Resilient or Scarred? Migration, Mortality, and Morbidity after Natural Disasters*

Tatyana Deryugina
University of Illinois and NBER

Andrew Ireland
University of Illinois

David Molitor
University of Illinois and NBER

Jiameng Zheng
Louisiana State University

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Abstract

Natural disasters generate severe disruption and billions of dollars in economic damages each year, yet their health consequences remain poorly understood. We use Medicare claims data and a difference-in-differences research design to estimate the effects of tornadoes and wildfires on the physical and mental health of elderly and disabled individuals in the United States. By combining spatially detailed disaster footprint data with 9-digit ZIP Codes of residence, we precisely identify individuals directly exposed to these events as well as those residing in close proximity. We find significant short-run health impacts that extend beyond outcomes easily attributable to the disasters themselves. These impacts are concentrated among disaster-affected individuals experiencing the highest levels of damage and those with pre-existing chronic conditions. By contrast, we find little evidence of spillovers or widespread longer-run health effects beyond a few months after the event.

Keywords: health, natural disasters

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1 Introduction

Extreme weather events are becoming more frequent and severe, and the risks they pose are likely to grow as the climate changes. Prior studies have examined the economic effects of disasters (e.g., Noy, 2009; Strobl, 2011; Deryugina, 2017; Botzen, Deschenes and Sanders, 2019), but most evidence on their health effects—which could in principle be substantial—remains short-run or limited to large individual events (e.g., Kishore et al., 2018*a*; Malik et al., 2018*a*; Deryugina and Molitor, 2020; Wettstein et al., 2025). In addition, relatively little is known about the extent to which health impacts differ among those who suffered direct damage from the event versus those living nearby whose homes were not directly impacted. Yet understanding how health and healthcare utilization evolve over both the short and long term following a disaster is essential both for welfare measurement and for the design of relief and insurance policies that currently focus on near-term assistance.

We estimate the effects of over 140 U.S. wildfires and tornadoes on health and health care utilization of individuals thought to be particularly vulnerable to such disruptions—adults aged 65 and older and those with long-term disability. By combining administrative Medicare data with ZIP+4 measures of beneficiary location with granular disaster footprint data, we identify those directly impacted much more precisely than the vast majority of prior work. Using a stacked difference-in-difference approach, we then compare short- and longer-run mortality and health care utilization of those living in the disaster footprint prior to the event to unaffected beneficiaries living further away. We also consider impacts on those living within 250 meters of the footprint but not inside it and conduct heterogeneity analyses by age, sex, and the number of pre-existing health conditions.

We find that wildfires and tornadoes lead to a large same-month increase in mortality, hospitalizations, ER visits, and healthcare costs. Effects on healthcare utilization 1–2 months after the event are smaller—less than half of the initial impact—but nonetheless nontrivial. We find no significant increases in mortality beyond the month of the event. Estimates of longer-run impacts (3–24 months after the disaster) are generally small and statistically insignificant. The evolution of health outcomes looks similar for tornadoes and wildfires. With the exception of the most severe tornado and wildfire, we observe only a small relocation

response. In total, we estimate that the events in our sample caused about 200 excess deaths, 2,400 additional ER visits, and 1,100 additional hospitalizations. Although these are non-trivial impacts, the corresponding mortality costs (about $2 billion using EPA's value of statistical life) and health care expenditures (about $28 million) are small in comparison to the direct damage caused by these events (nearly $20 billion for just the largest tornado and wildfire in our sample alone).

Turning to heterogeneity analysis, we find that the health impacts are largely limited to those directly in the disasters' path: outcomes for those 0–250 meters away from the disaster's perimeter barely change. Within the path of the disaster, the effects are substantially larger for those most severely impacted, as measured by having one's residence destroyed by a wildfire or hit by a tornado rated EF4 or higher.[1] We also find that pre-existing chronic conditions are strongly predictive of disasters' health impacts: controlling for age effects, those with three or more chronic conditions experience short-run impacts several times larger than those who have none. However, we find no evidence of longer-run impacts for any of these subgroups. There are short-run differences in some outcomes by age and sex, but no group shows a different longer-run response, suggesting that longer-run vulnerability is either absent, small, or determined by characteristics orthogonal to these.

Our study contributes to the understanding of how the environmentl affects health by examining settings in which the long-run effects of extreme events are *ex ante* ambiguous. On the one hand, the populations we study are largely out of the labor force, and the disasters in our sample are typically covered by homeowners' insurance, suggesting that direct financial losses may be limited for the average affected beneficiary. Moreover, wildfires and tornadoes tend to impact only a small portion of the administrative areas they strike, implying that disruptions to local healthcare systems may be modest—particularly for wildfires, which often occur in Wildland-Urban Interface (WUI) areas that are less likely to contain critical infrastructure. On the one hand, older individuals are generally viewed as more vulnerable to extreme weather events. Plausible mechanisms through which disasters may affect health include residual financial strain due to incomplete insurance coverage (e.g., Wagner, 2022;

[1]The Enhanced Fujita (EF) scale rates tornadoes based on the damage they cause, with estimated wind speeds ranging from EF0 (65–85 mph) to EF5 (over 200 mph).

Cornelissen, Heller and DeLong, 2024), disruptions that lead to delayed or foregone care, stress-induced physiological responses, and changes in daily routines or living conditions that alter health behaviors. Our results indicate that, even in these relatively favorable settings, extreme weather events generate meaningful short-run health impacts—especially among those suffering greater damage to their homes and those with poor baseline health—but do not lead to lasting deterioration in health.

We also build on previous literature by combining high-quality administrative data with a large sample of extreme weather events. The vast majority of quantitative studies of natural disasters' health impacts only consider a single event, such as hurricanes Sandy or Maria, raising questions about the generalizeability of their conclusions (e.g., Malik et al., 2018*b*; McQuade et al., 2018; Santos-Lozada and Howard, 2018; Cruz-Cano and Mead, 2019; Iqbal et al., 2019). Additionally, most studies rely on low-frequency survey data, often from a small, non-random subset of the affected population (e.g., individuals who remained in the affected area); typically lack a control group; or fail to use a longitudinal design (Armenian, Melkonian and Hovanesian, 1998; Norris et al., 2002; Sastry and VanLandingham, 2009; Rhodes et al., 2010; Adeola and Picou, 2012; Pietrzak et al., 2012; Inoue and Yamaoka, 2017; Kishore et al., 2018*b*, e.g.,).[2] Furthermore, few studies quantify racial-, sex-based, or other disparities in disaster health impacts, even though such disparities could be large (e.g., Moreno-Walton and Koenig, 2016; Bolin and Kurtz, 2018).

The rest of the paper is organized as follows. Section 2 describes our data and how we construct the analysis dataset. Section 3 outlines our empirical strategy. Section 4 presents our results, and Section 5 concludes.

[2]A notable exception is (Young and Hsiang, 2024), who estimate state-level mortality impacts of US tropical storms. Their estimates comprise both direct and indirect impacts, however, and they do not speak to healthcare utilization.

2 Data and construction of the analysis dataset

2.1 Medicare data

We construct a longitudinal beneficiary–month panel linking Medicare administrative records to spatially granular measures of exposure to wildfires and tornadoes. The analysis uses records for all Medicare beneficiaries from 1999 to 2021.

The core Medicare inputs are: (i) beneficiary enrollment and address histories from the Enrollment Database; (ii) Medicare Provider Analysis and Review (MedPAR) files for inpatient claims; (iii) Outpatient files; (iv) Carrier (Part B, physician and supplier) files; and (v) Part D prescription drug event files. We also use chronic condition indicators from the Beneficiary Summary Chronic Conditions File to measure baseline comorbidities.

Residential location is observed at the ZIP+4 level, a highly granular geographic unit defined by the U.S. Postal Service. A ZIP+4 code typically corresponds to a small set of addresses—often a single building, a floor or wing within a building, or a short segment of a street (e.g., one side of a block). As such, it provides near address-level precision while preserving a degree of anonymity. For each year $y \in [1999, 2021]$, we extract the most recent mailing ZIP+4 on record as of December 31 of year y. Records with missing ZIP+4s are dropped.

Our main outcomes include: (i) mortality; (ii) total health care spending (inpatient plus outpatient) in a given month; (iii) an indicator for having any emergency department visit; and (iv) an indicator for having any inpatient hospitalization. Mortality is defined for all beneficiaries. Dates of death are obtained from the Beneficiary Summary File. When conflicting values occur across years, we resolve them by prioritizing the first instance with a validated death date and, if none are validated, the most recently reported value. Spending and utilization measures are observed only for beneficiaries enrolled in fee-for-service Medicare (approximately 71 percent of the sample). Physician visits and associated charges are obtained from the Carrier file, which is available for a 20% random sample of beneficiaries. Spending and utilization are set to zero in months when a beneficiary is enrolled in fee-for-service Medicare but has no recorded claims.

Chronic condition indicators are constructed from diagnoses coded from claims by trained

medical coders. These indicators are only available for beneficiaries who have been continuously enrolled in fee-for-service Medicare for a condition-specific lookback period (usually two years). The most prevalent conditions in our sample are hypertension (47%), hyperlipidemia (35%), rheumatoid arthritis (26%), ischemic heart failure (25%), diabetes (22%), anemia (20%), cataracts (18%), and both chronic heart failure and depression (13% each). We classify beneficiaries at baseline according to the number of chronic conditions they have. Under our preferred definition, which excludes hypertension and hyperlipidemia, 41% of the sample has no chronic conditions, 39% has one to two conditions, and 20% has three or more. When hypertension and hyperlipidemia are included in the count, the distribution shifts to 29% with no conditions, 32% with one to two, and 39% with three or more.

