied homeowners insurance and exclude dwelling fire and tenant homeowners policies. This choice reflects our interest in understanding insurance coverage for individuals who both own and reside in their homes—those most directly exposed to financial losses from natural disasters. Dwelling fire policies often cover rental or investment properties, while tenant homeowners insurance typically covers personal belongings rather than the structure itself. Limiting our scope to owner-occupied policies ensures consistency across states and provides the most relevant measure of residential property protection. Moreover, this type of policy is by far the most prevalent form of property insurance across states.

[33]The results remain both quantitatively and qualitatively similar when using data restricted to the 1993–2021

and occupied households to construct, for each state-year, the proportion of households with property insurance.

Finally, we construct a weekly indicator of property insurance coverage per capita by holding the annual value constant within each year. Based on this measure, we categorize states into two groups—above and below the median coverage per capita in the week prior to each disaster—and use this classification in our empirical analysis. We therefore exploit cross-sectional variation in property insurance coverage in the week prior to each natural disaster to examine its influence on post-disaster economic outcomes. Specifically, we estimate the following regression:

$$ECI_{i,t+h} = \alpha_{i,h} + \beta_h \, Deaths_{i,t} + \theta_h \left(Deaths_{i,t} \times 1(PI_i > PI_{p50})\right) + \sum_{l=1}^{4} \delta_{h,l} \, Natural\ Disaster_{i,t-l} +$$
$$+ \phi_h \, Other\ Disaster_{i,t} + \gamma_h \, Pandemic_t + \sum_{l=1}^{4} \Gamma_{h,l} \, ECI_{i,t-l} + \varepsilon_{i,t+h}, \tag{3}$$

We use the state-level Weekly Economic Conditions Index (ECI) as our outcome variable, which provides a high-frequency measure of real economic activity at the state level. The main explanatory variable of interest is $Deaths_{i,t}$, which captures the total number of fatalities caused by natural disasters in state i at time t. To explore heterogeneity in the effects of natural disasters, we interact $Deaths_{i,t}$ with an indicator variable equal to one if the level of property insurance coverage per capita in state i is above the cross-sectional median in the week prior to the disaster, and zero otherwise. This allows us to estimate whether the economic impact of a disaster differs systematically depending on pre-disaster insurance coverage. Accordingly, the coefficient β_h traces the impulse response of the ECI at horizon h following a disaster-induced mortality shock in states with below-median property insurance coverage, while the interaction term coefficient θ_h captures how this response differs in states with above-median insurance coverage.

We also include an additional dummy variable to capture disaster events not reflected in the *Deaths* measure, which only takes positive values for storms and floods with fatalities above the historical median. In addition, we include four lags of the main disaster indicator to account for potential persistence in the effects of recent disasters. To control for macroeconomic disruptions unrelated to natural disasters, we include a pandemic dummy for the period between 2020w10 and 2020w31, capturing the sharp nationwide decline in economic activity at the onset of the

period.

COVID-19 pandemic. Finally, we include lagged values of the dependent variable to control for persistence in local economic conditions. We estimate the model using weekly data from 1987w14 to 2024w39.

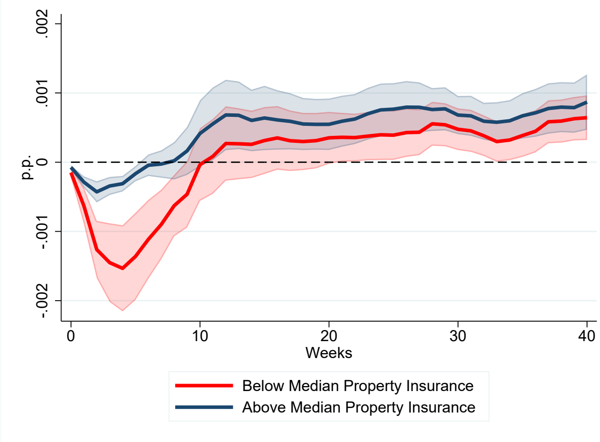
In earlier specifications, we defined disaster events using a binary indicator equal to one if the number of deaths from storms or floods in a given state-week exceeded the historical median. In this section, we instead use a continuous measure of disaster severity based on the total number of deaths. This choice is particularly important when comparing outcomes across states with different levels of property insurance coverage. By modeling severity continuously, we ensure that disasters with similar initial intensity—measured by the number of deaths—can be directly compared across states with above- and below-median insurance coverage. This approach allows us to isolate differences in post-disaster recovery that are plausibly driven by variation in pre-disaster insurance protection, rather than by differences in the magnitude of the shock itself. Our aim is therefore to compare disasters of similar severity and assess how recovery trajectories differ depending on the prevalence of property insurance.[34]

