

The Economic Impact of Natural Disasters: A High Frequency Approach*

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Abstract

We estimate the dynamic causal effects of natural disasters using weekly U.S. state-level data over the last forty years. Our results show that disasters immediately disrupt economic activity, generating negative effects across multiple dimensions beginning in the first week. In the short term, we find declines in regional labor markets, exports, new business formation, and economic sentiment, while household consumption exhibits more persistent negative effects. Although most disasters do not affect inflation, the most severe events create temporary inflationary pressures. Importantly, these regional shocks rarely translate into measurable effects at the national level. Our findings underscore the importance of high-frequency, regional data for capturing the full dynamics of geographically concentrated shocks like natural disasters. Finally, we compile new data on state-level property insurance and show that higher insurance coverage before a disaster plays a key role in mitigating its economic severity.

Key Words: Climate change; Natural Disasters; Local Projections; Economic Activity; High-Frequency.

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

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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.

To our knowledge, this is the first study to combine regional and high-frequency data to analyze the macroeconomic consequences of natural disasters. Using weekly state-level panel data within a local projection framework, we estimate the dynamic response of economic activity following such events. Our findings show that natural disasters cause a temporary deterioration in weekly economic conditions, leading to a short-term decline in overall economic performance.

At the state level, economic activity typically declines immediately following a natural disaster but recovers to its pre-disaster level within 20 to 40 weeks, depending on the type of event. Storms tend to disrupt economic activity for about 20 weeks (roughly five months), whereas floods have a more prolonged impact, with recovery often taking up to 40 weeks (around ten months).² Although the economic effects of most natural disasters dissipate within a year, their

¹Recent bulletins from the ECB (ECB, 2025) and the BIS (Ehlers et al., 2025) highlight central banks' growing concern about the economic consequences of natural disasters.

²The more persistent effects of flooding compared to storms may be partly explained by the fact that standard homeowners' insurance typically covers wind damage from storms but not flood-related damage. Flood insurance is often optional and can be costly, making it less commonly held (First Street Foundation, 2025).

magnitude and persistence vary significantly with disaster severity. Notably, disasters in the top 1% by fatalities generate economic shocks nearly ten times larger than those of the average event, with recovery taking approximately a year. To give a sense of the magnitude, these shocks correspond to roughly 25% of the average impact of the Global Financial Crisis across U.S. states, highlighting their sizeable effect.³

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.

We also empirically examine the effects of natural disasters on inflation. From a theoretical perspective, the impact of natural disasters on inflation is ambiguous, as supply factors, demand conditions, and policy responses can all push inflation in different directions. Using state-level inflation data from [Hazell et al. \(2022\)](#), we find that, on average, the impact of natural disasters on inflation is relatively 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,

³To 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).

natural disasters do not significantly affect national economic performance. This suggests that while such events can cause serious disruptions at the state or regional level, these effects rarely translate into measurable nationwide downturns—except in rare cases where a disaster affects a large share of the country simultaneously.⁴ In fact, only the most widespread disasters—those impacting the majority of states at once—produce a short-lived decline in national economic activity. This finding points to an important policy implication: while natural disasters can significantly disrupt regional economies, their limited aggregate impact suggests that a nationwide policy response may not be necessary. Nationwide tools—such as monetary policy—are not the most appropriate means of addressing these localized shocks. Instead, the evidence highlights targeted local interventions are better suited to mitigate the economic consequences of natural disasters at the regional level.

Motivated by recent empirical evidence from [Von Peter et al. \(2024\)](#), who use cross-country comparisons and low-frequency annual data to show that natural disasters have large and persistent negative effects on output—effects primarily driven by uninsured losses—we provide an answer to the following question: 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 temporal variation in insurance coverage, combined with high-frequency, state-level data on economic activity. Our results show that, conditional on experiencing a similar initial impact, states with above-median property insurance coverage in the week prior to a disaster experience significantly smaller declines in economic activity relative to less-insured states. This finding suggests that broad access to property insurance plays a key role in cushioning local economies against the disruptive effects of natural disasters. In this sense, property insurance acts as an automatic stabilizer, dampening the impact of adverse shocks and supporting a more rapid recovery.

The novelty of our approach lies in several key aspects of our dataset and empirical strategy. We argue that using detailed, high-frequency, state-level data on natural disasters and economic outcomes is crucial for addressing key empirical challenges in identifying causal effects and capturing the full dynamics of post-disaster recovery. By leveraging granular data on the magnitude of natural disasters across the U.S., we capture large-scale, plausibly unexpected events. More-

⁴While our findings are based on U.S. data, smaller economies or developing countries may exhibit different aggregate responses to localized disasters.

over, 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 due to temporal aggregation. This level of temporal granularity is particularly important because most disasters tend to have short-lived economic effects, typically lasting around five to six months, as we show in this paper. As a result, studies that rely on annual data risk significantly understating the true economic impact, since initial downturns may be masked by partial or total recoveries within the same year.

Finally, we complement our analysis by documenting key patterns in the occurrence of natural disasters across the U.S. Our findings reveal that natural disasters are unevenly distributed across time, location, and type, with several notable insights: (i) the frequency of natural disasters has increased significantly since the 1990s; (ii) storms and floods are the most common disaster types; and (iii) the Midwest has experienced relatively lower exposure compared to the Mid-East, while Texas stands out as the most frequently affected state.

Overall, our findings provide new insights into the increasing frequency of natural disasters, their immediate adverse effects on economic activity, and the mitigating role of property insurance in reducing economic severity. These results highlight the economic costs associated with 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., [Deschênes and Greenstone, 2011](#); [Dell et al., 2014](#); [Kahn et al., 2021](#); [Bilal and Rossi-Hansberg, 2023](#); [Kim, 2024](#); [Kim et al., 2025](#)).⁵ 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. A recent study by [Bilal and Känzig \(2024\)](#), however, 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%.

⁵Most studies rely on low-frequency annual data to assess the impact of temperature shocks on various aspects of economic activity, including economic growth. Notable exceptions include [Kim \(2024\)](#), which uses quarterly data, and [Kim et al. \(2025\)](#), which employs monthly data.

In this paper, we build on existing empirical evidence by quantifying the economic impact of extreme climate-related events, specifically natural disasters, emphasizing their temporary yet significant adverse effects on state-level economic activity. Our findings indicate that natural disasters lead to short-term declines in regional labor markets, mobility, exports, and manufacturing sentiment, while causing a persistent reduction in household spending. Moreover, we show that severe natural disasters can significantly disrupt regional economies across multiple dimensions, even though their impact at the national level remains relatively limited.

While there is a growing body of research on the macroeconomic impacts of natural disasters, the number of studies remains relatively limited (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](#)).⁶ 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 data.⁷

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.⁸ 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.