2.2 Disaster data

We construct a sample of large U.S. wildfires and tornadoes occurring between 2000 and 2019.

Wildfire perimeters are obtained from the GeoMAC dataset (Walters, Schneider and Guthrie, 2011). To focus on events with meaningful population exposure, we rank fires by the population of census blocks located within 500 meters of the burn perimeter and retain the 100 largest events. ZIP+4s located inside each fire perimeter are then linked to Medicare beneficiaries residing in those ZIP+4s in the year prior to the event. Fires with no treated beneficiaries in the Medicare data are dropped. The final wildfire sample consists of 78 events.

Tornado events are constructed from 76 tornado path polygons with Enhanced Fujita (EF) scale labels, which were obtained from the National Weather Service. Each tornado may consist of multiple polygons corresponding to different damage intensities along the path. The final sample contains 67 tornado events in which at least one Medicare beneficiary was directly affected.

Figure 1 shows the locations of the events in our sample. Wildfires are overwhelmingly concentrated in California, although there are also a handful of them in other states, including a few on the East Coast. By contrast, tornadoes are concentrated in the Midwest and the South and are more geographically dispersed than wildfires.

2.3 Disaster exposure and cohorts

Disaster footprints are linked to Medicare beneficiaries using their residential ZIP+4 location at the end of the calendar year prior to the event, which avoids assigning exposure based on post-disaster migration.

Beneficiaries whose ZIP+4 centroid lies inside the disaster footprint are classified as treated. To examine potential spillovers, we also define a buffer group consisting of beneficiaries residing within 250 meters of the event footprint. Our primary control group consists of beneficiaries residing 1–10 km from the footprint. We also construct an alternative control group by randomly selecting beneficiaries from the same state(s) as the disaster who were never located within 10 km of any event in our sample.

We restrict individuals to appear at most once in the stacked dataset to avoid potential contamination of treatment effects. Beneficiaries who are treated in multiple events are assigned to the first event in which they are treated and are excluded from subsequent events. Among beneficiaries who are never directly treated, those appearing in the spillover group for multiple events are assigned to the first spillover occurrence. It is worth noting that such occurrences are very rare. Remaining beneficiaries who appear as controls for multiple events are dropped.

Even after these restrictions, the number of beneficiaries residing 1–10 km from the disaster footprint is typically much larger than the number of treated beneficiaries. For computational purposes, the number of control beneficiaries is capped at the combined size of the treated and spillover groups within each event. When the available control pool is smaller than this threshold, all controls are retained. Otherwise, control beneficiaries are selected at random from the available pool.

Next, we construct a stacked event-time panel. For the monthly analysis, observations begin 12 months before the disaster and extend through 12–24 months afterward.

For wildfires, we merge ZIP+4-by-year indicators of property damage from Baylis and Boomhower (2022) to identify high-damage areas within the burn perimeter. For tornadoes, we define high-damage areas as those with EF4 or EF5 intensity. This approach allows us to estimate separate effects for locations with high versus lower damage for both disaster

types.

The final dataset contains 77,359 treated beneficiaries from 140 disaster events. Figure 2 shows the distribution of treated beneficiaries across events. There are slightly more beneficiaries affected by wildfires than by tornadoes (about 43,000 versus about 39,000, respectively). The largest fire in our sample—the 2018 Camp Fire—affected over 11,000 beneficiaries, while the largest tornado—the 2011 Joplin, MO tornado—affected over 6,000. The top ten events across both disaster types affected about 58% of the sample.

3 Empirical Strategy and Analysis

We estimate dynamic effects of disaster exposure on monthly mortality and health care utilization using a stacked difference-in-differences design. Our estimating equation is:

$$Y_{ie\tau} = \sum_{t=-12}^{12} \beta_t \cdot (\mathbf{1}[\tau = t] \times \mathit{Treated}_i) + \alpha_e \times \mathit{Treated}_i + \gamma_{e\tau} + \varepsilon_{ie\tau} \tag{1}$$

where $Y_{ie\tau}$ is the outcome of interest for beneficiary i in event e at relative month $\tau \in [-12, 12]$. Outcomes include binary indicators (e.g., mortality, any hospitalizations), counts (e.g., number of hospitalizations), and dollar amounts (total health care spending).[3] Post-estimation, coefficients are adjusted to report treatment effects relative to the mean coefficient in the pre-disaster period. The indicator $\mathit{Treated}_i$ equals 1 if beneficiary i belongs to the treated cohort and 0 if he or she is in the control group. The coefficients β_t therefore capture the difference in outcomes between treated and control beneficiaries t months relative to the disaster, adjusted for pre-disaster differences.

The term $\alpha_e \times \mathit{Treated}_i$ represents an event-specific fixed effect for the treated cohort, absorbing any time-invariant differences between treated and control beneficiaries within that event. $\gamma_{e\tau}$ are event-by-relative-month fixed effects that absorb shocks common to all beneficiaries in event e at month τ. Standard errors are clustered at the beneficiary's baseline 5-digit ZIP Code to account for spatial correlation.

To improve statistical precision, we also use a specification that bins post-disaster months

[3] All dollar amounts are expressed in 2022 USD, adjusted using the CPI-U for Medical Care (U.S. Bureau of Labor Statistics, 2026). All counts and dollar amounts are winsorized at the 99% level.

in which effects appear similar:

$$
\begin{aligned}
Y_{ie\tau} = \beta_0\Big(\mathbf{1}[\tau = 0] \times \mathit{Treated}_i\Big) + \beta_{1\text{-}2}\Big(\mathbf{1}[\tau \in \{1,2\}] \times \mathit{Treated}_i\Big) \\
+ \beta_{3\text{-}12}\Big(\mathbf{1}[\tau \in \{3,\ldots,12\}] \times \mathit{Treated}_i\Big) \\
+ \beta_{13\text{-}24}\Big(\mathbf{1}[\tau \in \{13,\ldots,24\}] \times \mathit{Treated}_i\Big) \\
+ \alpha_e \times \mathit{Treated}_i + \gamma_{e\tau} + \varepsilon_{ie\tau}
\end{aligned}
\tag{2}
$$

In this binned specification, each coefficient β captures the average treatment effect for the corresponding post-disaster period relative to the pre-disaster period. For example, $\beta_{1\text{-}2}$ captures the average effect during the first two months following the disaster.

4 Results

Migration. Figure 3 shows the effect of disasters on out-migration in the years following the event, measured using county of residence at the end of each calendar year. In the year of the disaster, there is a significant 2.0 percentage point increase in migration—defined as residing in a different county than in the previous year—among the treated group relative to the control group. The effect is larger in the year following the disaster (4.0 percentage points) and remains elevated in the two subsequent years (0.70–1.1 percentage points). When excluding the largest fire and tornado (the 2018 Camp Fire and the 2011 Joplin, MO, tornado), however, the effects become substantially smaller in magnitude (0.96–1.1 percentage points in the year of the event and the subsequent year). While these effects are sizeable relative to the mean pre-disaster migration rates of 3.2–3.3 percent, the absolute number of additional migrants is small. As a result, relocation to other areas is unlikely to drive the main results.

Immediate health impacts. Figure 4 shows the estimated effects of disasters on monthly mortality (panel A), healthcare costs (panel B), emergency room visits (panel C), and hospitalizations (panel D). Across all four outcomes, there is a substantial spike in the month of the disaster. For mortality, treated individuals experience a 0.0032 percentage point (3.2

per 1,000) increase in mortality. This represents an approximately 70% increase in monthly mortality relative to the pre-disaster mean of 4.4 deaths per 1,000.

Health utilization—including total costs, emergency visits, and hospitalizations—also increases substantially and significantly at the time of the disaster. Total healthcare costs rise by $188 per capita (more than 25% of the pre-disaster mean), the probability of any emergency room visit increases by 19 per 1,000 (almost 45% of the pre-disaster mean), and the probability of any hospitalization increases 7.5 per 1,000 (almost 30%).

The effects are substantially smaller in the months following the disaster. We discuss these in the following section using the specification with post-disaster months grouped into bins (Equation (2)).

Overall, the effects for tornadoes and wildfires are similar across these outcomes (Figures A.1 and A.2). For both types of events, there is an immediate increase in mortality and healthcare utilization followed by a return to baseline within a few months. The magnitudes of the same-month increases are also quantitatively similar, supporting our decision to combine these two events for our analysis.

Figure A.3 shows event-study estimates that exclude the 2011 Joplin, MO, tornado and the 2018 Camp Fire. The estimates are qualitatively similar but slightly smaller in magnitude, suggesting that the scale of the event plays a role in determining individual-level impacts. Future versions of this paper will consider additional sample splits by event size.

Medium-run impacts. Figure 5 presents the effects for the same four outcomes in the month of the disaster, 1—2 months following, 2—12 months following, and 13—24 months following, relative to the 12 months prior to the disaster.