Figure 10 presents our main empirical result, illustrating how the economic impact of natural disasters—measured by disaster-related deaths—varies with the level of property insurance coverage. Specifically, the figure shows that in states with above-median property insurance per capita in the week prior to the disaster, the negative effect of each additional death on economic activity is significantly attenuated. In contrast, states with below-median insurance coverage experience a larger and more persistent decline in economic conditions following a disaster.

These findings underscore the important role of property insurance in cushioning the economic impact of natural disasters. They support the broader view that insurance coverage helps explain differences in post-disaster economic outcomes. This is consistent with Von Peter et al. (2024), who use aggregate country-level data and cross-country comparisons to show that natural disasters have large and lasting negative effects on output—effects that are primarily driven by uninsured losses. In contrast, insured losses are associated with more neutral or even slightly positive growth outcomes due to their role in financing recovery. We complement this evidence by collecting novel data on property insurance at the state level and combining it with high-frequency data, which—as discussed in detail in Section 3—allow for a more precise estimation of the full dynamics of economic activity following natural disasters.

[34]Table B.1 presents summary statistics comparing states with above- and below-median property insurance coverage per capita in the week prior to each disaster. This comparison helps validate our empirical strategy by showing that disaster severity proxied by the number of fatalities is similar across both groups.

Figure 10: Dynamic Response of Weekly Economic Activity to Natural Disasters: The Role of Property Insurance Coverage



Notes: This figure shows estimated changes in the Weekly Indicator Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 2, \ldots, 40$ following a natural disaster. The analysis focuses on storms and floods in which the number of reported deaths exceeds the historical median, forming our baseline disaster measure. We estimate state-dependent responses based on whether property insurance per capita in the week prior to the disaster is above or below the cross-sectional median. The sample period is 1987w14–2024w39. Shaded areas represent 68% confidence intervals based on robust standard errors.

6 Robustness Analyses

Heterogeneity. Our baseline analysis uses a single natural disaster indicator combining storms and floods. However, these disaster types may have distinct economic effects. To explore this heterogeneity, we construct separate indicators for storms and floods. We then re-estimate our baseline regression, specified in Equation 1, separately for each disaster type, with results presented in Appendix B.

Since storms dominate the variation in our baseline disaster measure, the storm-specific results closely match those presented in Figure 5. Specifically, storms lead to a decline in weekly economic conditions, which typically recover to their pre-disaster average within approximately 20 weeks. Floods, however, exhibit more prolonged effects, with economic performance taking around 40 weeks—twice as long as storms—to fully recover.[35]

All Types of Natural Disasters. We also construct an aggregate natural disaster indicator that encompasses all disaster types. Specifically, this indicator takes a positive value for a given week and state if any of the following disasters occur: volcanic activity, mass movement, drought,

[35]Floods occur less frequently in our baseline measure, resulting in wider standard error bands for their estimated impulse responses.

extreme temperature, earthquake, epidemic, wildfire, flood, or storm, with reported deaths exceeding the median. We incorporate this comprehensive indicator into our baseline regression, as specified in Equation 1. The results, provided in Appendix B, demonstrate that including all disaster types yields nearly identical outcomes to our baseline results, which focus exclusively on storms and floods. This finding expands the empirical evidence regarding the aggregate economic impacts of natural disasters, reinforcing that these events significantly disrupt 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 three 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. Third, we construct a measure of disaster intensity based on the number of deaths relative to the affected state's population (deaths per capita), again focusing on events above the median. These additional analyses are presented in Appendix B.

