Natural Disasters and Elective Medical Services: How Big is the Bounce-Back?*

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Abstract

COVID-19 has created a dual set of stresses on health care systems worldwide: a rise in expensive intensive care services and a dramatic decline in elective services. In the U.S., elective services are the major source of profits for many health care providers, leading to concerns that some providers may not survive the COVID-19 crisis. The U.S. government has responded with both grant and loan programs to help health care providers weather the storm. But the optimal size and nature of such programs are hard to evaluate without an understanding of the ability of providers to make up their lost elective service revenues over time. In this paper, we study the closest relevant parallel to the reduction in elective services seen under COVID-19: hurricanes. We match information on hurricanes to data on Medicare hospital elective visits and charges from 1997–2013, comparing counties impacted by hurricanes to nearby unaffected counties. We find that the average hurricane reduces elective services by about 7% in the month it makes landfall. For the most severe hurricanes, we estimate a reduction of more than 20%. Services return to baseline fairly rapidly, but for severe hurricanes it takes a year or more to make up lost revenues. Similar responses in the months after hurricanes of different severity suggest that capacity constraints limit the ability of providers to make up for lost revenues; correspondingly, we find a much larger "bounce-back" for outpatient than for inpatient services. Projections based on variation in hurricane severity suggest that it will take over 3 years for providers to make up the lost revenue from COVID-19.

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1 Introduction

COVID-19 has placed an enormous strain on health care systems worldwide. Much of the focus has been on the inability of some health care systems to handle the volume of COVID-19 cases. In particular, the overwhelmed hospital system in Italy and nursing home systems in the U.S. and Europe have potentially led to thousands of needless deaths (Stockman et al., 2020; Rudan, 2020; Bisserbe and Dalton, 2020; Kamp and Mathews, 2020).

But the surge in cases of extreme illness is not the only pressure point for health care providers. On the other side is the financial pressure from a reduced volume of elective care. Social distancing desires as well as explicit rules put in place by local and federal leaders have dramatically reduced the volume of elective care throughout the health care system, with inpatient discharge volume declining by as much as 40% in the Northeast (FAIRHealth, 2020; CMS, 2020). Other providers, such as primary care physicians, have also experienced a dramatic drop in the number of patients, with initial estimates suggesting that such visits decreased by nearly 60% (Mehrotra et al., 2020). For some providers, such as hospitals, the decline means a reduction in high-margin services at exactly the moment when they face the strain of caring for the sickest.

Policymakers in the U.S. have struggled to appropriately respond to the needs of providers. The first source of pressure—high volumes of COVID-19 cases—is readily addressed through higher reimbursement rates. In the U.S., hospital rates for the categories of care required by COVID-19 patients were increased by 20% (Congress, 2020). There is an ongoing debate about the right level of such adjustment, particularly given the extra requirements on providers for new ventilators and personal protective equipment. But further adjustment of reimbursement rates for providers treating COVID-19 patients can in principle address the primary source of additional costs.

The second source of pressure—reduced elective care—has proven more contentious. The U.S. Congress appropriated $175 billion to the Trump Administration to distribute as grants to providers to help them address this shortfall, but providers have argued that this is not

sufficient (Tardi, 2020). In addition, the Centers for Medicare and Medicaid Services (CMS) has provided $34 billion in loans to providers in the form of advance payments of expected Medicare charges—to be repaid 120 days later out of future payments at an interest rate of 10.25% (Morse, 2020). The HEROES Act recently proposed by the House of Representatives would provide more grant funds as well as extend the repayment period and lower the interest rate for CMS loans.

This mixed set of grants and loans, and controversy over amounts and repayment conditions, reflects a lack of clarity about whether this reduction in elective care represents a permanent or temporary shock. Many health care providers have strong access to capital markets, and others may benefit from emergency loan programs. If the reduced elective procedures are simply delayed, rather than canceled entirely, then such loans can be easily paid back. But if elective surgeries return only to their pre-virus levels, or even remain below, then providers may struggle to make up for this permanent loss in revenues.

There is no experience in recent history exactly like COVID-19 that we can use to inform this debate, but the impact of natural disasters offers a close parallel. Much like the virus, natural disasters may lead to a dramatic reduction in the volume of elective care. On the demand side, hurricanes, especially the most powerful, lead to significant increases in non-employment, potentially reducing demand for health care (Deryugina, 2017). On the supply side, hurricanes also cause widespread damage to hospital infrastructure, taking hospitals offline for weeks, months, and even years (DeSalvo, Sachs and Hamm, 2008; Deryugina and Molitor, 2019).[1]

We therefore use U.S. hurricanes to help inform COVID-19's long-term impact. We recognize the limitations of such a parallel. Some are partially addressable. For example, the impact of COVID-19 will last much longer than that of most natural disasters. But some hurricanes are more severe and we can examine how the impact varies with the magnitude of elective surgery reductions. There are some fundamental differences, however, like the fact

[1]The cost of natural disasters is also high and growing faster than GDP, making disasters an increasingly relevant phenomenon to study in isolation (Freeman and Mani, 2003; Bouwer et al., 2007).

that disasters may destroy physical provider capital in a way that COVID-19 does not. But for a variety of reasons we argue that the lessons from disasters are quite informative about what we can expect from COVID-19.