Panel A shows that the increased mortality for the treated group is limited to the month of the event. Health costs and utilization remain elevated in 1-–2 months following the disaster, although by less than in the month of the disaster. Total costs (Panel B) increase by $83 per capita, any ER visits (Panel C) increase by 5.6 per 1,000, and any hospitalizations (Panel D) increase by 3.1 per 1,000, all relative to the 12 months prior to the disaster.

Across all four outcomes, effects return to baseline or are at best slightly elevated in months 3–12 and 13–24, relative to the 12 months before the disaster. Using an alternative

control group that is further away renders estimates 3+ months after the disaster statistically insignificant but estimated with similar precision (see Figure A.4), suggesting that health effects dissipate after this time, at least on average. Mortality estimates return to baseline starting one month after the event in this alternative sample.

The magnitude of health-related costs is small relative to the overall economic burden of natural disasters. Aggregating across events, we estimate approximately 200 excess deaths in the Medicare population. Valuing these deaths using the EPA's value of a statistical life (VSL) yields an estimated cost of roughly $2 billion. In addition, disasters generate approximately 2,400 excess emergency room visits and 1,100 hospitalizations, with associated costs of about $28 million. These health impacts are modest compared to the roughly $20 billion in non-health damages from the Camp Fire and the Joplin tornado alone, indicating that health-related costs constitute a relatively small share of total disaster losses.

High-damage areas and spillovers to nearby areas. To examine how effects vary by exposure intensity and whether they extend to nearby populations, Figure 6 presents event-study estimates for the same four outcomes, separately for high-damage areas and nearby spillover regions. High-damage areas are defined as ZIP+4s within EF4+ tornado paths or with recorded wildfire property damage. These areas experience substantially larger impacts across all outcomes, with pronounced spikes in mortality, health care costs, emergency room visits, and hospitalizations in the month of the disaster. Specifically, mortality increases by 6.9 per 1,000, health care costs by $276 per capita, ER visit probability by 33 per 1,000, and hospitalization probability by 11 per 1,000.

In contrast, nearby areas exhibit almost no increase across outcomes. The estimated effects for beneficiaries residing 0–250m away are close to zero and mostly statistically insignificant, indicating limited spillovers. There is a statistically significant increase in ER visits and hospitalizations in the month of the disaster (3.3 per 1,000 and 1.7 per 1,000, respectively), but these effects are small relative to the treated areas and does not persist beyond a single month. These patterns suggest that the health impacts of disasters are highly concentrated in the most severely affected locations, with limited effects extending to surrounding areas.

Heterogeneity in disaster vulnerability. Figure 7 examines heterogeneity in impacts by pre-existing health status. Because age is strongly correlated with both baseline health and the number of chronic conditions, we flexibly control for age effects with age-by-treated-by-event-time fixed effects. We also include age-by-gender fixed effects and allow for age-specific trends over event time.

We find that chronic conditions are a strong predictor of disaster-related health effects. Individuals without chronic conditions experience little to no short- or long-run impacts across outcomes. In contrast, those with three or more chronic conditions experience substantially larger effects. These patterns suggest that underlying health status is a key determinant of vulnerability to disasters, with the burden of health impacts falling disproportionately on individuals with greater pre-existing morbidity.

Figure 8 shows heterogeneity estimates by age group (under 65, 65–74, and 75+ at baseline). Same-month mortality impacts for those aged 75 and over are about twice as large as for younger individuals, although the confidence intervals overlap. Increases in ER visit rates are largest for those who are 75 and older and for those who are under 65 (and are therefore on long-term disability). Same-month changes in costs and hospitalizations are more similar across all age groups, and no age group shows a persistent change in any of these outcomes.

Figure 8 shows heterogeneity estimates by sex.[4] Same-month costs among male beneficiaries increase by over twice as much as for female beneficiaries, and rates of hospitalization are about 50% higher, although the confidence intervals overlap. Same-month mortality and ER visit are more similar, as are estimates 1 or more months after the disaster, suggesting that there is no differential longer-run vulnerability by sex.

Physician visits and prescription drugs. We next look at a a broader set of outcomes to understand how non-urgent care and prescription medications are impacted by disasters. Disasters may cause disruptions access to usual care, so non-emergency outcomes may exhibit different trends. Figure 10 presents the estimated event study effects for any physician encounter (panel A); number of days of drug supply (panel B); physician costs (panel C);

[4]Note that these estimates are currently not controlling for age effects.

and drug costs (panel D).

Physician encounters and costs both decrease modestly in the month of disasters and remain lower for the next 1–2 months before returning to baseline. By contrast, in the month of the disaster, the per-capita number of prescriptions (measured in days) and drug costs increase by about 2.9 days (baseline mean: 22.6 days) and $8.2 (baseline mean: $65), respectively. We again find no longer-run impacts on drug utilization.

Mental health effects. Disasters can be traumatic and stressful events, and may affect the mental health of affected individuals. Figure 11 considers mental health claims, costs, and prescriptions. We find no significant changes in mental health claims or costs. With 95% confidence, we can rule out increases in mental health claims or about 0.25 per 1,000 (relative to a baseline mean of 4.2). However, we cannot rule out per-capita spending increases of $7.5 (relative to a baseline mean of $21). We also observe a significant same-month increase in the supply of mental health drugs (0.29 days, relative to a mean of 3.1 days) but no significant increase in mental health drug costs. This pattern is consistent with increased use of relatively low-cost medications or shifts toward cheaper drugs within therapeutic classes, such that days supplied rises without a commensurate increase in total spending. It may also reflect institutional features of Part D pricing that compress variation in costs, as well as limited statistical power to detect changes in spending relative to utilization. We interpret this evidence as consistent with some short-run mental health impacts but recognize that it is far from definitive.

5 Conclusion

We provide new evidence on the health consequences of natural disasters using large-scale administrative data and highly granular measures of exposure to wildfires and tornadoes. Despite the substantial disruption caused by these events, we find that their health impacts are sharp but short-lived. Mortality and healthcare utilization increase significantly in the immediate aftermath, particularly among individuals directly in the disaster path and those with multiple pre-existing chronic conditions, but these effects dissipate within a few months.

We find little evidence of meaningful spillovers to nearby but unaffected areas or of persistent medium- or long-run impacts on average.

These findings have several implications. First, they suggest that the primary health burden of the disasters we study operates through acute channels rather than sustained deterioration in health. Second, they highlight the importance of exposure intensity and underlying health status in shaping vulnerability. Third, they indicate that, in this setting, health-related costs represent a relatively small share of total disaster losses.

Taken together, the results point to the value of policies that prioritize rapid deployment of medical resources in the immediate aftermath of disasters and that target individuals with high baseline morbidity. More broadly, the framework developed here—combining high-resolution exposure measures with administrative health data—can be applied to study a wider range of environmental shocks and to better quantify their welfare consequences.

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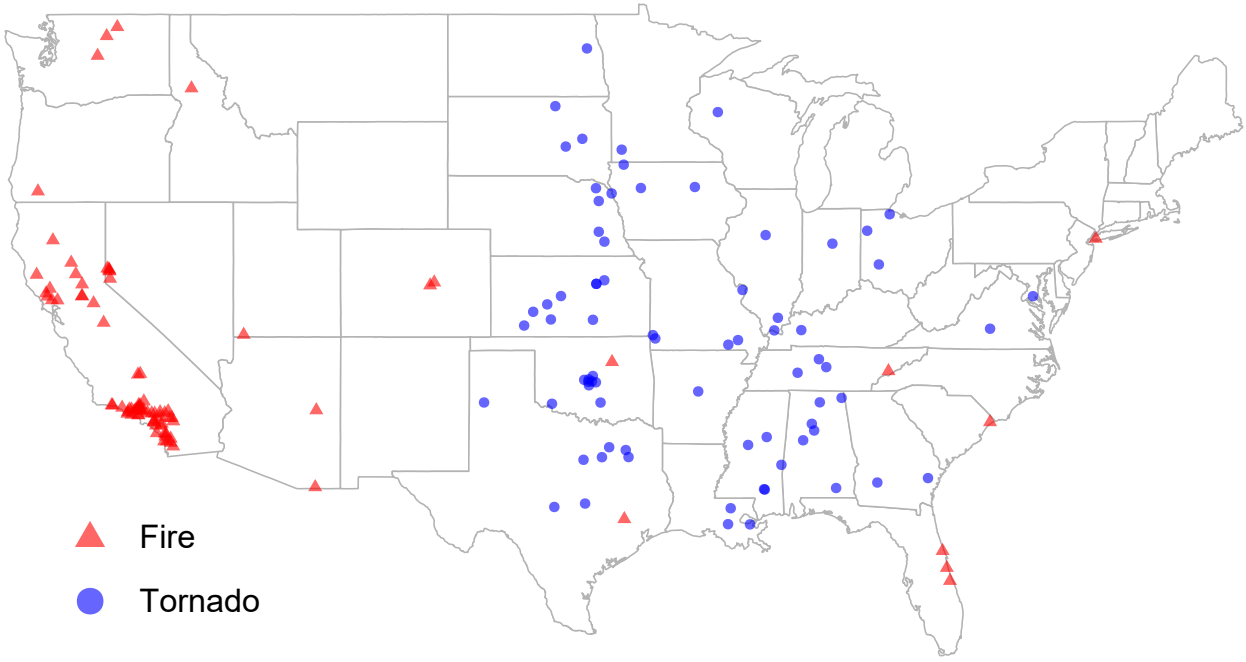
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Edmund Seto, and Jeremy J Hess. 2025. "Emergency care, hospitalization rates, and floods." *JAMA Network Open*, 8(3): e250371.