⁶For 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.

⁷This 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.

⁸Our 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.

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 economic response to localized shocks such as natural disasters.

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 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 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.⁹ 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.¹⁰

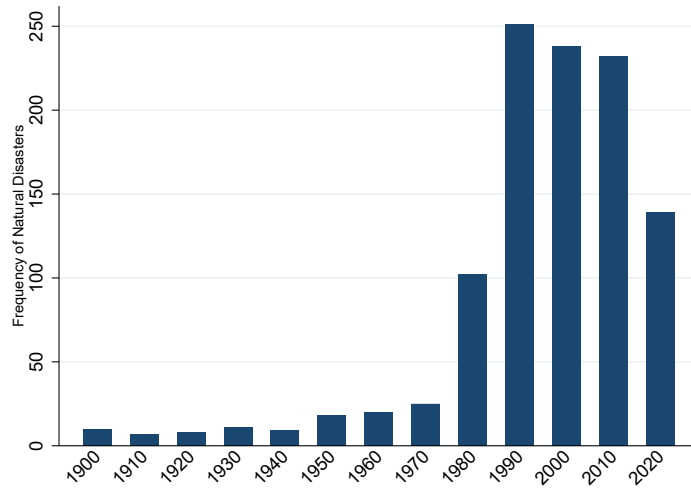
In this section, we analyze data on all natural disasters affecting the U.S. since 1900 and present key trends related to their frequency by decade, type, and state.

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.

⁹Disasters 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.

¹⁰The reported damages in the database include only direct damages (e.g., destruction of infrastructure, crops, and housing).

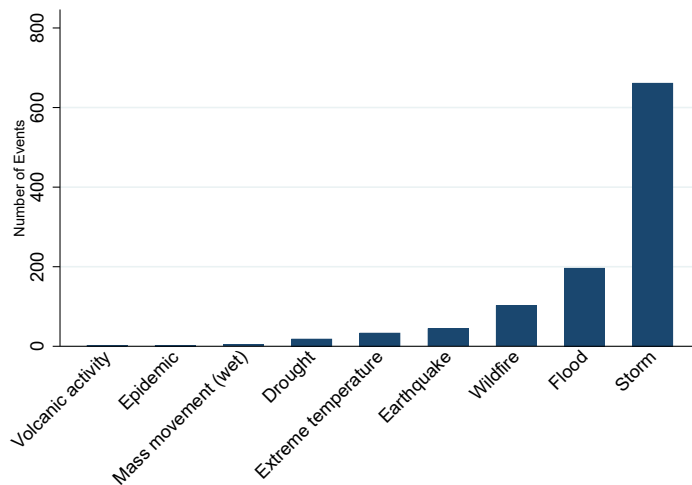
Figure 1: Frequency of natural disasters by decade.



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

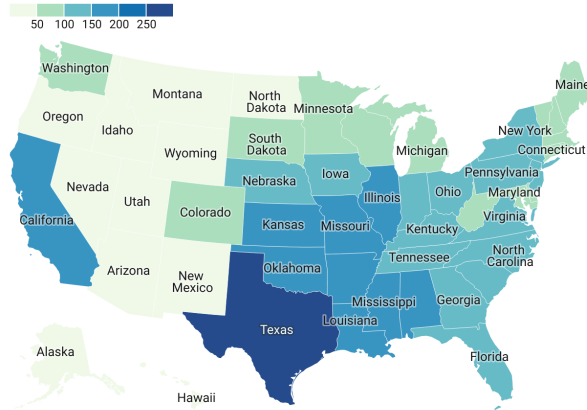
Frequency of natural disasters by type. Figure 2 presents the total number of events for each type of natural disaster from 1900 to 2024. The data reveal that storms and floods constitute the majority of disasters affecting US states. In contrast, wildfires, earthquakes, extreme temperature events, droughts,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

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 2024.¹¹ 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, 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

¹¹Given the lower frequency of disasters before the 1980s, we note that the map looks very similar in our effective sample starting in 1987.

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.¹² 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](#)):

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

where $\alpha_{i,h}$ represents the state fixed effects, $h = 0, 1, 2, 3, \dots, 40$, and $\text{Natural Disaster}_{i,t}$ 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.¹³ This approach controls for the effects of both concurrent and past disaster

¹²The 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.

¹³For 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

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. 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 2024w39.¹⁴ The maximum horizon considered is $h = 40$. For inference, we compute cluster-robust standard errors at the state level.¹⁵

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 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.¹⁶ 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.¹⁷ 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.¹⁸ First, this threshold allows us to capture the impact of significant natural disasters, filtering out

non-flood events, as well as storms or floods with fatalities below the median—that may occur concurrently in the same state and week.

¹⁴The selection of this sample is determined by the availability of the Weekly Economic Conditions Index (ECI).

¹⁵See [Jordà and Taylor \(2024\)](#) for a comprehensive discussion on inference in the local projection (LP) framework.

¹⁶We 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.

¹⁷Although wildfires are not outlier events in the U.S., we exclude them from our analysis because many are human-induced and may not be entirely random.

¹⁸In practice, our *Natural Disaster* $_{i,t}$ 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.

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 4.2.

Additionally, in our main analyses, 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.¹⁹ The impulse response defined in Equation 1 represents a counterfactual difference in mean outcomes:

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

where, in our framework, $s_t \in \{0, 1\}$, $s_t = \text{Natural Disaster}_t$, 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, stock-

¹⁹We 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.

piling 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.²⁰ To address this issue, Panel (a) examines the time-series evolution of economic conditions during the four weeks preceding all recorded natural disasters in our sample. If natural disasters were genuinely random and unpredictable, we would expect a broad distribution of economic trajectories before their occurrence. Specifically, disasters would sometimes strike when economic conditions—as measured by our weekly economic indicator—are historically strong, sometimes when conditions are weak, and most frequently when conditions are near historical averages.