We carry out this analysis in three steps. First, we collect data on all hurricanes from 1997–2012. For each hurricane, we gather information on the location of each storm in six-hour intervals, the maximum sustained wind speed at that time, as well as the distance across which the wind speed extends. Second, we match information on the location, timing, and intensity of hurricanes to health insurance claims for those enrolled in the Medicare program, the U.S. program of universal coverage for its seniors. We use a nearly universal sample of hospitals and clinics covering almost two billion inpatient and outpatient visits in 1997–2013. Third, we quantify the impact of hurricanes on the health care delivery system. Leveraging the size and scope of the Medicare data, we compare counties that do and do not experience a hurricane using a differences-in-differences event study. Following recent literature, we assume that hurricane strikes are quasi-random for identification (Deryugina, 2017; Deryugina, Kawano and Levitt, 2018; Deryugina and Molitor, 2019). Outcomes of treated and control counties trend similarly before the strike, supporting our assumption that treated counties are comparable to counties that do not experience a hurricane.

We find that, even for the most severe hurricanes, hospitals appear to recover lost revenue from elective services—but that the time it takes to recoup those revenues varies with the severity of the hurricane. For a broad set of hurricanes, we find that elective services fall by about 7% in the month of the event, with revenues made-up within 10-11 months post-landfall. But for the most severe hurricanes, we find that elective services fall by more than 20% in the month of the event, and that those revenues are not recouped within 12 months. Moreover, for the most severe hurricanes, inpatient elective revenues are not made up, but increased outpatient revenue offsets those losses.

The decline in elective services under COVID-19 appears to be even larger, and to last longer, than the most severe hurricanes in our sample. We perform an extrapolation exercise

based on the variation in hurricane severity in our sample to project the recovery time for declines as severe as those seen under COVID-19. While these projections are out of sample, they indicate that it will be more than three years before hospitals recover the elective revenues lost from COVID. This conclusion suggests that short loan repayment periods and high interest rates could lead to significant long-term losses for providers.

Our findings also contribute to society's understanding of how natural disasters affect the health care sector. While there is a substantial amount of research focusing on disaster preparedness (e.g., Kaji, Langford and Lewis, 2008) and on how the health care sector performs in the immediate aftermath of a disaster (e.g., Eastman et al., 2007; Mortensen and Dreyfuss, 2008; Wang et al., 2008), there is little systematic evidence on longer-run impacts. An exception is DeSalvo, Sachs and Hamm (2008), who provide quantitative evidence on hospital capacity in the New Orleans area two years after Hurricane Katrina. To the best of our knowledge, we are the first to provide systematic quantitative evidence on longer-run health care utilization and revenue in the aftermath of natural disasters. Our findings imply that the health care infrastructure in the U.S. is quite resilient to natural disasters in both the medium- and long-run.

Our paper proceeds as follows. Section 2 discusses our data and how we created the sample of hurricanes to study. Section 3 describes our empirical methodology for evaluating the impact of hurricanes. Section 4 presents our results, while Section 5 concludes with implications for the current COVID-19 crisis.

2 Data

2.1 Medicare data

Our analyses rely on Medicare administrative records from 1997–2013. The majority of U.S. individuals aged 65 and older are eligible for Medicare. Individuals under the age of 65 are eligible if they have been enrolled in the Social Security Disability Insurance program

for at least two years or have end-stage renal disease or amyotrophic lateral sclerosis. For beneficiaries enrolled in Traditional Medicare (TM), we observe 100% of inpatient admissions and outpatient claims (e.g. visits to ambulatory surgery centers).[2] In total, we observe nearly two billion inpatient and outpatient visits from 1997–2013. These data therefore allow us to capture a nearly nationally representative sample of hospitals and clinics.

We focus our analysis on visits and charges for elective services because changes in emergency visits in response to hurricanes are likely a poor parallel for emergency visits during COVID-19. To give a sense of the differences, we later show that emergency services increase by 2-4% in the month of a hurricane (Appendix Table A2). In contrast, emergency department volume from March 29–April 25, 2020 decreased by 42% relative to previous years, leaving excess capacity in many emergency departments across the country (Hartnett et al., 2020).

We define elective services to include all outpatient claims (excluding emergency department visits) and elective inpatient claims. We define elective inpatient services using an indicator created by CMS for whether the visit was for an elective, urgent, or emergency condition created by Medicare. CMS derives the indicator based on the characteristics of the inpatient admission associated with the service.[3] We classify procedures into specific categories (e.g. orthopedic, chemotherapy, radiation therapy) using the Agency for Health Research and Quality's Clinical Classifications Software linked to ICD-9/ICD-10 procedure codes as well as Healthcare Common Procedure Coding System codes.