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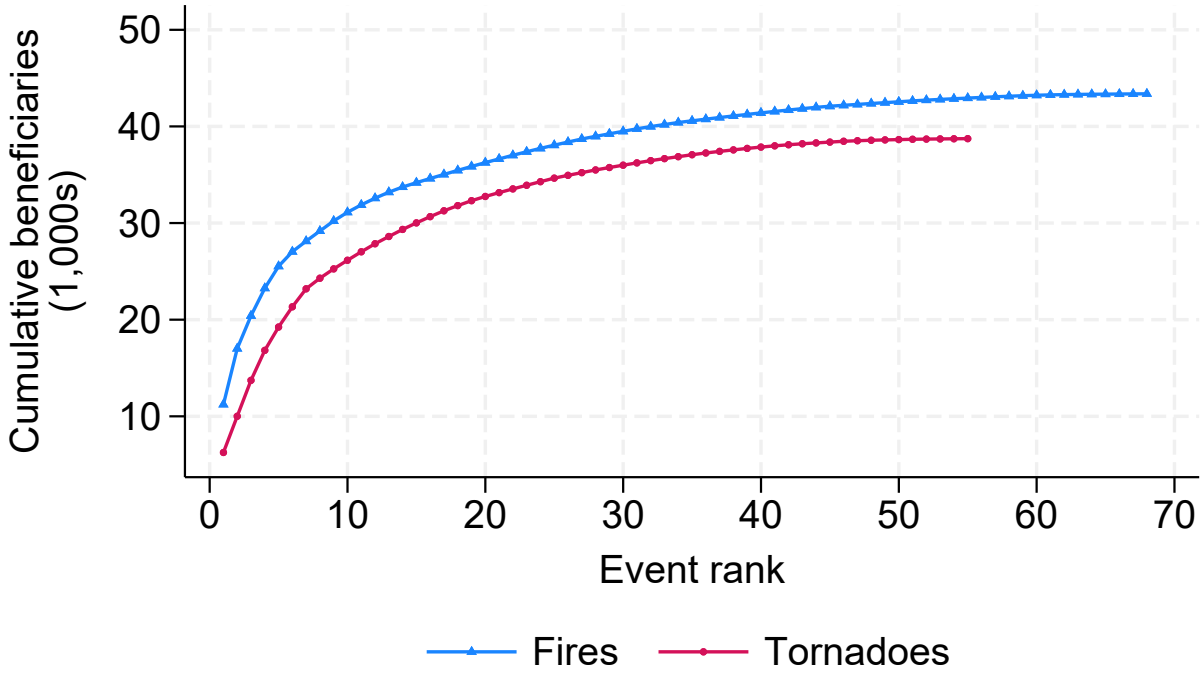
Figures

Figure 1: Tornado and Wildfire Events in the United States



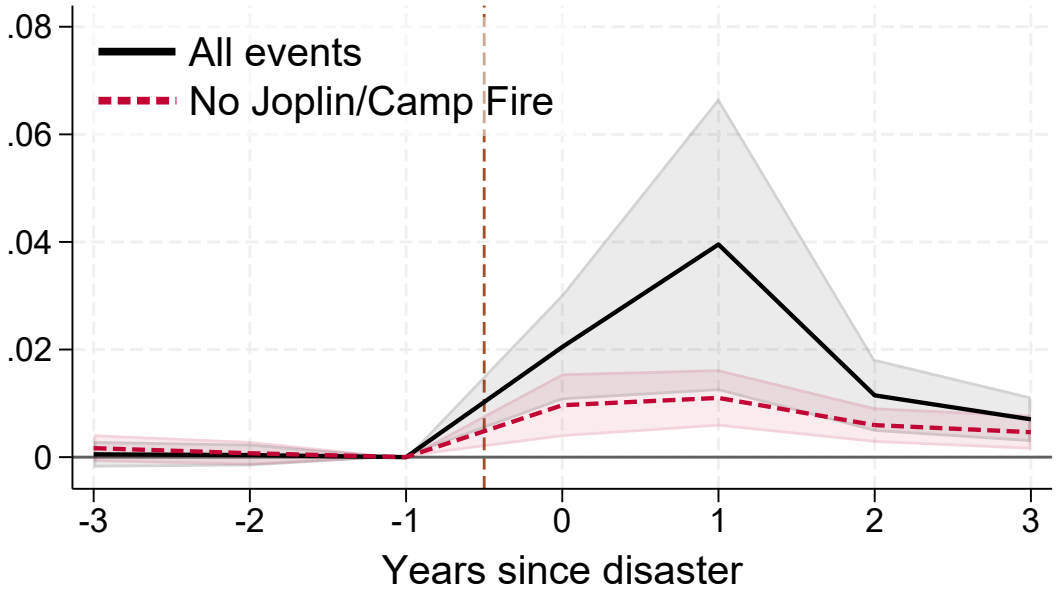
Notes: The figure plots the wildfire and tornado events used in the analysis. The sample includes large events from 2000 to 2019 with detailed spatial footprint data that can be linked to Medicare beneficiaries' residential ZIP+4 locations. Each point marks the centroid of an event footprint.

Figure 2: Number of Treated Beneficiaries Across Events



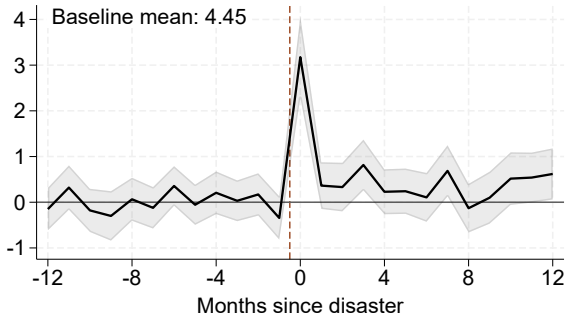
Notes: The figure shows the cumulative number of treated beneficiaries across wildfire and tornado events used in the analysis, with events ranked from largest to smallest within each disaster type. Treated beneficiaries are Medicare beneficiaries whose residential ZIP+4 centroid at the end of the previous calendar year lies inside the disaster footprint. Events with fewer than 11 treated beneficiaries are omitted to comply with disclosure rules.

Figure 3: Effects of Disaster Exposure on Migration

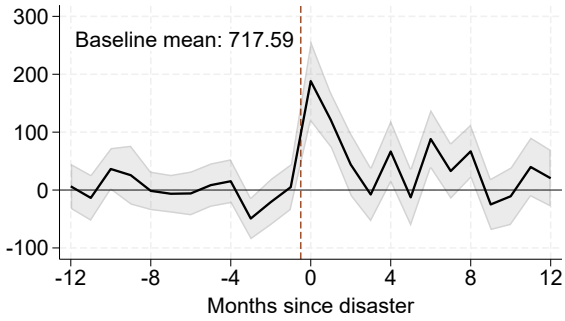


Notes: The figure shows event-study estimates of the effect of disaster exposure on the annual probability of migration, measured as a change in county of residence relative to the previous calendar year. The estimates compare treated beneficiaries to the control group and are reported relative to the year before the disaster. Error bars denote 95% confidence intervals.

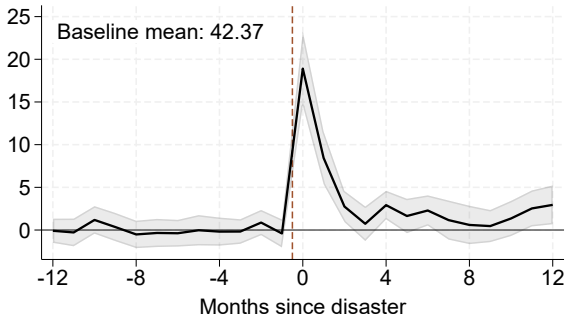
Figure 4: Short-Run Effects of Disaster Exposure on Health Outcomes