Panel (a) of Figure 4 illustrates this clearly: economic trajectories prior to natural disasters vary considerably, with most disasters occurring when weekly economic conditions are near average, or only slightly above or below it.²¹ Additionally, the distribution is symmetric, indicating that disasters are equally likely to occur during favorable and unfavorable economic periods. If anticipation were influencing economic conditions, we would expect a systematic decline in the weeks preceding disasters. The absence of such a pattern suggests that disaster anticipation does not meaningfully impact our results.²²

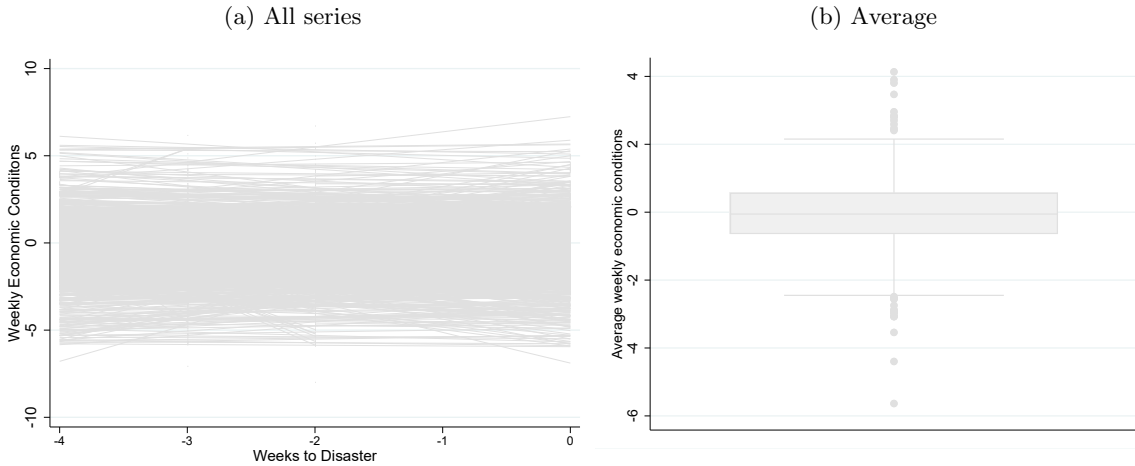
Panel (b) of Figure 4 further supports this finding by displaying the average weekly economic conditions during the four weeks preceding disasters for all events in our sample. Consistent with Panel (a), most disasters occur when economic conditions are close to zero, with comparable outliers appearing on both positive and negative sides. To further ensure our analysis excludes anticipated events, our baseline specification specifically targets natural disasters with historically high death tolls, as these events are more likely to be unexpected.

²⁰In particular, if a natural disaster is anticipated, it is expected to have a smaller, temporary effect on economic activity.

²¹The Weekly Economic Conditions Index (ECI) from [Baumeister et al. \(2024\)](#) has a state-level mean around zero across the entire sample.

²²We also formally test whether economic conditions systematically differ in the week preceding large, unexpected natural disasters—as defined by our baseline disaster indicator—and find that the coefficient is close to zero, with no evidence to reject the null hypothesis at the conventional 5% significance level.

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.

State-Level Data. Another important consideration is the level of data aggregation. Most existing studies on natural disasters rely on country-level data, which poses significant limitations. Since natural disasters typically impact only specific states or regions within the US, using aggregate country-level data can underestimate their true effects. This occurs because economic activity in unaffected regions often remains stable, partially offsetting the negative impact in the affected areas. This issue is especially pronounced when disasters affect regions contributing only a small portion of the country’s total economic activity. To address this limitation, our study employs state-level data, allowing us to accurately identify and analyze the specific regions impacted by each disaster.²³ Consistent with this approach, in Section 4.4, we estimate the dynamic effects of natural disasters using aggregate US economic data and find no discernible impact on overall economic activity.

High-Frequency Data. Another concern is that public and private entities may partially or fully offset the economic impacts of natural disasters through post-event interventions. Specifically, insurance payouts, family transfers, and government support to affected households and

²³Although county- or metropolitan-level data would be ideal, the availability of high-frequency data at these levels is extremely limited. As we discuss in detail in this section, high-frequency data are essential for accurately estimating the short-term impact of natural disasters. State-level data provides a practical balance, offering sufficient regional disaggregation to effectively capture the impacts of disasters while ensuring the availability of necessary high-frequency information.

businesses are typically correlated with the occurrence of natural disasters, often in the same direction.²⁴ Although these offsetting mechanisms usually occur with some delay and may not fully counteract the negative consequences of natural disasters, they can still attenuate the estimated effects in studies that rely on low-frequency data.

Moreover, to the extent that most disasters have a short-term economic impact—typically lasting around 5-6 months, as we show later—studies using annual data are likely to underestimate the true effect. This is because the initial negative impact may be partially or fully offset by a rebound in the months that follow. Much of the existing literature on natural disasters predominantly uses annual data, which increases the risk of underestimating—or even entirely missing—these effects due to temporal aggregation.²⁵

To address this limitation, our analysis employs high-frequency (weekly) data. By using weekly data, we are able to capture the immediate and significant economic disruptions caused by natural disasters—effects that typically dissipate within a year. This approach highlights the limitations of previous studies that rely on lower-frequency data, which fail to fully account for the short-term dynamics and true magnitude of the economic consequences of natural disasters.

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,

²⁴For 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](#)).

²⁵Moreover, the reliance on lower-frequency data can make estimated effects highly sensitive to the timing of the disaster. For instance, events occurring early in the year may be offset by economic responses in subsequent months, resulting in underestimated or muted measured effects.

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 percent relative to the historical national average growth rate. Importantly, the effects on economic performance are short-lived, with the economy returning to its pre-disaster average within 20–25 weeks, or about 5–6 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.

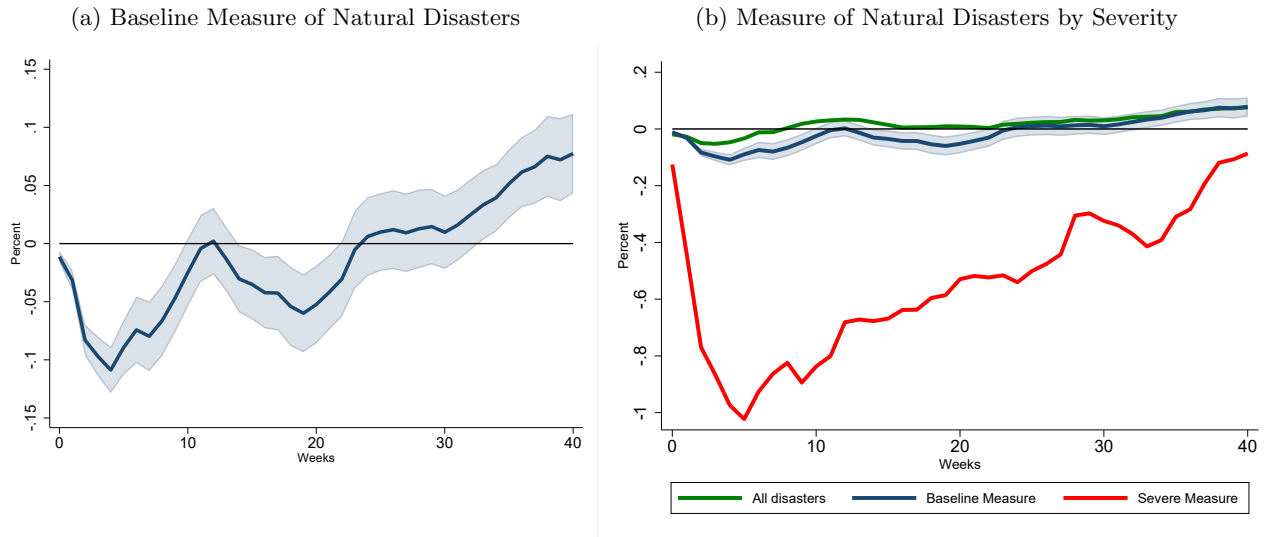
Panel (b) of Figure 5 extends our baseline analysis from Panel (a) by incorporating two additional measures of natural disasters. First, we construct an indicator that captures all storms and floods occurring in a given state and week, without restricting it to high-fatality events. This indicator captures 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 percent below the national historical long-run economic growth. To provide a sense of scale, the peak decline in average weekly economic activity across U.S. states during the aftermath of the Global Financial Crisis was around 4 percent 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.²⁶