For our analyses, we calculate the total charges, visits, and procedures at the county-month level. The visit date is the day a beneficiary was admitted to the hospital, or the first day of the billing statement for procedures performed in the outpatient setting.

[2]Claims occurring when beneficiaries are enrolled in Medicare Advantage (MA) are not observed. The share of Medicare beneficiaries enrolled in MA ranges from 7% in 2007 to 14% in 2013 (Henry J. Kaiser Family Foundation, 2019).

[3]For instance, orthopedic, hernia, chemotherapy, and diagnostic procedures for patients not admitted through the emergency department are considered elective.

2.2 Hurricane data

Cyclones are tropical storm systems with circulating winds that sometimes form over warm ocean water. Cyclones that form in the Atlantic Ocean and attain maximum one-minute sustained wind speeds of 74 miles per hour or more are called "hurricanes." While many hurricanes dissipate without reaching land, those that make landfall can cause massive damage and disruption.

Our hurricane data come from The Tropical Cyclone Extended Best Track Dataset.[4] The dataset reports the location of each storm's center in six-hour intervals, the maximum sustained wind speed at that time, as well as the distance across which this wind speed extends ("radius of maximum wind" or RMS). We linearly interpolate between the reported storm locations to infer the path of the storm. We do the same for the maximum wind speed and the RMS.

We consider a county affected by a storm if its centroid fell within the RMS of the point on the storm path that is closest to the centroid. If the RMS is not reported, we consider a county affected if its centroid was within 50 miles of the storm path. We consider two definitions of treatment. The "all hurricanes" treatment considers counties impacted by wind speeds of at least 74 miles per hour (mph). The "strong hurricane" treatment considers counties impacted by wind speeds of at least 100 mph. We exclude the city of New Orleans, LA from our sample because the extensive population outflow in the aftermath of Hurricanes Katrina could jeopardize the generalizability of our estimates (Deryugina, Kawano and Levitt, 2018; Deryugina and Molitor, 2019). We exclude Galveston County, TX, for similar reasons. In 2008, Hurricane Ike damaged approximately 80% of homes and essentially all public infrastructure in the island city of Galveston, resulting in long-lasting population declines (White, 2013).

To avoid the econometric difficulties associated with a treated unit experiencing multiple

[4] Available from http://rammb.cira.colostate.edu/research/tropical_cyclones/tc_extended_best_track_dataset/.

events, we only include multiple hurricane instances if these have sufficiently long gaps between them to avoid overlapping events during the event study time window of interest (19 months in our case). Specifically, if a county experiences multiple hurricanes within any given 19-month period, we ignore all events beyond the first one within that period.[5] Given the random nature of hurricane paths, this approach should not bias our results. However, we also perform robustness checks where we exclude counties that experience more than one event of interest within a 19-month window, obtaining similar estimates.

Table 1 lists the hurricanes in our sample, the dates on which they formed, and the states they impacted. For our "all hurricanes" definition (wind speeds of at least 74 miles per hour), our sample includes 25 hurricanes that affected 169 counties and 1,020 medical providers in the years 1997–2012. For our definition of strong hurricanes (wind speeds of at least 100 miles per hour), our sample includes 13 hurricanes that affected 33 counties and 280 medical providers in the years 1997–2012.

Figures 1 and 2 illustrate the areas impacted by the hurricanes in our sample. Hurricanes only affect certain parts of the U.S., so we only allow coastal counties and counties within 75 miles of coastal counties in states that typically experience hurricanes to enter as controls (yellow counties). Hurricane states include: Alabama, Texas, Mississippi, Louisiana, New York, New Jersey, Pennsylvania, Delaware, Maryland, Virginia, North Carolina, South Carolina, Georgia, and Florida. Figure 1 shows the spatial distribution of all hurricanes in our sample, with counties becoming increasingly dark with the number of hurricanes in that county over our sample period. Figure 2 shows the same for strong hurricanes, which impacted a more limited set of counties. No county experienced more than one year with a strong hurricane during our sample period.

Table 2 shows differences between control and treated counties affected by all hurricanes as well as strong hurricanes. We compare means and changes in 1997, our baseline year.[6]

[5] For example, if a county experienced a hurricane in September of 1998, October of 1999, and August of 2004, our analysis will only consider the 1998 and 2004 hurricanes, ignoring the 1999 strike.

[6] We consider 1997 to be a reasonable baseline year because there was only one county that experienced a hurricane in that year and results are not sensitive to its exclusion.

Treated counties in the all hurricane sample experienced at least one hurricane with wind speeds of 74 mph or more in 1997–2012. The strong hurricane sample includes a subset of treated counties that experienced hurricanes with wind speeds of 100 mph or more. Control counties did not experience a hurricane in 1997–2012.