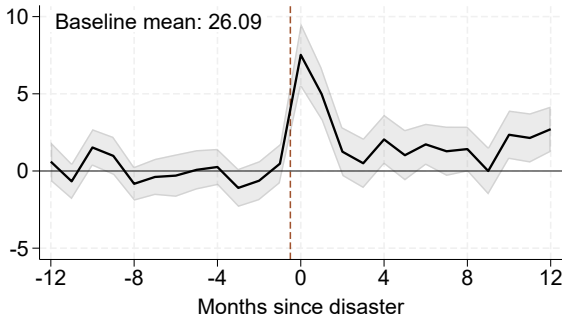
(a) Deaths per 1,000



(b) Total cost



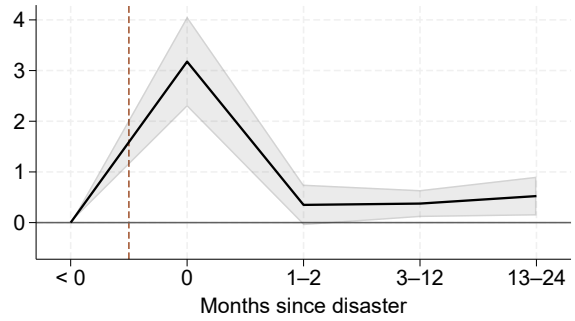
(c) Any ER visits per 1,000



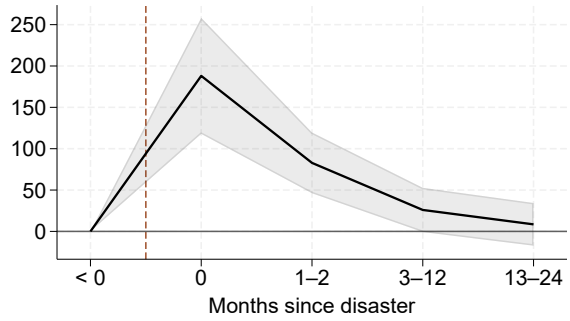
(d) Any hospitalizations per 1,000

Notes: The figure shows monthly event-study estimates of the effect of disaster exposure on monthly mortality, health care costs, emergency room visits, and hospitalizations up to 12 months post-disaster. Panel (a) shows deaths per 1,000 beneficiaries, panel (b) shows total health care costs, panel (c) shows any emergency room visit per 1,000 beneficiaries, and panel (d) shows any hospitalization per 1,000 beneficiaries. The estimates compare treated beneficiaries to the control group and are reported relative to the 12 months before the disaster. Error bars denote 95% confidence intervals. Standard errors are clustered by baseline ZIP Code of residence at the end of the calendar year prior to the disaster.

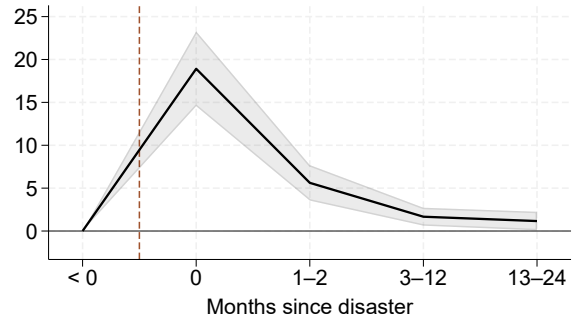
Figure 5: Longer-Run Effects of Disaster Exposure on Health Outcomes



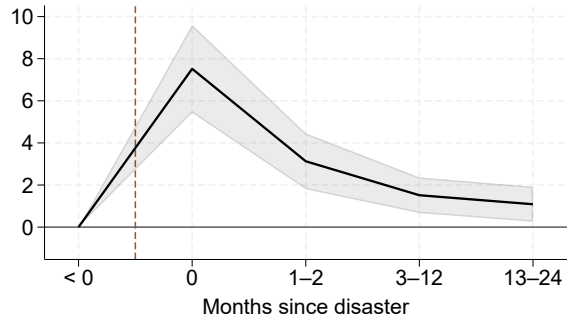
(a) Deaths per 1,000



(b) Total cost



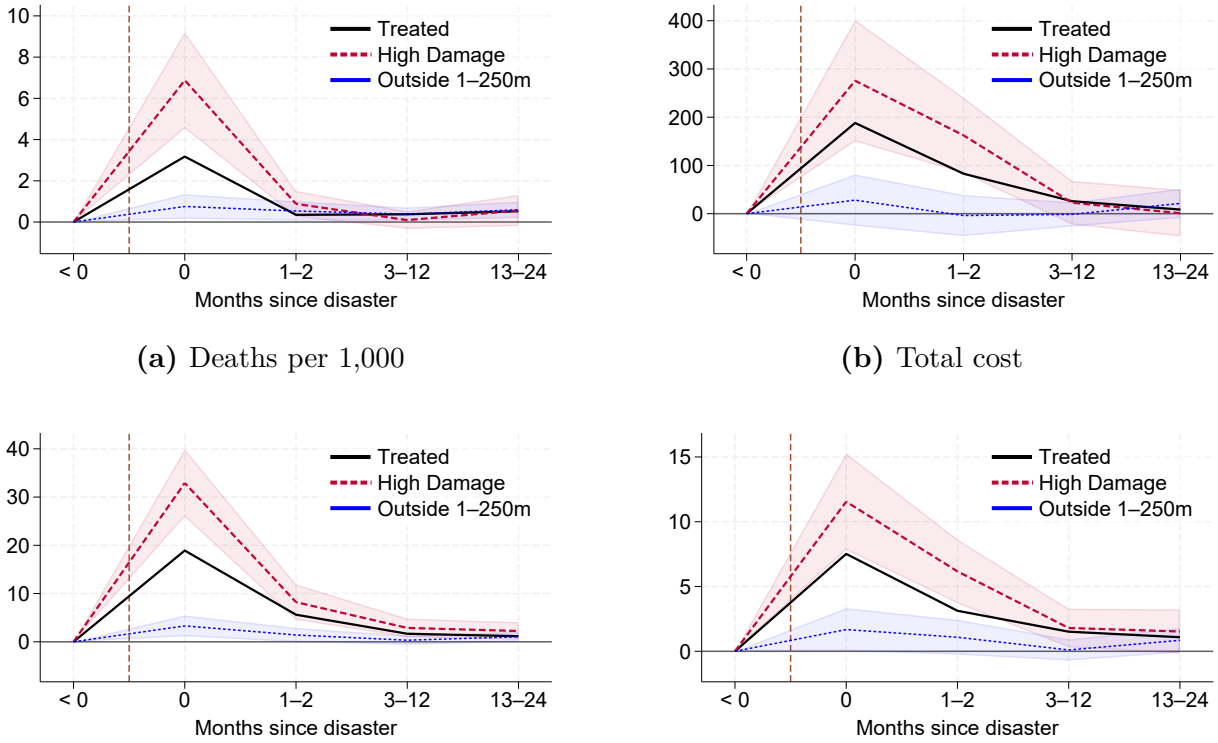
(c) Any ER visits per 1,000



(d) Any hospitalizations per 1,000

Notes: The figure shows estimates of the effect of disaster exposure on monthly mortality, health care costs, emergency room visits, and hospitalizations using the specification that groups post-disaster months into bins. Panel (a) shows deaths per 1,000 beneficiaries, panel (b) shows total health care costs, panel (c) shows any emergency room visit per 1,000 beneficiaries, and panel (d) shows any hospitalization per 1,000 beneficiaries. The estimates compare treated beneficiaries to the control group and report average effects for the month of the disaster, months 1–2 after the disaster, months 3–12 after the disaster, and months 13–24 after the disaster, each relative to the 12 months prior to the disaster. Error bars denote 95% confidence intervals. Standard errors are clustered by baseline ZIP Code of residence.

Figure 6: Effects of Disaster Exposure in High-Damage and Nearby Areas



(a) Deaths per 1,000

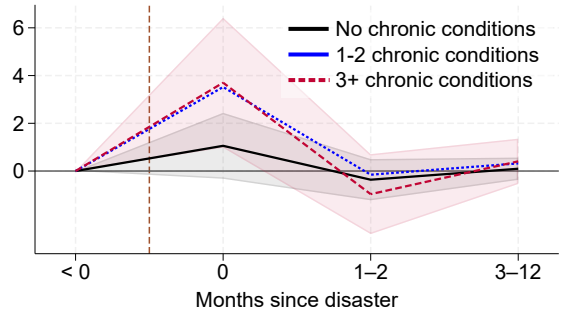
(b) Total cost

(c) Any ER visits per 1,000

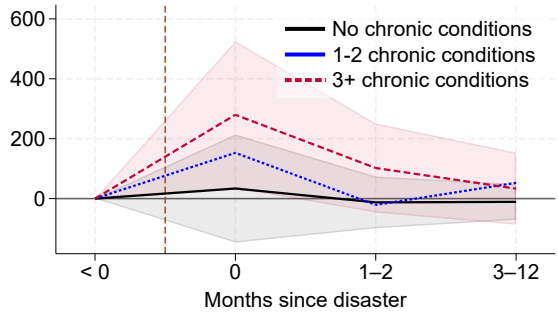
(d) Any hospitalizations per 1,000

Notes: The figure shows estimates of the effect of disaster exposure on (a) mortality, (b) health care costs, (c) emergency room visits, and (d) hospitalizations for beneficiaries in high-damage areas and nearby spillover areas, using the specification that groups post-disaster months into bins. High-damage areas are defined as ZIP+4s within EF4 or EF5 tornado paths or ZIP+4s with wildfire property damage in the year of the event. Nearby spillover areas consist of ZIP+4s located outside the disaster footprint but within 250 meters. The estimates compare beneficiaries in each exposure group to the control group and report average effects for the month of the disaster, months 1–2 after the disaster, months 3–12 after the disaster, and months 13–24 after the disaster, each relative to the 12 months prior to the disaster. Error bars denote 95% confidence intervals. Standard errors are clustered by baseline ZIP Code of residence.