This result highlights that although the negative effects of natural disasters on overall economic performance are generally short-lived, the magnitude of these effects varies significantly with disaster severity. 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).²⁷

²⁶Estimating 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%.

²⁷For 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.

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



Notes: Estimated changes in the Weekly Indicator Index (ECI) of [Baumeister et al. \(2024\)](#) at horizons $h = 0, 2, \dots, 40$, 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.

These discrepancies underscore the advantages of utilizing state-level, high-frequency data rather than country-level, low-frequency data, as the former allows a more precise evaluation of both the magnitude and persistence of economic disruptions caused by natural disasters. This point aligns with findings by [Jacobson et al. \(2022\)](#) and [Baumeister et al. \(2024\)](#), who 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 4.3 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 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.²⁸

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, 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

²⁸Floods occur less frequently in our baseline measure, resulting in wider standard error bands for their estimated impulse responses.

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.1 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.²⁹ 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.

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.

²⁹In each replication, we set the probability of a natural disaster to 1.5%, matching the actual frequency of natural disasters in our sample.

4.3 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.

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.

To assess the impact of natural disasters on different aspects of economic activity, we estimate the following local projections:

$$\begin{aligned} \Delta^h y_{i,t+h} = & \alpha_{i,h} + \beta_h \text{Natural Disaster}_{i,t} + \sum_{l=1}^4 \delta_{h,l} \text{Natural Disaster}_{i,t-l} + \\ & \theta_h \text{Other Disaster}_{i,t} + \gamma_h \text{Pandemic}_t + \sum_{l=1}^4 \Gamma_{h,l} \text{ECI}_{i,t-l} + \varepsilon_{i,t+h}. \end{aligned} \quad (2)$$

The dependent variable, $\Delta^h y_{i,t+h}$, captures the h -period-ahead change in the outcome of interest. We include lags of changes in the weekly economic conditions index to control for pre-disaster economic conditions at the state level. To account for the potential persistence of past disaster effects, we also include lags of the main disaster indicator, along with a dummy for other disasters not captured by the main measure to address potentially overlapping shocks, even if such cases are relatively rare. When the outcome variable is available at a monthly frequency, we aggregate the weekly index to the corresponding month and include year-month

fixed effects to account for common shocks affecting all states simultaneously. In this case, the baseline disaster indicator is defined as a dummy equal to one if a state experiences at least one disaster during the month.³⁰ The pandemic dummy is equal to one from 2020m3 to 2020m7 for monthly outcomes, and from 2020w10 to 2020w31 for weekly outcomes, capturing the period of sharp economic disruption following the outbreak.

4.3.1 Weekly Outcomes

Panels (a)–(f) of Figure 6 illustrate the average weekly dynamics of card spending, initial jobless claims, new business applications, and mobility following natural disasters.³¹ 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.

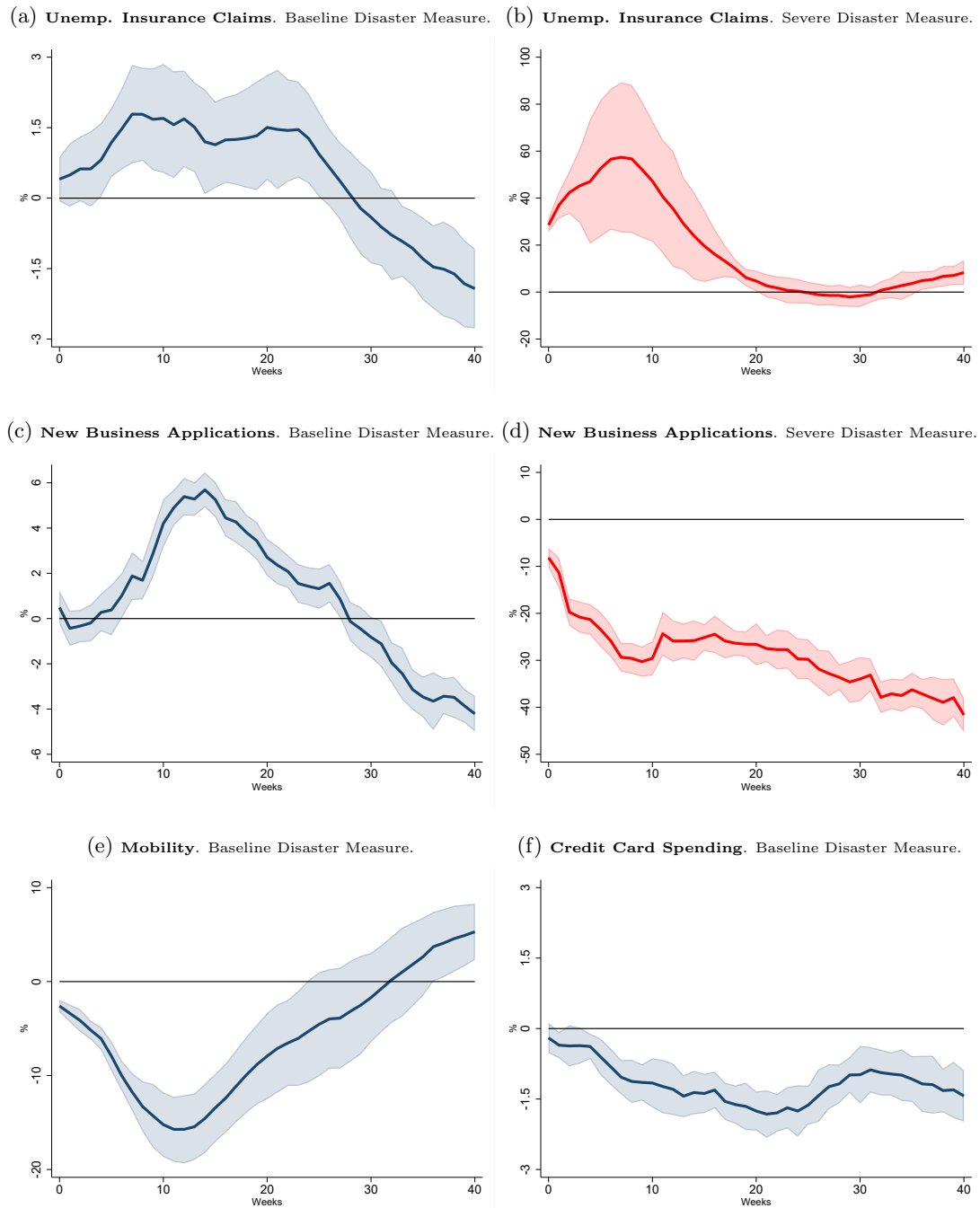
Focusing on panels (a) and (b) of Figure 6, initial jobless claims show no immediate response but begin to rise approximately five weeks after a natural disaster, increasing by around 1.5%. This effect is relatively persistent, with claims gradually returning to pre-disaster levels after about 30 weeks. However, the impact of extreme natural disasters is substantially larger, causing jobless claims to increase sharply by approximately 60% within ten weeks—a magnitude far exceeding that of the baseline measure. Although 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. Taken together, these results imply that natural disasters exert a significant impact on state-level labor markets, with severe disasters exerting a dramatic impact on 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. Following typical natural disasters, new business applications experience minimal disruption and even rise above historical levels between 8 and 30 weeks after the event. In contrast, the aftermath of severe disasters shows a markedly different pattern: new business applications drop significantly—by approximately 30%