While our identification strategy relies on *trends* between treated and control counties being similar, understanding how treated and control counties differ in levels is useful for interpretation. It is immediately clear from Table 2 that treated and control counties are significantly different at baseline. Counties that experience hurricanes have larger elderly populations and more hospitals, which leads to differences in the number of medical services and charges. All specifications therefore include county fixed effects to address level differences. What is potentially more concerning for estimation is that differences in levels may indicate differences in trends. Fortunately, 1997 trends in our main outcomes of interest—log visits and charges—are largely similar for counties affected by the average hurricane and control counties. Differences between treated counties that experienced strong hurricanes and control counties are larger and sometimes significant. However, we later verify that trends six months before hurricane strikes are similar for control and treatment counties for all main outcomes.

3 Empirical approach

To illuminate the dynamics of health care utilization following a hurricane, we begin with a standard event study specification:

$$\ln\left(Y_{cmy}\right) = \sum_{\tau=-6,\tau\neq-2}^{12} \beta_\tau H_{c\tau} + \beta_{PP} H_{c,PP} + \alpha_{cm} + \alpha_{my} + \varepsilon_{cmy}, \tag{1}$$

where Y_{cmy} is some measure of health care utilization for county c in month m and year y. The variable $H_{c\tau}$ is a hurricane indicator equal to 1 if, as of month-year my, the county experienced a hurricane τ months ago. To account for the small share of county-months in

our data with zero values, we add one before taking logs.[7]

Hurricanes can be anticipated several days ahead of when they strike, and in some cases a hurricane forms in the month before it makes landfall. For example, Hurricane Frances formed as a tropical depression on August 25, 2004, but did not make strike Florida until the early morning of September 5, 2004. Similarly, Hurricane Lili formed on September 21, 2002, but made landfall in Louisiana only on October 3, 2002. To account for potential anticipation effects, we therefore normalize the effect *two* months before the hurricane (β_{-2}) to zero.

The indicator $H_{c,PP}$ in Equation (1) is equal to 1 if a county experienced a hurricane outside of the time window of interest. The variables α_{cm} and α_{my} are county-by-month and month-by-year fixed effects, respectively. Standard errors are clustered by county. We weight our estimates by each county's monthly average of the outcome variable at baseline, calculated using data for January–June of 1997.

To interpret β_τ for $\tau \geq 0$ as the causal effect of a hurricane on health care utilization, it must be the case that, absent the hurricane, outcomes in the treated counties would have evolved in parallel with outcomes in the control counties. Given the random nature of hurricanes, verifying that β_τ is not statistically different from zero for $\tau < -2$ provides strong evidence in support of this assumption.

To estimate the effect of a hurricane more concisely, we also present a pooled version of the event study specification illustrated by Equation (1):

$$\begin{aligned} \ln\left(Y_{cmy}\right) = \quad & \gamma_{-1}H_{c,-1} + \gamma_0 H_{c0} + \gamma_1 H_{c1} + \gamma_2 H_{c2} + \gamma_3 H_{c,3 \text{ to } 12} \\ & + \beta_{PP} H_{c,PP} + \alpha_{cm} + \alpha_{my} + \varepsilon_{cmy}. \end{aligned} \tag{2}$$

In this equation, we estimate treatment effects from the month before to two months after the hurricane separately ($H_{c,-1}, H_{c0}, H_{c1}$, and H_{c2}) but combine the estimated treatment effects in months 3–12 ($H_{c,3 \text{ to } 12}$), over which the effect appears to be roughly constant. All

[7] Only 5% of county-months have zero elective procedures.

other variables are the same as Equation (1).

We estimate the *cumulative* effects of a hurricane by first calculating the implied level change in each outcome for each month $\tau \geq -1$. To do so, we multiply $e^{\beta_\tau} - 1$ by the mean of the outcome variable among the treated counties at $\tau = -2$. We then sum these estimates over the desired time period to obtain the cumulative hurricane-caused change. To calculate confidence intervals, we re-estimate the set $\{\beta_\tau\}$ in 1,000 clustered bootstraps, reporting the 5th and 95th percentiles of the cumulative estimates.

4 Results

4.1 Overall Impacts

Figure 3 presents the event study results for all elective procedures and charges, along with associated 95% confidence intervals. There are four panels, corresponding to two measures of outcomes (visits and charges) and two measures of hurricane strength (all hurricanes or strong hurricanes). The vertical line at $\tau = 0$ indicates that treated counties experience a hurricane in that month. The horizontal line at zero provides a reference point. We show results for the six months preceding a hurricane's landfall to assess the presence of pre-trends. Reassuringly, visits and charges are not significantly different between hurricane and control counties before $\tau = -2$ in all cases.

Our results reveal that hurricanes have significant and notable effects on elective care. In the month preceding the hurricane ($\tau = -1$), visits and charges increase slightly, which is likely due to providers and patients anticipating a hurricane strike. In the month a hurricane hits, elective care declines sharply. For the full sample of hurricanes, shown in panels (a) and (c), elective care declines by 6.5% in the month of the hurricane. Elective care remains below its baseline level in the first month after the hurricane but returns to the baseline level two months later. Starting in the third month post-landfall, elective care increases above baseline, both for visits and charges, and largely stays higher than baseline until at least 12

months after a hurricane strike.