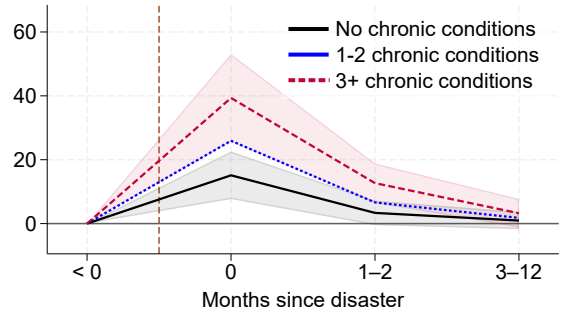
Figure 7: Effects of Disaster Exposure by Baseline Chronic Conditions



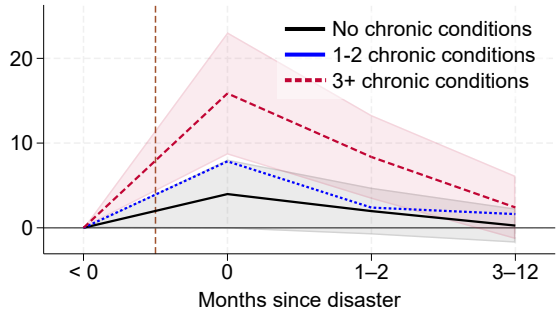
(a) Deaths per 1,000



(b) Total cost



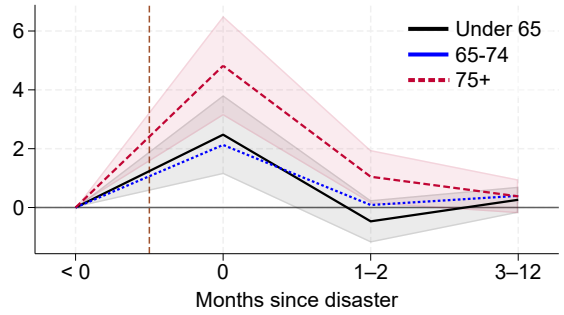
(c) Any ER visits per 1,000



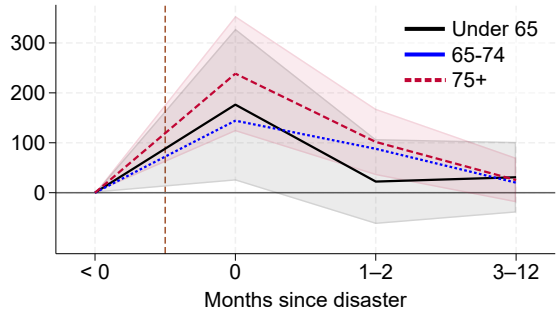
(d) Any hospitalizations per 1,000

Notes: The figure shows estimates of the effect of disaster exposure on (a) mortality, (b) health care costs, (c) emergency room visits, and (d) hospitalizations by beneficiaries' baseline number of chronic conditions, using the specification that groups post-disaster months into bins. Chronic condition groups are defined based on the number of pre-existing chronic conditions at baseline. The estimates compare treated beneficiaries to the control group within each chronic condition group and report average effects for the month of the disaster, months 1–2 after the disaster, and months 3–12 after the disaster, each relative to the 12 months prior to the disaster. Error bars denote 95% confidence intervals. Standard errors are clustered by baseline ZIP Code of residence.

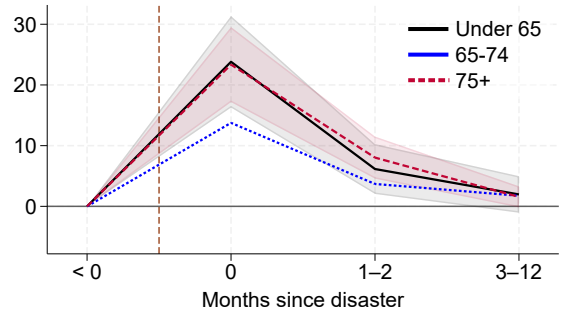
Figure 8: Effects of Disaster Exposure by Age Group



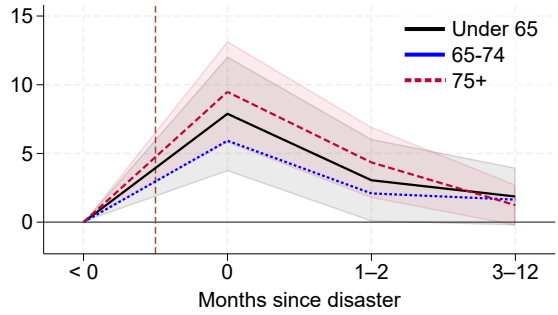
(a) Deaths per 1,000



(b) Total cost



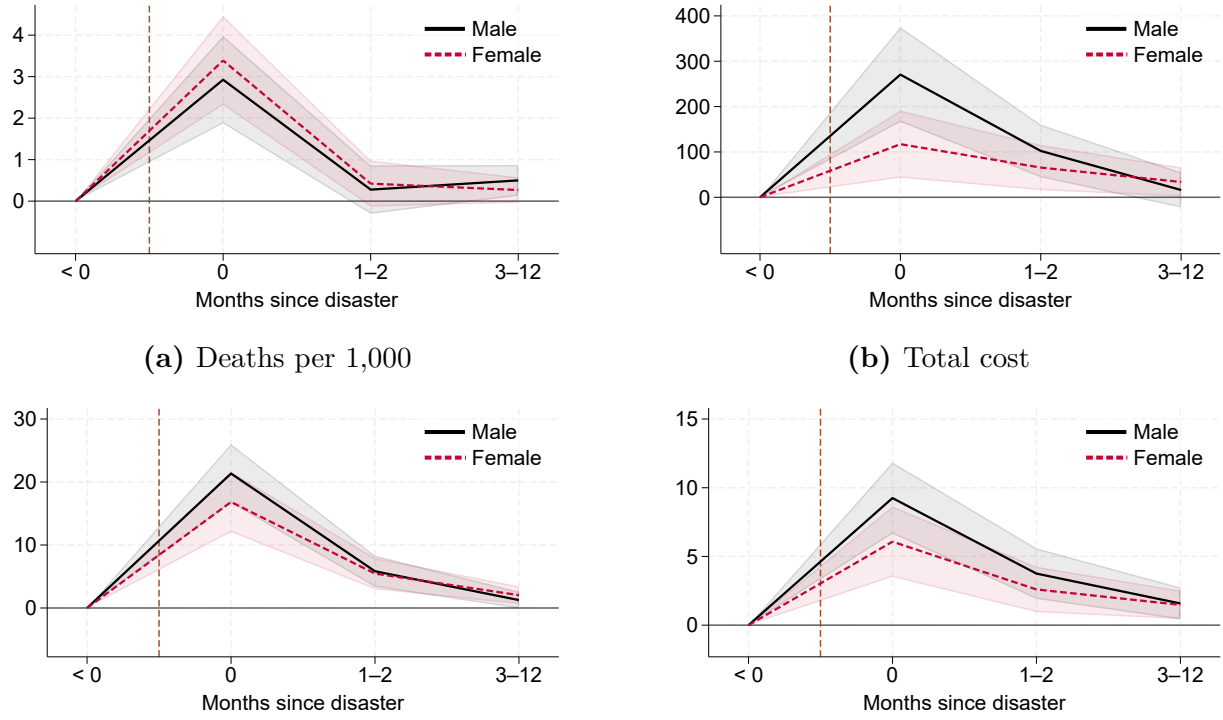
(c) Any ER visits per 1,000



(d) Any hospitalizations per 1,000

Notes: The figure shows estimates of the effect of disaster exposure on (a) mortality, (b) health care costs, (c) emergency room visits, and (d) hospitalizations by beneficiaries' baseline age group (under 65, 65–74, and 75+), using the specification that groups post-disaster months into bins. The estimates compare treated beneficiaries to the control group within each age group and report average effects for the month of the disaster, months 1–2 after the disaster, and months 3–12 after the disaster, each relative to the 12 months prior to the disaster. Error bars denote 95% confidence intervals. Standard errors are clustered by baseline ZIP Code of residence.