³⁰The results remain nearly identical if, instead, we construct our baseline disaster indicator by summing the total number of disasters occurring within each state and month. We aggregate weekly economic conditions by summing the weekly values within each month.

³¹Initial 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



Notes: Estimated cumulative changes in selected outcomes following a natural disaster. Horizons $h = 1, 2, \dots, 40$. 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.

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 extreme disasters on business expectations, in contrast to the relatively mild effects observed following less severe events.

The trajectories of unemployment claims and new business applications following natural disasters align with our main findings on weekly economic activity. While natural disasters negatively affect various dimensions of economic performance, severe events—those with fatalities in the top 1%—exert a substantially greater impact.

Measures of mobility gained prominence during the pandemic as a means of tracking economic activity. Given the nature of natural disasters, mobility is similarly expected to serve as a reliable proxy for short-term economic performance following such events. Panel (e) of Figure 6 depicts the evolution of mobility indicators following natural disasters. Mobility declines sharply, falling by approximately 15%-20% within 10 weeks of a disaster. However, it gradually recovers, returning to its historical trend within 35 weeks (approximately eight months). As a result, the evolution of mobility closely resembles the path observed for weekly economic activity discussed in the previous section.

Natural disasters appear to have a more prolonged negative impact on household consumption, as proxied by credit and debit card transactions, compared to other economic indicators. Panel (f) of Figure 6 shows that 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 1.5% below its historical average. This suggests that while the broader economic disruptions caused by natural disasters may be temporary, their impact on household spending—and, by extension, on household consumption—is more persistent, likely reflecting increased financial caution among households in the aftermath of such events.

4.3.2 Monthly Outcomes

Panels (a)–(d) of Figure 7 illustrate the impact of natural disasters on monthly state-level economic outcomes, including manufacturing sentiment and exports.³² Each panel presents responses across different time horizons following a natural disaster, showing estimates based on both the baseline disaster indicator and the more severe disaster classification.

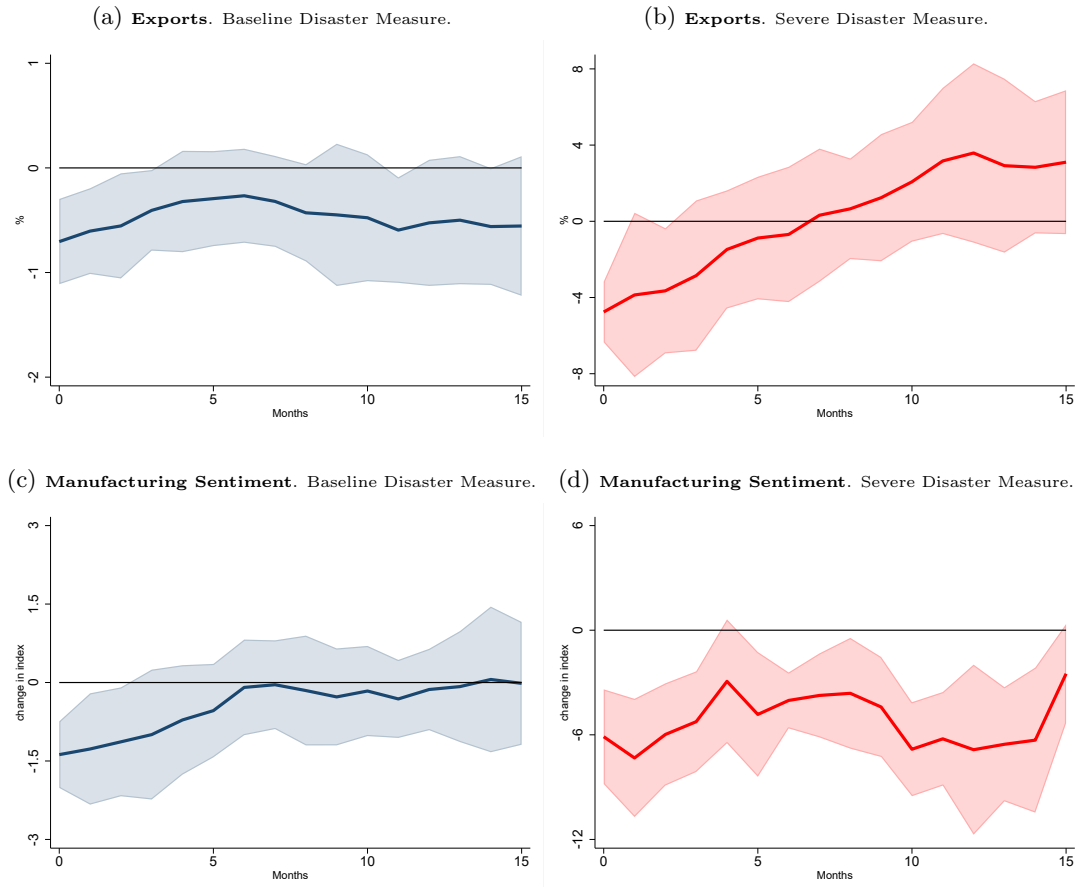
Exports of manufactured and non-manufactured commodities experience a prolonged decline

³²Manufacturing sentiment is constructed using a combination of survey-based indicators, including the Production Index, Capacity Utilization, New Orders, Employment, and Hours Worked.

following natural disasters, decreasing by approximately 1% in the disaster month and showing no clear signs of recovery even after 15 months. However, these estimates carry considerable uncertainty, with statistically significant effects observed only in the initial months. In contrast, extreme natural disasters induce a much more severe initial shock, causing exports to decline by about five times more than in typical disasters. Despite this pronounced initial drop, the impact of extreme disasters is relatively short-lived, with exports returning to their historical trend within six months. This notable contrast underscores the disproportionately large but less persistent effect of severe disasters on export. These results therefore suggest that state-level trade is significantly affected by natural disasters, likely reflecting a combination of reduced external demand and local supply chain disruptions in their aftermath.