Panel (b) and (d) show the results for the stronger set of hurricanes (note that the scale is different from the all-hurricane sample). For the stronger sample of hurricanes, the initial drop in elective visits and charges is much larger, exceeding 20%. The bounce-back is somewhat slower as well, although both visits and charges are not statistically distinguishable from baseline by month two. Elective visits are significantly above baseline 8–12 months after the hurricane.

Figure 4 graphs the cumulative effects implied by our event study graphs. The cumulative impact is normalized to zero two months before the hurricane. We find that, for the full sample of hurricanes, the negative cumulative effect on elective care lasts 9–10 months, although we can only state with statistical certainty that losses are significant for 4–5 months. For the strongest hurricanes, we can say with statistical certainty that providers do not make up lost visit and revenues for 8–9 months. After 12 months, both cumulative visits and cumulative charges remain negative (419 visits and $21 million below the baseline level, respectively). However, neither of these estimates is significantly different from zero (Table A4), and both are fairly small relative to the mean, amounting to less than half a month of charges in cumulative terms. Thus, for the most severe hurricanes, hospitals appear to make up their lost revenues in about a year.

Table 3 shows regression results corresponding to event study graphs in Figure 3. The slight uptick in the month before the hurricane is statistically insignificant across outcomes with one exception: elective charges the month before a strong hurricane increase 3.0%. Strikingly, elective visits in months 3–12 increase similarly for the sample of all hurricanes as they do for the sample of strong hurricanes. During this post-event window, elective visits increase significantly by 2.0% per month in response to all hurricanes and by 1.5% per month in response to strong hurricanes. Charges significantly increase by 1.6% per month for all hurricanes and by 2.3% per month for strong hurricanes.

These findings suggest that providers are unable to immediately compensate for lost

services, instead increasing capacity at a low and constant rate for several months. As a result, providers appear to be less able to bounce back from larger shocks because they may be constrained in their ability to expand capacity. This has important implications for COVID-19, which likely represents a much larger shock to the provision of elective services.

4.2 Impacts by Place of Service

Figures 5 and 7 present event study estimates and corresponding 95% confidence intervals for inpatient elective and outpatient services. Figures 6 and 8 graph the cumulative impact of hurricanes on these outcomes, along with 95% confidence intervals.

For elective inpatient care, the results are quite different depending on the strength of the hurricane. For the average hurricane, both charges and visits bounce back quickly (Figure 5). Cumulative effects for visits and charges are positive by months 6 and 10, respectively and cease to be significantly negative by months 2–3 (Figure 6). For stronger hurricanes, the effects are significantly negative until months 6–8, and even by month 12 remain 517 visits and $20 million below the baseline level, although not significantly different from zero (Table A6).

Table 4 shows the difference-in-differences estimates corresponding to the event studies in Figure 5. Elective visits and charges are not significantly different from zero the month before the hurricane, except for a 3.5% increase in elective charges in response to a strong hurricane. In the hurricane month, visits decrease by 6.5% in response to all hurricanes and by 23.5% in response to strong hurricanes. Charges decrease even more: by 7.9% in response to all hurricanes and by 28.1% in response to strong hurricanes. Three to 12 months after landfall, inpatient elective visits and charges do not significantly increase, and the point estimate ranges from -1.9% to 1.5%. This suggests that providers are unable to increase their inpatient capacity to offset losses caused by severe hurricanes.

For outpatient care, the results follow similar patterns across the two hurricane samples, albeit with somewhat different timing and magnitudes. Both visits and charges largely

bounce back by month two for both samples of hurricanes (Figure 7). For the average hurricane, the overall cumulative effect looks fairly similar to inpatient elective services, crossing zero 9–11 months after landfall (Figure 8 and Table A8). But, unlike inpatient elective care, for stronger hurricanes the cumulative effect for outpatient visits trends up and crosses zero only 12 months after landfall. Outpatient charges remain below zero at the end of our sample period, although the estimates is small (−$1.9 million) and statistically insignificant.

Table 5 shows the difference-in-differences estimates corresponding to the event studies in Figure 7. Estimates for the month before the hurricane are not significantly different from zero and range from 0.01 to 2.9%. The month of the hurricane, visits decline by 6.7% in response to all hurricanes and by 24.0% in response to strong hurricanes. Charges decrease similarly, by 8.7% among counties experiencing the average hurricane and by 23.8% among counties experiencing strong hurricanes. Three to 12 months after a hurricane, the monthly number of visits increases by 2.1% in response to all hurricanes and by 1.8% in response to strong hurricanes. Charges increase by 1.1% in response to all hurricanes and by 3.3% in response to strong hurricanes. Thus, unlike for elective inpatient services, providers appear to be able to expand their capacity to ultimately make up for their foregone outpatient elective revenue—although, once again, for the most severe hurricanes, this takes a year or more.

Our results are very similar if, in addition to county-by-month and month-by-year fixed effects, we control for state-by-year fixed effects or for county-specific annual trends (interactions between county indicators and the year variable). The results are also robust to omitting counties that experience more than one hurricane event within any 19-month rolling window.