Figure 9: Effects of Disaster Exposure by Sex



(a) Deaths per 1,000

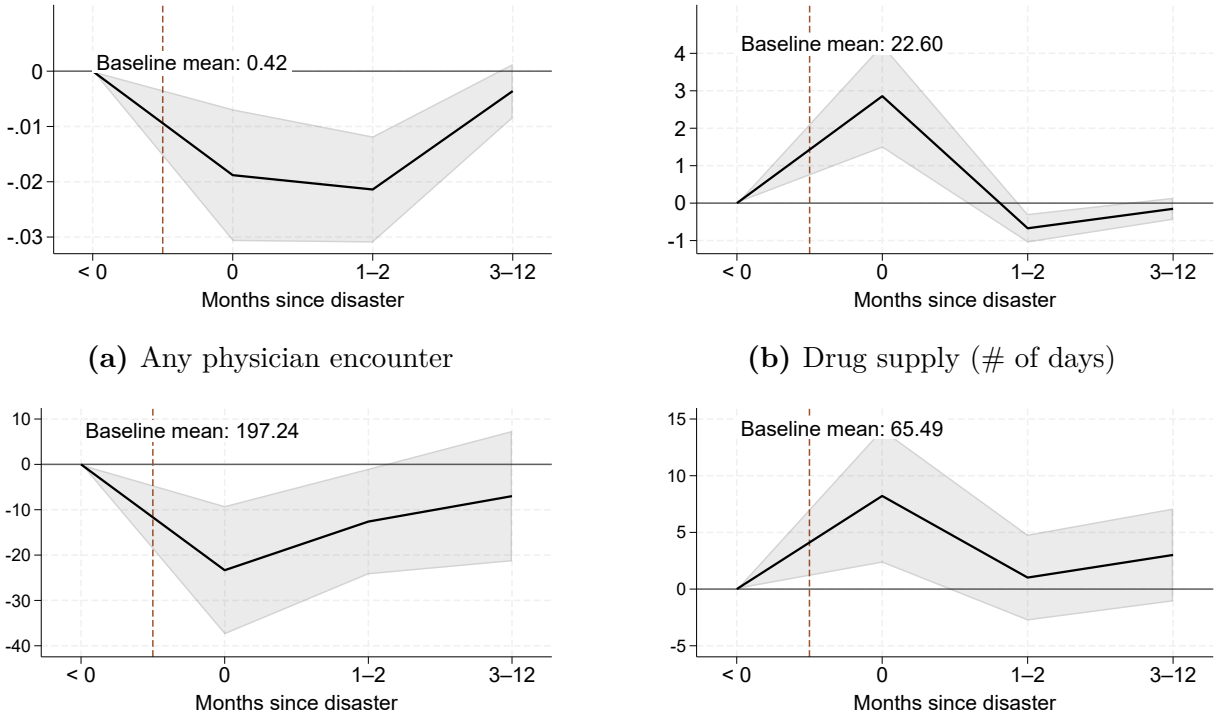
(b) Total cost

(c) Any ER visits per 1,000

(d) Any hospitalizations per 1,000

Notes: The figure shows estimates of the effect of disaster exposure on (a) mortality, (b) health care costs, (c) emergency room visits, and (d) hospitalizations by beneficiary sex, using the specification that groups post-disaster months into bins. The estimates compare treated beneficiaries to the control group within each sex group and report average effects for the month of the disaster, months 1–2 after the disaster, and months 3–12 after the disaster, each relative to the 12 months prior to the disaster. Error bars denote 95% confidence intervals. Standard errors are clustered by baseline ZIP Code of residence.

Figure 10: Effects of Disaster Exposure on Physician Encounters and Prescription Drugs



(a) Any physician encounter

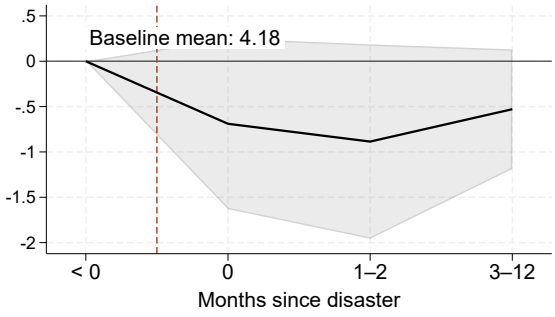
(b) Drug supply (# of days)

(c) Physician costs

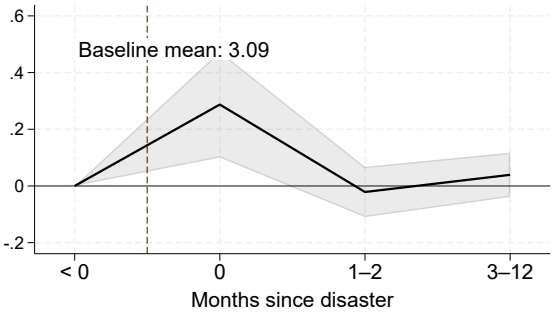
(d) Drug costs

Notes: The figure shows estimates of the effect of disaster exposure on (a) any physician encounter, (b) days of prescription drug supply, (c) physician costs, and (d) prescription drug costs, using the specification that groups post-disaster months into bins. Physician encounters and costs are measured from the Carrier (Part B) file; drug supply and costs are measured from Part D prescription drug event files. The estimates compare treated beneficiaries to the control group and report average effects for the month of the disaster, months 1–2 after the disaster, and months 3–12 after the disaster, each relative to the 12 months prior to the disaster. Error bars denote 95% confidence intervals. Standard errors are clustered by baseline ZIP Code of residence.

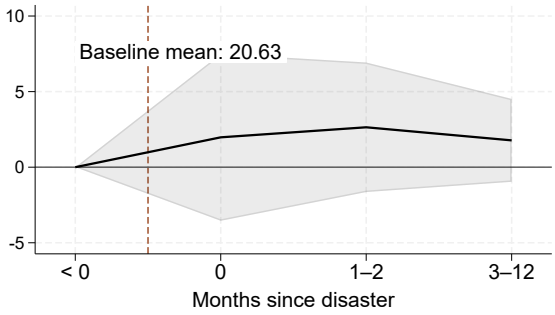
Figure 11: Effects of Disaster Exposure on Mental Health Outcomes



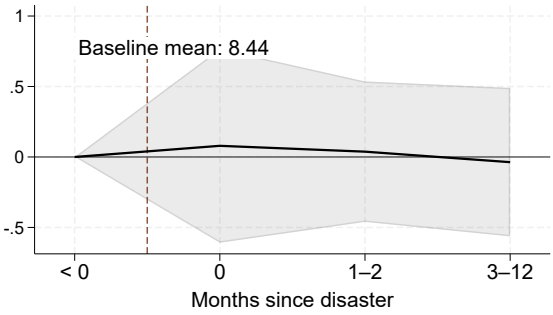
(a) Any mental health claim per 1,000



(b) Mental health drugs (# of days)



(c) Mental health costs



(d) Mental health Part D costs

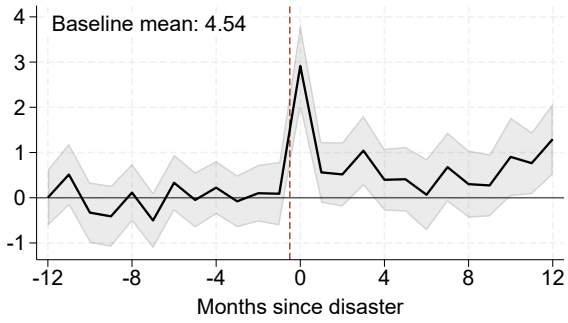
Notes: The figure shows estimates of the effect of disaster exposure on (a) any mental health claim, (b) days of mental health drug supply, (c) mental health costs, and (d) mental health Part D drug costs, using the specification that groups post-disaster months into bins. Mental health claims and costs are identified from inpatient, outpatient, and carrier claims with mental-health-related diagnosis codes; mental health drug supply and costs are measured from Part D prescription drug event files. The estimates compare treated beneficiaries to the control group and report average effects for the month of the disaster, months 1–2 after the disaster, and months 3–12 after the disaster, each relative to the 12 months prior to the disaster. Error bars denote 95% confidence intervals. Standard errors are clustered by baseline ZIP Code of residence.

Online Appendix

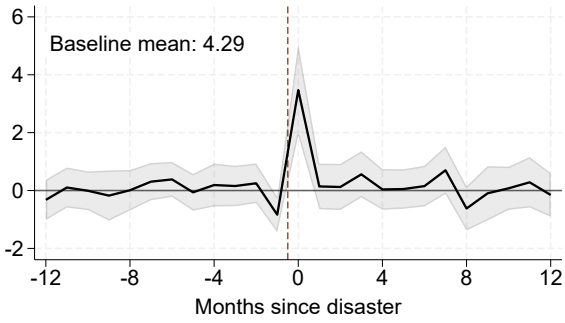
"Resilient or Scarred? Migration, Mortality, and Morbidity after Natural Disasters"

Tatyana Deryugina, Andrew Ireland, David Molitor, and Jiameng Zheng

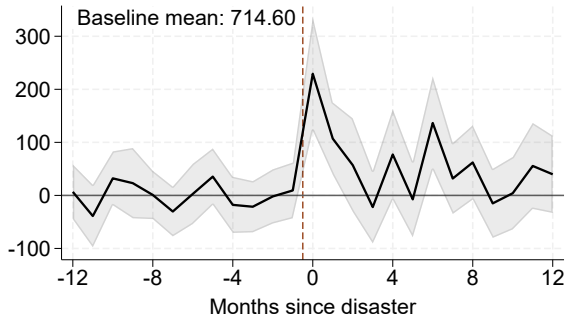
A Appendix Figures and Tables



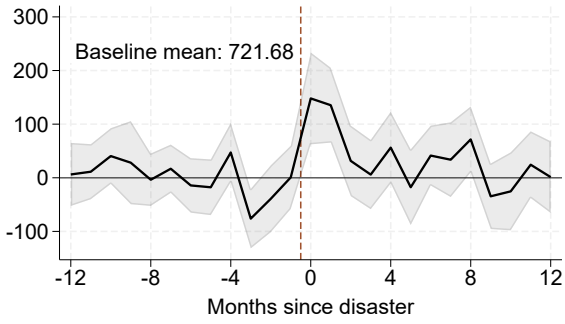
(a) Mortality, Wildfires



(b) Mortality, Tornadoes



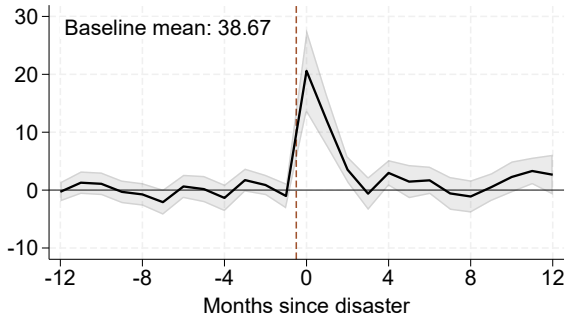
(c) Total cost, Wildfires



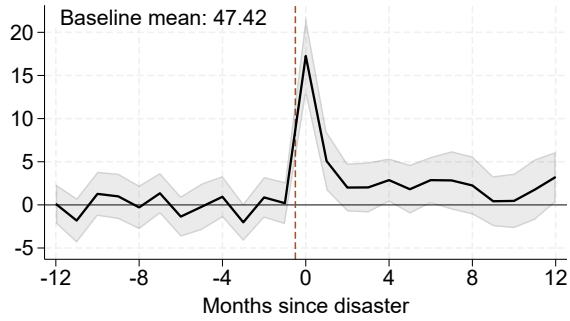
(d) Total cost, Tornadoes

Figure A.1: Event-study estimates by disaster type: mortality and healthcare costs