Overall, our findings for large natural disasters remain consistent with the baseline results shown in Figure 5. Specifically, when large disasters are measured by the number of affected states, the trajectory of state-level economic conditions closely mirrors that of our baseline indicator. When using reported total direct damage, we observe a slightly faster economic recovery, typically within approximately 15 weeks. Finally, when disaster intensity is measured by deaths per capita, the results again closely resemble our baseline, with slightly more persistent effects but an almost identical impact pattern on economic activity.

Placebo Exercise. One potential concern is whether the observed results could be driven by random chance. To investigate this, Figure B.2 presents the results of a placebo test in which we randomly reshuffle the timing of natural disasters. Specifically, we assign disaster weeks by randomly drawing from a uniform distribution and estimate the impulse responses across 500 replications.[36] We then plot the median point estimates for each forecast horizon, along with the 5th–95th percentile bands of the impulse responses across all simulations.

[36]In each replication, we set the probability of a natural disaster to 1.5%, matching the actual frequency of natural disasters in our sample.

The placebo results show negligible effects of these randomized natural disasters on weekly economic activity, confirming that our main findings are not driven by random chance.

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 1, using only data prior to March 2020. When excluding post-pandemic data, we find results that are consistent with our baseline estimates.

7 Conclusion

What are the causal effects of natural disasters on economic activity? This paper answers that question using high-frequency data on overall activity and a comprehensive dataset of natural disasters across U.S. states. Focusing on large, plausibly unexpected events, we find a temporary decline in state-level economic activity that fully dissipates within a year. We show that the size and persistence of the shock depend strongly on the severity of the initial disaster, and that the decline is driven primarily by short-run disruptions to mobility, manufacturing sentiment, household spending, and the labor market, while inflation shows no discernible response.

Overall, our findings provide novel evidence on the increasing frequency of natural disasters and their detrimental effects on economic activity. These results highlight the significant economic costs associated with climate change and serve as an important warning about the consequences of extreme climate-related events. By clarifying these impacts, our study offers valuable insights for policymakers and central banks worldwide, emphasizing the importance of proactive and adaptive strategies. Specifically, our findings suggest that national-level policies, such as monetary policy, are less suited to addressing the localized impacts of natural disasters, whereas targeted regional policies are essential for effectively mitigating their adverse economic consequences. In addition, our results underscore the importance of property insurance as a private financial buffer: we show that states with broader insurance coverage experience significantly less severe downturns following disasters. This highlights a complementary policy implication—the potential role of promoting insurance adoption as part of a broader climate resilience strategy.

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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
Inflation Rate	Quarterly	Hazell et al. (2022)

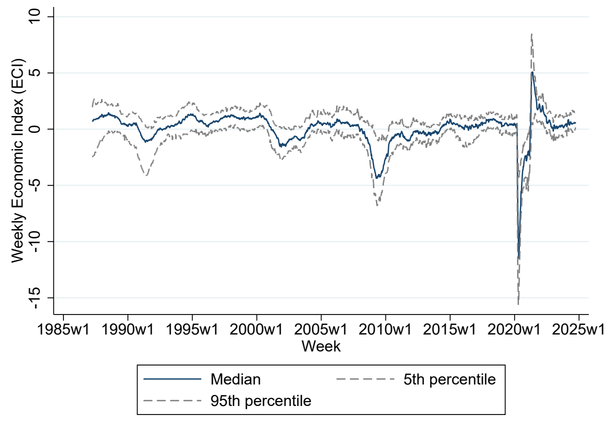
A.2 Summary Statistics

Table A.2.1: Descriptive Statistics of Natural Disasters

Variables	Mean	Median	Std. Dev.	Min	Max
Total Damage ('000 US$)	2,871,123	1,000,000	8,347,558	170	125,000,000
Number Affected States	12.02	9	10.28	1	50
Total Deaths	42.81	12	144.57	1	6,000
No. Injured	105.18	40	288.11	1	7,000
No. Affected	882,450.80	1,200	7,938,792	9	85,000,000
No. Homeless	7,276.71	597	22,430.74	12	250,000