4.3 Impacts by Type of Elective Care

The results thus far have focused on the impacts by type of care for all elective services. It is separately of interest to assess which elective services respond the most to hurricanes. We therefore consider a number of different major elective services. The results across services are strongly indicative of which services are cut back the most after hurricanes—and how strong the bounce-back appears to be.

In particular, we quantify how hurricanes affect elective orthopedic (Table 6), hernia (Table 7), radiation therapy (Table 9), and chemotherapy (Table 8) treatments. Because this exercise further divides our sample, we are unable to estimate event studies with meaningful precision. We therefore estimate a modified version of equation 2 that omits the indicator for the month before the hurricane and combines indicators for post-hurricane months 1, 2, and 3–12 into a single month 1–12 indicator.

In the month of the hurricane, orthopedic procedures decline by 9.4% in response to all hurricanes and by 27.3% in response to strong hurricanes. Hernia procedures decline by 7.1% in the response to all hurricanes and by 39.5% in response to strong hurricanes. Radiation therapy is not significantly impacted and chemotherapy declines by an insignificant 3.3% in response to all hurricanes and by a significant 8.9% in response to strong hurricanes. These patterns suggest that elective orthopedic and hernia procedures are the most sensitive to cut-backs in elective care. They also happen to be the two most profitable services of the four: at baseline, charges per visit are largest for orthopedics (Table 6), followed by hernias (Table 7), and smallest for chemotherapy (Table 8). This suggests that revenue from orthopedics and hernias are important inputs into hospital profitability, while simultaneously bearing the largest cuts.

4.4 Projected Recovery Times for Larger Shocks

Although the strongest hurricanes in our sample reduce elective care by over 20% in the month of the hurricane, these magnitudes are still smaller than what we observe with COVID-

19, which has led to larger and longer-lasting reductions. To infer recovery times for such shocks, we combine projections of the in-sample initial decrease in elective services with the average observed bounce-back.

We first re-estimate equation (2) for every integer wind speed between 74 and 100. In other words, we progressively increase the threshold for what constitutes a "treated" county, first counting as treatments all hurricanes, then only hurricanes with wind speed of 75 miles per hour or more, and so on. Figure 9 shows the relationship between the initial decline in elective visits and charges and the wind speed threshold. That is, we show the coefficient γ_0 from equation (2) for each wind speed threshold. The relationship appears to be very close to linear (as shown by cluster of dots between 74 and 100 miles per hour), so we extend this linear relationship outwards. We project that wind speeds of around 130 miles per hour would generate a one-month drop in elective services and charges of about 40%.

We assume the initial decline of 40% lasts for three months and is then followed by observed changes in months 1–2 (γ_1, and γ_2).[8] For each of the following months, we assume that visits and charges evolve according to the bounce-back in months 3–12 (γ_3) and calculate the number of months it takes elective services to reach a cumulative change of zero. Because we do not observe a strong relationship between wind speed and the size of the bounce-back in months 3–12, we use the average estimated bounce-back of 0.59% for elective visits and 2.2% for elective charges.

This back-of-the-envelope exercise implies that elective charges would be made up within about 40 months, while elective visits would take over 150 months (or more than 12.5 years) to be made up. The stark difference between the projections for visits and charges suggests that less expensive (and, potentially, less urgent) care is more likely to be forgone completely.

[8]For completeness, we also include γ_{-1} in this calculation.

5 Conclusion

COVID-19 represents an unprecedented shock to our nation's health care system. Never before has there been the combination of a massive economic displacement with forced reductions in many medical services. Medical providers have been hit hard, and they have been vocal about the implications for their ultimate financial viability (AHA, 2020; FAIRHealth, 2020).

In the face of this enormous shock, policymakers have struggled to address the problems facing the U.S. health care sector. Issues such as providing grants versus loans, the size and targeting of grants, and the terms at which loans should be repaid are being debated in real time as the virus moves around the country.

This debate faces the important challenge that the long-term implications for providers are unknown. There is clearly a short-term reduction in use of elective services (Mehrotra et al., 2020; FAIRHealth, 2020). But to what extent will providers be able to recoup those losses—and over what time period? The answer to this question is centrally important for designing policy responses.

Hurricanes represent the closest possible parallel to the COVID-19 shutdown. They are severe events that lead to sizeable reductions in elective care. Additionally, the comparison of more to less severe hurricanes can provide some sense of how the magnitude of the crisis impacts hospital finances.

Our results show that hurricanes cause a significant decline in the provision of hospital elective services lasting more than one month and as long as three months. For the average hurricane, that drop is roughly 7%, and hospitals make up their financial losses about 10–11 months later. But for the most severe hurricanes, the drop is more than 20%, and financial losses are at best made up within 12 months, if at all.

We also find that the "bounce-back" in elective services is much larger for outpatient than inpatient elective care. In particular, for the strongest hurricanes, we find that the losses from inpatient elective care have the potential to be long-lasting.