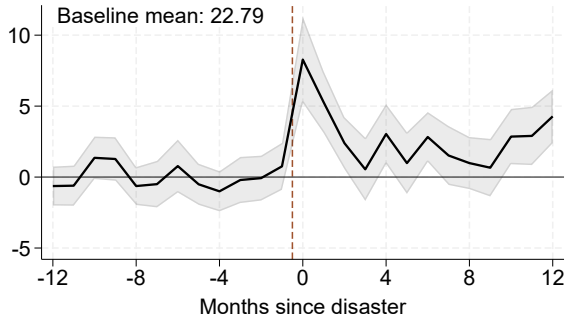
Notes: Panel (a) shows mortality, panel (b) healthcare costs, panel (c) emergency department visits, and panel (d) inpatient hospitalizations. Points show event-study coefficients relative to the omitted pre-disaster period. Error bars denote 95% confidence intervals. Standard errors are clustered by baseline ZIP Code (end of year before the disaster).



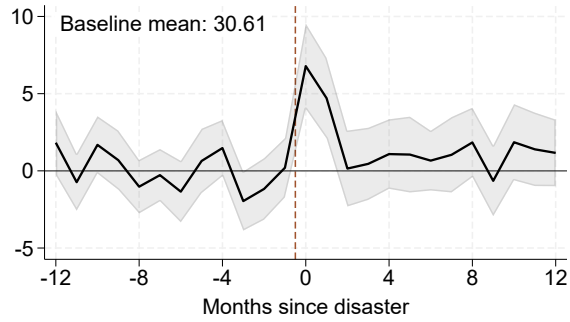
(a) ER visits, Wildfires



(b) ER visits, Tornadoes



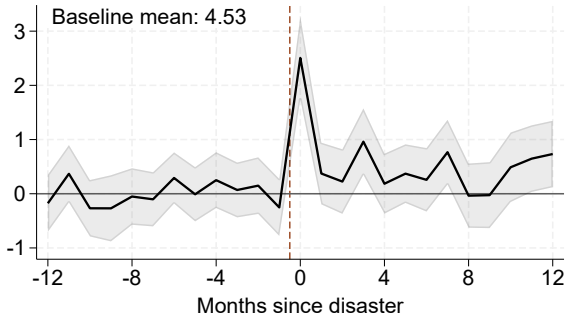
(c) Hospitalizations, Wildfires



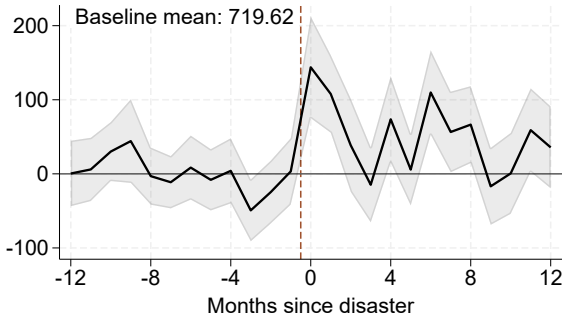
(d) Hospitalizations, Tornadoes

Figure A.2: Event-study estimates by disaster type: healthcare utilization

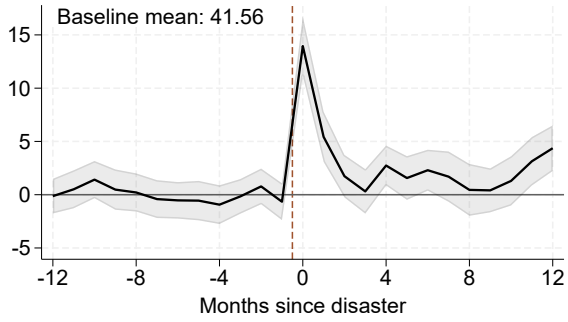
Notes: Panel (a) shows mortality, panel (b) healthcare costs, panel (c) emergency department visits, and panel (d) inpatient hospitalizations, estimated separately for tornadoes and wildfires. Points show event-study coefficients relative to the omitted pre-disaster period. Error bars denote 95% confidence intervals. Standard errors are clustered by baseline ZIP Code (end of year before the disaster).



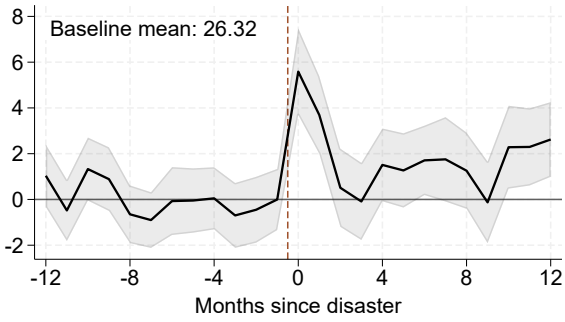
(a) Deaths per 1,000



(b) Total cost



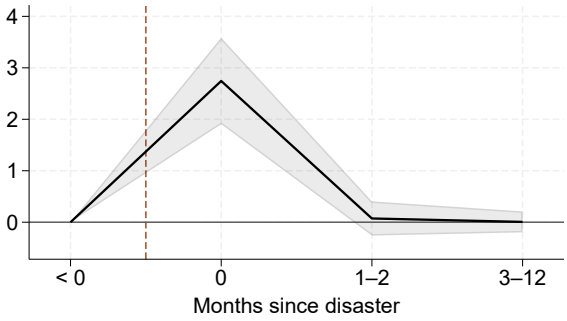
(c) Any ER visits per 1,000



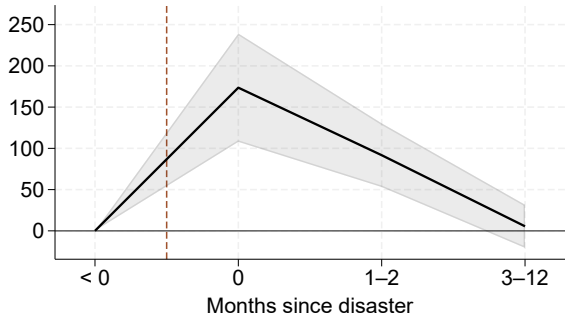
(d) Any hospitalizations per 1,000

Figure A.3: Event-study estimates excluding Camp Fire and Joplin tornado

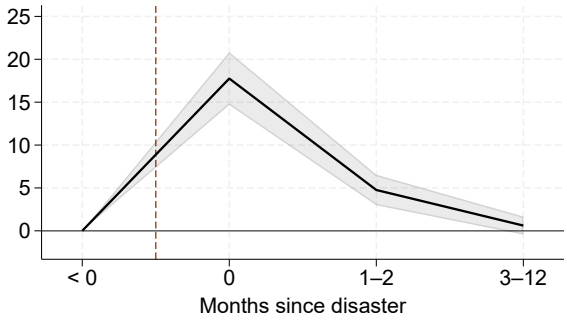
Notes: Panel (a) shows mortality, panel (b) healthcare costs, panel (c) emergency department visits, and panel (d) inpatient hospitalizations. Sample excludes treated and control individuals corresponding to the 2018 Camp Fire and the 2011 Joplin tornado. Points show event-study coefficients relative to the omitted pre-disaster period. Error bars denote 95% confidence intervals. Standard errors are clustered by baseline ZIP Code (end of year before the disaster).



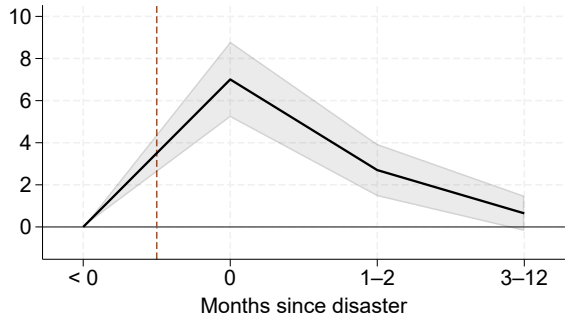
(a) Deaths per 1,000



(b) Total cost



(c) Any ER visits per 1,000



(d) Any hospitalizations per 1,000

Figure A.4: Event-study estimates using alternative control group

Notes: Panel (a) shows mortality, panel (b) healthcare costs, panel (c) emergency department visits, and panel (d) inpatient hospitalizations. Control group consists of individuals living in the same state but at least 10 kilometers away from the disaster footprint in the year before the event. Points show event-study coefficients relative to the omitted pre-disaster period. Error bars denote 95% confidence intervals. Standard errors are clustered by baseline ZIP Code (end of year before the disaster).