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

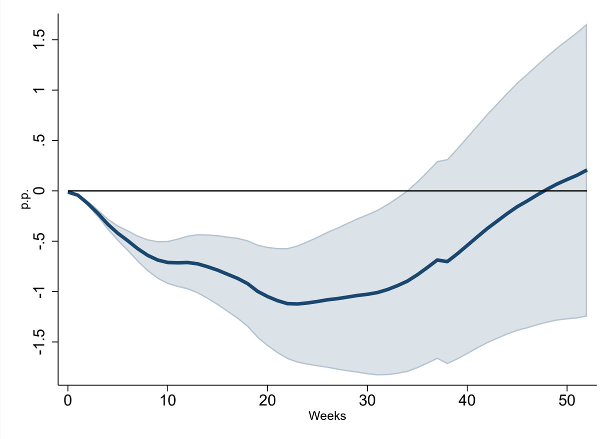
Figure A.2.1: Weekly Economic Conditions Index (ECI)



Notes: The figure presents the time series of the state-level Weekly Economic Conditions Index (ECI) from Baumeister et al. (2024). Each week, we calculate the median ECI across states, along with the 5th and 95th percentiles. The sample period spans from 1987w14 to 2024w39.

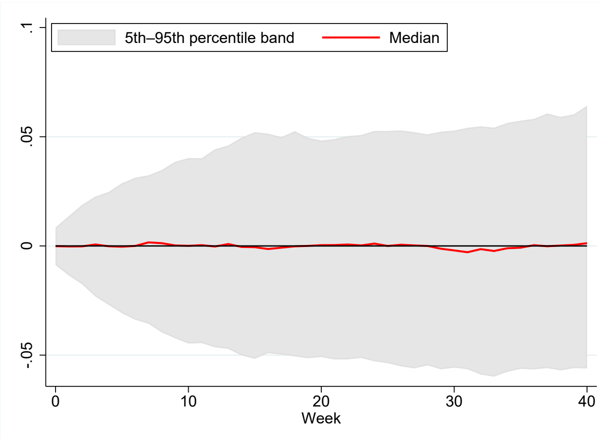
B Sensitivity Checks

Figure B.1: Cumulative response of weekly economic activity (ECI) to natural disasters



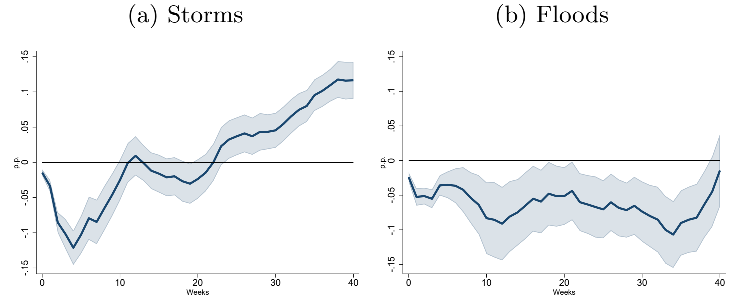
Notes: Estimated responses using local projections where the dependent variable is the cumulative sum of weekly growth rates, $\sum_{q=0}^{h} \mathrm{ECI}_{i,t+q}$, from Baumeister et al. (2024). We report horizons $h = 0, 2, \ldots, 52$ after a natural disaster. Natural disasters include storms and floods with the number of reported deaths above the median. Sample: 1987w14–2024w39. Shaded bands denote 68% confidence intervals based on state-clustered standard errors.