These results have important implications for policy. For example, the existing CMS loan program has a repayment period of six months. Based on our findings, it seems extremely unlikely that providers will have made up their lost revenues in that period. Even for the strongest hurricanes, where the decline in elective procedures was less than is reported under COVID-19, cumulative revenues from elective procedures took more than a year to recover. It is therefore extremely unlikely that providers will be able to fully pay back their loans even within a year under these circumstances. Allowing for longer repayment periods or grants is likely necessary if the goal is to preserve the earnings of the health care sector.

References

AHA. 2020. "Hospitals and Health Systems Face Unprecedented Financial Pressures Due to COVID-19." *American Hospital Association*. https://www.aha.org/system/files/media/file/2020/05/aha-covid19-financial-impact-0520-FINAL.pdf.

Bisserbe, Noemie, and Matthew Dalton. 2020. "How Coronavirus Outmaneuvered France's Health-Care System." *The Wall Street Journal*. https://www.wsj.com/articles/how-coronavirus-outmaneuvered-frances-health-care-system-11587906000?mod=djemHL_t.

Bouwer, Laurens M., Ryan P. Crompton, Eberhard Faust, Peter Höppe, and Roger A. Pielke, Jr. 2007. "Confronting Disaster Losses." Science (Policy Forum) 318 (5851): 753.

CMS. 2020. "Non-Emergent, Elective Medical Services, and Treatment Recommendations." *Centers for Medicare & Medicaid Services*. https://www.cms.gov/files/document/cms-non-emergent-elective-medical-recommendations.pdf.

Congress, The United States. 2020. "Coronavirus Aid, Relief and Economic Security (CARES) Act, Pub. L. No. 116-136." https://www.aha.org/system/files/media/file/2020/05/aha-covid19-financial-impact-0520-FINAL.pdf.

Deryugina, Tatyana. 2017. "The Fiscal Cost of Hurricanes: Disaster Aid versus Social Insurance." *American Economic Journal: Economic Policy*, 9(3): 168–198.

Deryugina, Tatyana, and David Molitor. 2019. "Does when you die depend on where you live? Evidence from Hurricane Katrina." NBER Working Paper 24822.

Deryugina, Tatyana, Laura Kawano, and Steven Levitt. 2018. "The Economic Impact of Hurricane Katrina on its Victims: Evidence from Individual Tax Returns." *American Economic Journal: Applied Economics*, 10(2).

DeSalvo, Karen B., Benjamin P. Sachs, and L. Lee Hamm. 2008. "Health Care Infrastructure in Post-Katrina New Orleans: A Status Report." *The American Journal of the Medical Sciences*, 336(2): 197–200.

Eastman, Alexander L, Kathy J Rinnert, Ira R Nemeth, Raymond L Fowler, and Joseph P Minei. 2007. "Alternate site surge capacity in times of public health disaster maintains trauma center and emergency department integrity: Hurricane Katrina." *Journal of Trauma and Acute Care Surgery*, 63(2): 253–257.

FAIRHealth. 2020. "Illuminating the Impact of COVID-19 on Hospitals and Health Systems." *A FAIR Health Brief*. https://s3.amazonaws.com/media2.fairhealth.org/brief/asset/Illuminating%20the%20Impact%20of%20COVID-19%20on%20Hospitals%20and%20Health%20Systems%20-%20A%20Comparative%20Study%20of%20Revenue%20and%20Utilization%20-%20A%20FAIR%20Health%20Brief.pdf (accessed May 20, 2020).

Freeman, Paul K., Michael Keen, and Muthukumara Mani. 2003. *Dealing with Increased Risk of Natural Disasters: Challenges and Options.* International Monetary Fund (IMF) Working Paper 03/197.

Hartnett, Kathleen P., Aaron Kite-Powell, Jourdan DeVies, Michael A. Coletta, Tegan K. Boehmer, Jennifer Adjemian, Adi V. Gundlapalli, and National Syndromic Surveillance Program Community of Practice. 2020. "Impact of the COVID-19 Pandemic on Emergency Department Visits–United States, January 1, 2019–May 30, 2020." *Centers for Disease Control and Prevention Morbidity and Mortality Weekly Report*, 69.

Henry J. Kaiser Family Foundation. 2019. "Medicare Advantage Fact Sheet."

Kaji, Amy H, Vinette Langford, and Roger J Lewis. 2008. "Assessing hospital disaster preparedness: a comparison of an on-site survey, directly observed drill performance, and video analysis of teamwork." *Annals of emergency medicine*, 52(3): 195–201.

Kamp, Jon, and Anna Wilde Mathews. 2020. "Coronavirus Deaths in U.S. Nursing, Long-Term Care Facilities Top 10,000." *The Wall Street Journal*. https://www.wsj.com/articles/coronavirus-deaths-in-u-s-nursing-long-term-care-facilities-top-10-000-11587586237.

Mehrotra, Ateev, Michael Chernew, David Linetsky, Hilary Hatch, and David Cutler. 2020. "The Impact of the COVID-19 Pandemic on Outpatient Visits: A Rebound Emerges." *To the Point (blog), Commonwealth Fund*. https://www.commonwealthfund.org/publications/2020/apr/impact-covid-19-outpatient-visits.