Firm activity and expectations in the manufacturing sector, as measured by manufacturing sentiment, experience a significant and prolonged decline following natural disasters, with full recovery taking up to 15 months. However, these estimates involve considerable uncertainty, reflected in wide confidence intervals, and are statistically significant only during the initial months. The impact is particularly severe in cases of high-fatality disasters, as illustrated in panel (d) of Figure 7. In these severe events, manufacturing sentiment declines by approximately six times more than after a typical disaster and remains persistently low, only beginning to recover after about 40 weeks. This sharp contrast underscores the disproportionately large and enduring effect of severe natural disasters on manufacturing sentiment. Consequently, natural disasters negatively affect both realized and expected production capacity utilization, new orders, employment, and hours worked—all components captured by this sentiment indicator.

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



Notes: Estimated cumulative changes in selected outcomes following a natural disaster. Horizons $h = 1, 2, \dots, 15$. 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.

4.3.3 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 2017.³³ To capture the short-run dynamics of inflation following natural disasters, we interpolate the quarterly data to a monthly frequency.³⁴ 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](#)).³⁵ 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.

To quantify the impact of natural disasters on state-level inflation, we estimate the following local projections:

$$\begin{aligned} \pi_{i,t+h} = & \alpha_{i,h} + \delta_{t,h} + \beta_h \text{Natural Disaster}_{i,t} + \sum_{l=1}^4 \delta_{h,l} \text{Natural Disaster}_{i,t-l} + \\ & \theta_h \text{Other Disaster}_{i,t} + \sum_{l=1}^4 \Gamma_{h,l} \text{ECI}_{i,t-l} + \sum_{l=1}^4 \Phi_{h,l} \pi_{i,t-l} + \varepsilon_{i,t+h}, \end{aligned} \quad (3)$$

where, $\alpha_{i,h}$ state fixed effects, capturing time-invariant differences in average inflation dynamics across states at each forecast horizon. $\delta_{t,h}$ represents year-month fixed effects, which control for shocks that are common across all regions, such as global commodity price shocks or nationwide monetary policy changes. As in previous specifications, we control for the potential persistence of disaster effects by including lags of the main disaster indicator, and include a dummy for other disasters not captured by the main variable to account for additional shocks.

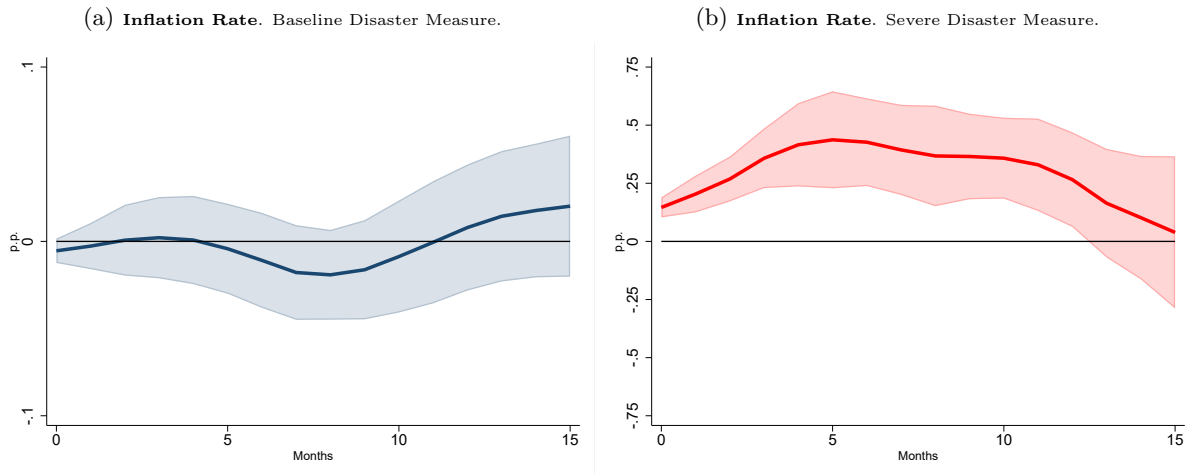
³³[Hazell et al. \(2022\)](#) provides inflation rates for twenty-nine out of the fifty U.S. states.

³⁴We 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.

³⁵For 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.

We also include lags of the outcome variable to account for autocorrelation in inflation, as well as lagged values of the Economic Conditions Index (ECI) to control for pre-disaster macroeconomic conditions. The coefficient β_h captures the dynamic effect of a natural disaster occurring at time t on monthly inflation at horizon h .

Figure 8: Dynamic Response of Inflation Rate to Natural Disasters



Notes: Estimated changes in inflation rate following a natural disaster. Horizons $h = 1, 2, \dots, 15$. 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.

Panel (a) of Figure 8 highlights the contrasting effects of most natural disasters on economic 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. A natural follow-up question is whether these disasters also have measurable impacts on overall U.S. economic performance. To explore this, we construct a weekly national natural disaster indicator, activated whenever at least one disaster occurs anywhere in the country during a given week. We then utilize this indicator to evaluate the impact of natural disasters on national economic activity.³⁶