Figure B.2: IRFs from Random Natural Disasters



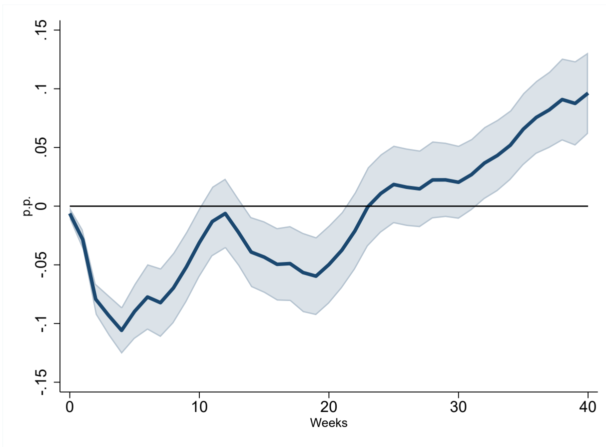
Notes: The figure illustrates the impulse responses from a placebo test in which the occurrence of natural disasters is randomly reshuffled. In each iteration, the week of the natural disaster indicator is drawn from a uniform distribution, with the probability of a natural disaster randomly set to 1.5%—consistent 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.3: Heterogeneity



Notes: Estimated 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. The shaded area denotes the 68% confidence interval, based on state-level clustered standard errors.

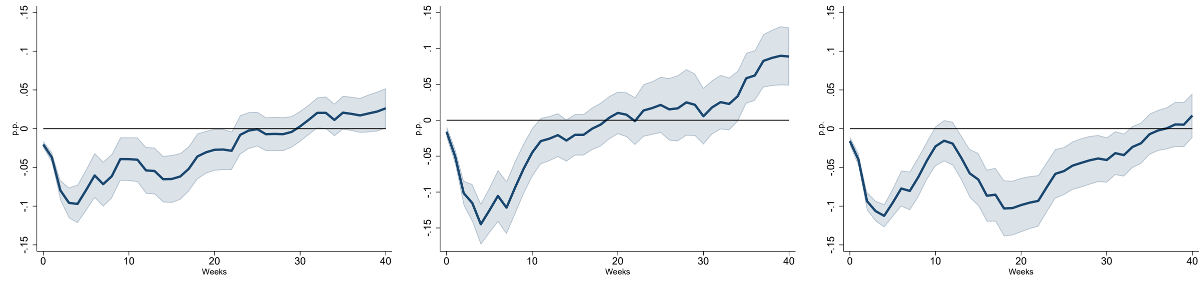
Figure B.4: All types of natural disasters



Notes: Estimated 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.

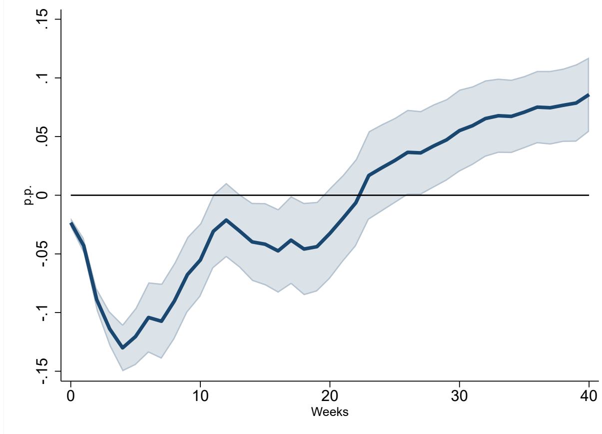
Figure B.5: Impact of Large Natural Disasters

(a) By Number of Affected States (b) By Total Damage (c) By Deaths Per Capita



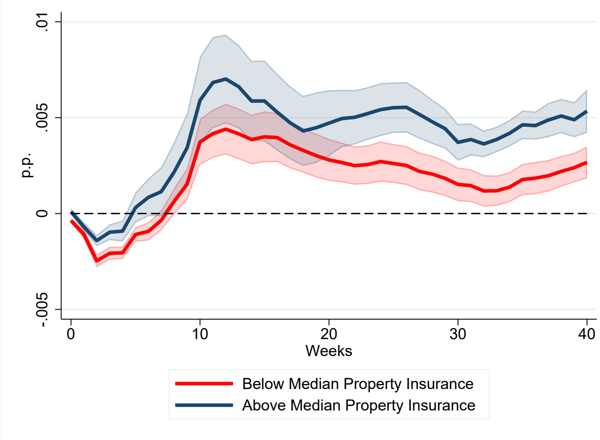
Notes: Estimated changes in the Weekly Indicator Index (ECI) of Baumeister et al. (2024) at horizons $h = 0, 2, ..., 40$, following a natural disaster. Panel (a) includes storms and floods for which the number of affected states is above the median, panel (b) includes those where the reported total cost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

Figure B.6: Subsample: Excluding post-Pandemic Data



Notes: Estimated 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.