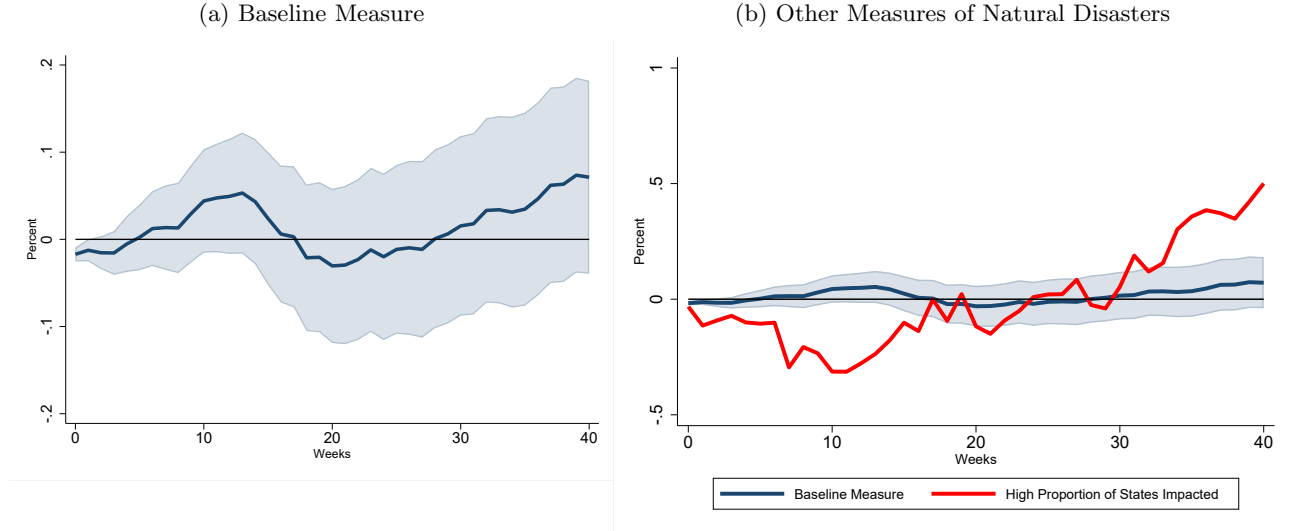
In particular, we estimate the following local projections:

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

³⁶We also create an alternative national indicator based on the total number of disasters occurring each week and confirm our primary finding that natural disasters have no significant aggregate impact on the U.S. economy.

Here, $ECI_{i,t+h}^{US}$ represents the h -period-ahead weekly economic conditions for the U.S. as a whole, while $Natural\ Disaster_{i,t}^{US}$ is a dummy variable activated when at least one natural disaster occurs in the U.S in week t .³⁷

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



Notes: Estimated changes in the Weekly Indicator Index (ECI) of [Baumeister et al. \(2024\)](#) at horizons $h = 0, 2, \dots, 40$, following a natural disaster. Panel (a) includes all storms and floods where the number of reported deaths exceeds the median. Panel (b) uses two measures: the baseline measure includes all storms and floods with fatalities above the median, while the “high proportion of states” measure includes only those 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 present our main findings, showing that most natural disasters have little to no impact on overall U.S. economic activity. Focusing on our baseline measure—shown in Panel (a)—we find a small and statistically insignificant effect across all horizons.³⁸ This muted aggregate response likely reflects the fact that the median disaster affects only 9 of the 50 states (see Table A.2.1), while economic activity in the remaining states remains largely stable, offsetting localized disruptions. Panel (b) complements this analysis by examining disasters that affect a much larger share of the country. Specifically, when more than 70% of states are impacted simultaneously, we observe a noticeable decline in economic activity lasting approximately 10–15 weeks, followed by a recovery and rebound in the weeks thereafter.

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

³⁷Since 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.

³⁸With 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 Property Insurance Coverage

Thus far, we have documented the average effects of natural disasters on both individual U.S. states and 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 seek to complement this evidence by exploiting both time-series and cross-sectional variation in property insurance coverage across U.S. states. By leveraging high-frequency, state-level data on economic activity, we assess whether property insurance influences the trajectory of post-disaster economic 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.³⁹

We extract the number of insured house years at an annual frequency between 1993 and 2021.⁴⁰ 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 over time.⁴¹ In addition, we collect data on state-level population and the number of

³⁹This 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.

⁴⁰In 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, further justifying its use as the focus of our analysis.

⁴¹The results remain both quantitatively and qualitatively similar when using data restricted to the 1993–2021

occupied households.

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:

$$\begin{aligned}
 ECI_{i,t+h} = & \alpha_{i,h} + \beta_h Deaths_{i,t} + \theta_h (Deaths_{i,t} \times \mathbb{1}(PI_i > PI_{p50})) + \sum_{l=1}^4 \delta_{h,l} Natural\ Disaster_{i,t-l} + \\
 & + \phi_h Other\ Disaster_{i,t} + \gamma_h Pandemic_t + \sum_{l=1}^4 \Gamma_{h,l} ECI_{i,t-l} + \varepsilon_{i,t+h}, \tag{5}
 \end{aligned}$$

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 subnational 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 COVID-19 pandemic. Finally, we include lagged values of the dependent variable to control

period.

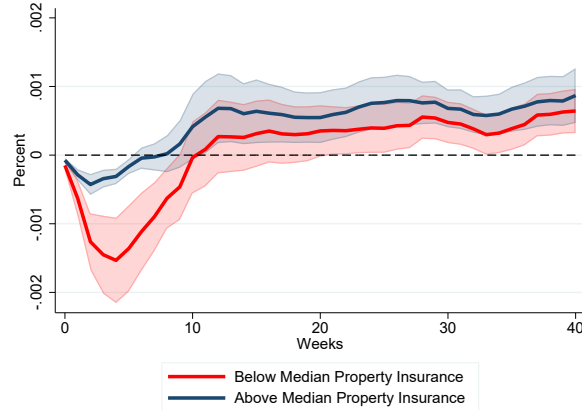
for persistence in local economic conditions. We estimate the model using weekly data from 1987w14 to 2024w39.

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.

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](#) 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.

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 $h = 0, 2, \dots, 40$ 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.

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.

6 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 primarily driven by short-term disruptions in mobility, manufacturing sentiment, and the labor market. However, household spending experiences a more prolonged impact, remaining significantly below its historical average even a year after the disaster. In contrast, our findings indicate that natural disasters have no discernible effect on inflation. We also show that the prevalence of property insurance plays a critical role in shaping recovery: states with above-median insurance coverage experience significantly milder declines in economic activity following disasters, highlighting insurance as a key factor in regional resilience. Additionally, we document key stylized facts about natural disasters in the U.S. throughout the twentieth century, emphasizing a sharp increase in their frequency in recent decades.

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)

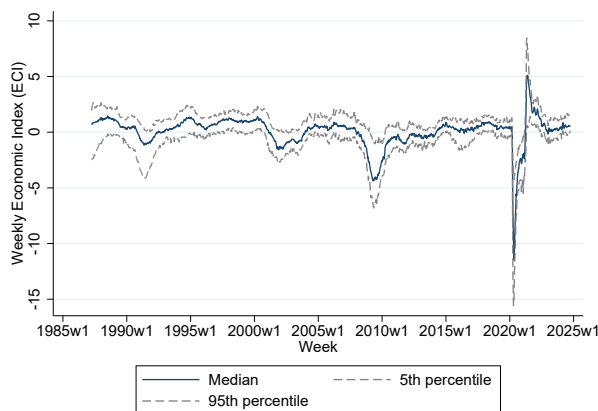
A.2 Summary Statistics

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.

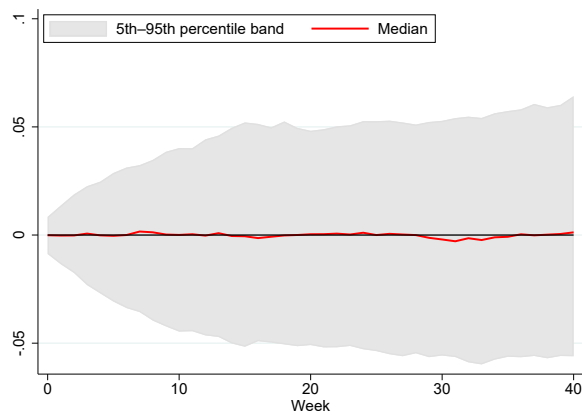
Figure A.2.1: Weekly Economic Conditions Index (ECI)



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.

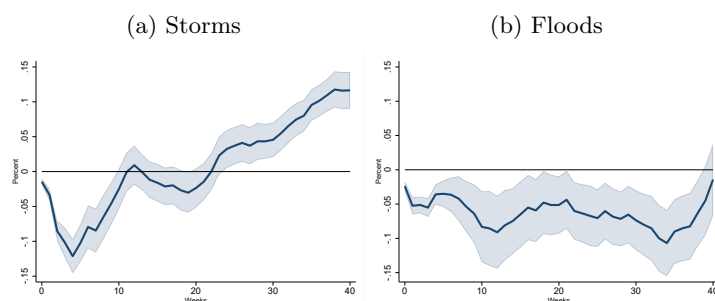
B Sensitivity Checks

Figure B.1: IRFs from Random Natural Disasters



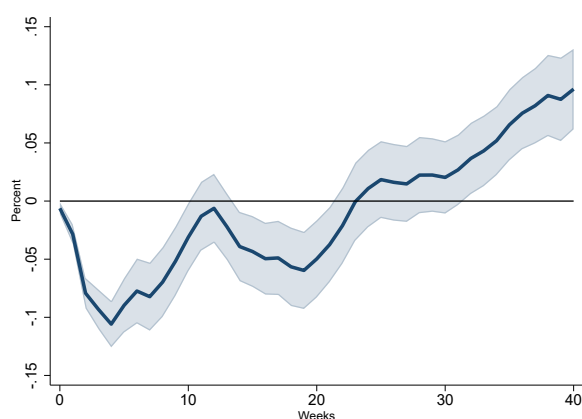
Notes: The figure illustrates the impulse responses from a placebo test in which the occurrence of natural disasters is randomly reshuffled. In each iteration, the week of the natural disaster indicator is drawn from a uniform distribution, with the probability of a natural disaster randomly set to 1.5%—consistent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



Notes: Estimated changes in the Weekly Indicator Index (ECI) of [Baumeister et al. \(2024\)](#) at horizons $h = 0, 2, \dots, 40$, 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.

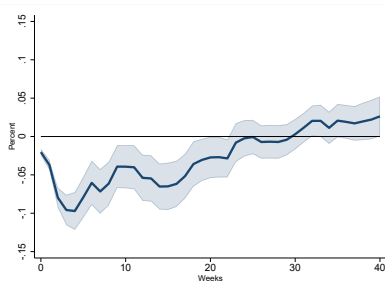
Figure B.3: All types of natural disasters



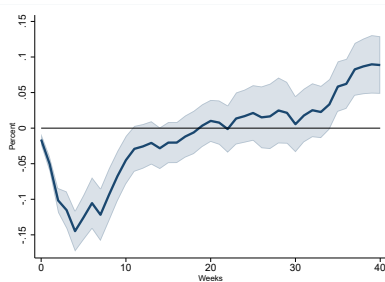
Notes: Estimated changes in the Weekly Indicator Index (ECI) of [Baumeister et al. \(2024\)](#) at horizons $h = 0, 2, \dots, 40$, following a natural disaster. Natural disasters include all types of disasters with the number of reported deaths above the median. The sample period is 1987w14–2024w39.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

Figure B.4: Impact of Large Natural Disasters

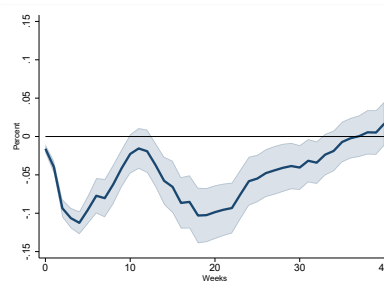
(a) By Number of Affected States



(b) By Total Damage

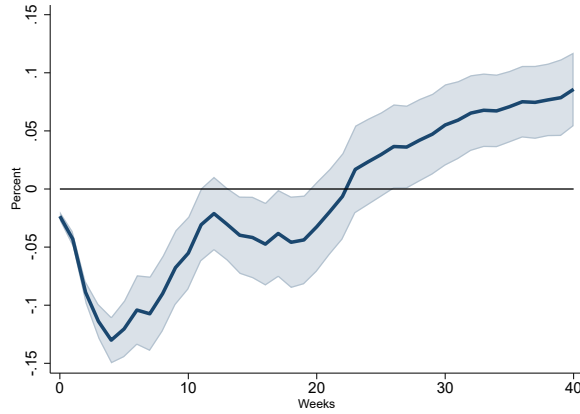


(c) By Deaths Per Capita



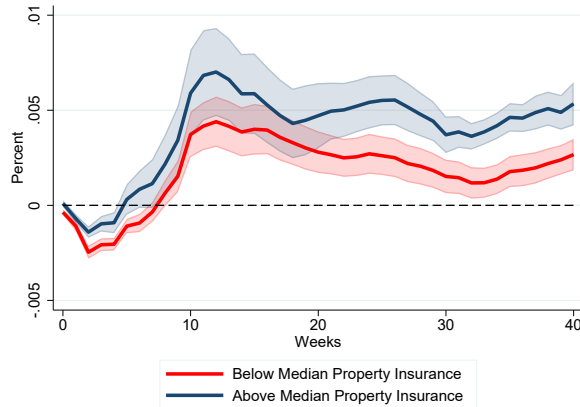
Notes: Estimated changes in the Weekly Indicator Index (ECI) of [Baumeister et al. \(2024\)](#) at horizons $h = 0, 2, \dots, 40$, following a natural disaster. Panel (a) includes storms and floods for which the number of affected states is above the median, panel (b) includes those where the reported 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.5: Subsample: Excluding post-Pandemic Data



Notes: Estimated changes in the Weekly Indicator Index (ECI) of [Baumeister et al. \(2024\)](#) at horizons $h = 0, 2, \dots, 40$, 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.6: 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 $h = 0, 2, \dots, 40$ 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 State-Level Property Insurance

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. This comparison supports the validity of our empirical strategy, presented in Section 5, by showing that disaster 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.