Figure B.7: Dynamic Response of Weekly Economic Activity to Natural Disasters: The Role of Property Insurance Coverage



Notes: This figure shows the estimated changes in the Weekly Economic Conditions Index (ECI) from Baumeister et al. (2024) at horizons $h = 0, 2, \ldots, 40$ following a natural disaster. The analysis focuses on storms and floods in which the number of reported deaths exceeds the historical median, which serves as our baseline disaster measure. We estimate state-dependent responses based on whether property insurance per occupied housing unit in the week prior to the disaster is above or below the cross-sectional median. The sample period is 2010w1–2023w52. Shaded areas represent 68% confidence intervals based on robust standard errors.

C Other Results

In this Appendix, we present summary statistics comparing states with above- and below-median per capita property insurance coverage in the week preceding each disaster (Table B.1). That comparison supports the validity of our empirical strategy, presented in Section 5, by showing that disasters severity—proxied by the number of fatalities—is similar across both groups.

Table B.1: Summary Statistics by Property Insurance Coverage

	Mean	**Std. Dev.**	**N**
Panel A: Deaths			
Low Insurance ($PI_i \leq PI_{p50}$)	48.84	123.89	747
High Insurance ($PI_i > PI_{p50}$)	43.87	101.68	777
Total	46.31	113.10	1524
Panel B: Property Insurance per Capita			
Low Insurance ($PI_i \leq PI_{p50}$)	0.177	0.024	747
High Insurance ($PI_i > PI_{p50}$)	0.230	0.019	777
Total	0.204	0.034	1524
Panel C: Property Insurance per Occupied Housing Unit			
Low Insurance ($PI_i \leq PI_{p50}$)	0.477	0.059	384
High Insurance ($PI_i > PI_{p50}$)	0.601	0.041	344
Total	0.535	0.080	728

Notes: Summary statistics by whether state-level property insurance per capita is above the cross-sectional median in the week prior to the disaster. Panel A reports disaster-related deaths and is based on data from 1987w14–2024w39. Panel B shows the distribution of property insurance per capita over the same period. Panel C reports property insurance per occupied household using data available from 2010w1 to 2023w52. The above/below median categorization used in Panel A is based on the distribution of property insurance per capita. N indicates the number of disasters in each category.

Panel A focuses on disaster-related deaths and covers the full sample period from 1987w14 to 2024w39. To construct the comparison groups, we classify states as above or below the median based on property insurance per capita, as reported in Panel B. The average number of deaths is nearly identical across the two groups, suggesting that states with high and low insurance coverage experienced disasters of comparable initial severity. This supports our identifying assumption that differences in post-disaster recovery are driven by variation in insurance coverage, rather than by differences in the intensity of the initial shock.

Panel B displays the distribution of property insurance coverage per capita, which we are able to construct for the entire sample period using state-level population data. In contrast, Panel C reports insurance coverage per occupied household, which is available only from 2010w1 to 2023w52 due to data limitations on the number of occupied housing units. For instance, Panel B shows that property insurance coverage is approximately 6 percentage points higher, on average, in states with above-median insurance (per capita) than in those below the median. This difference increases to over 13 percentage points when using the property insurance per occupied housing unit measure, as shown in Panel C. Together, the panels confirm that the insurance split captures meaningful variation in coverage while holding disaster severity roughly constant across groups. We therefore use the per capita measure in our baseline specification and for the results presented below in Figure 10. Results based on insurance coverage per occupied housing unit are reported in the appendix and yield similar conclusions.

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