Morse, Susan. 2020. "CMS Makes $34 Billion Loan Available to Providers, Suppliers." *Healthcare Finance*. https://www.healthcarefinancenews.com/news/cms-makes-34-billion-loan-available-providers-suppliers.

Mortensen, Karoline, and Zachary Dreyfuss. 2008. "How many walked through the door?: the effect of hurricane Katrina evacuees on Houston emergency departments." *Medical Care*, 46(9): 998–1001.

Rudan, Igor. 2020. "A Cascade of Causes that led to the COVID-19 Tragedy in Italy and in other European Union Countries." *Journal of Global Health*, 10(1).

Stockman, Farah, Matt Richtel, Danielle Ivory, and Mitch Smith. 2020. "'They're Death Pits': Virus Claims at Least 7,000 Lives in U.S. Nursing Homes." *The New York Times*. https://www.nytimes.com/2020/04/17/us/coronavirus-nursing-homes.html.

Tardi, Joe. 2020. "Treating Coronavirus is Draining Hospital Coffers of Millions and Threatening Resources." *NBC News*. https://www.nbcnews.com/news/us-news/treating-coronavirus-draining-hospital-coffers-millions-threatening-resources-n120154
cid=eml_mrd_20200507&utm_source=Sailthru&utm_medium=email&utm_campaign=Morning%20Rundown%20Special%20Edition:%20The%20Coronavirus%20Crisis%2C%207%20May%202020.

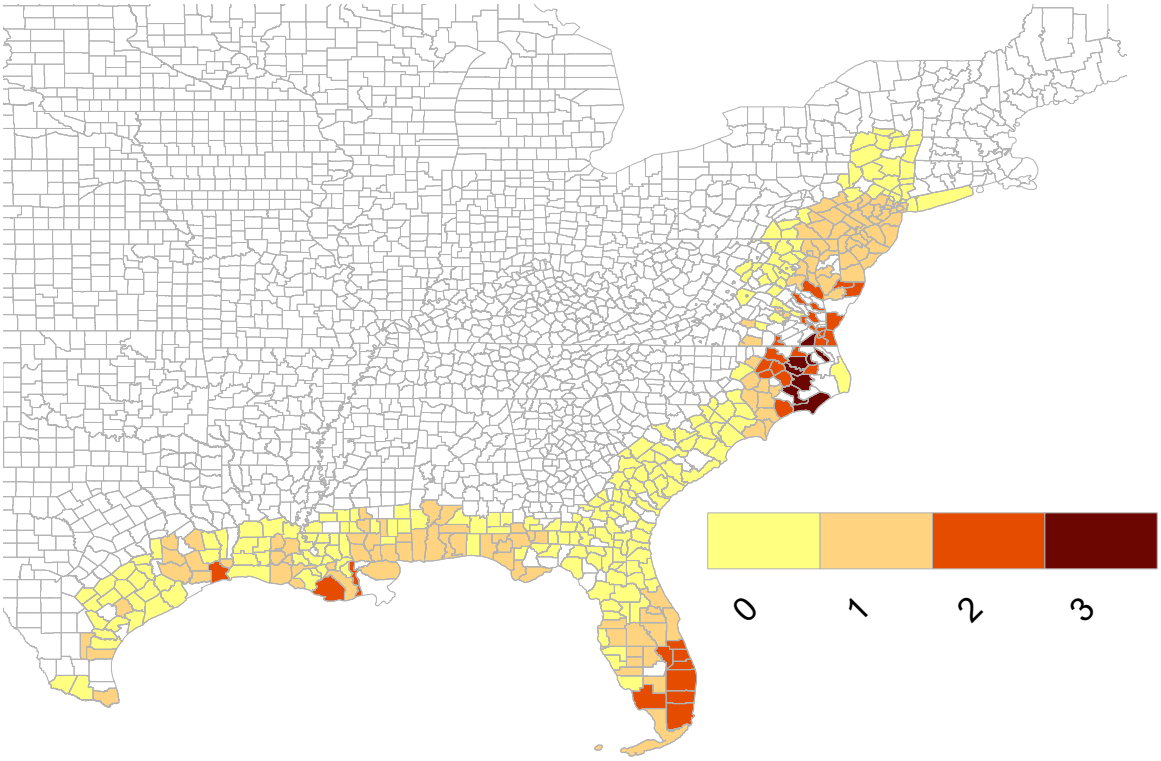
Wang, Philip S, Michael J Gruber, Richard E Powers, Michael Schoenbaum, Anthony H Speier, Kenneth B Wells, and Ronald C Kessler. 2008. "Disruption of existing mental health treatments and failure to initiate new treatment after Hurricane Katrina." *American Journal of Psychiatry*, 165(1): 34–41.

White, Audrey. 2013. "Five Years After Ike, Galveston Is Still Picking Up the Pieces." *The New York Times*. https://www.nytimes.com/2013/04/26/us/

galveston-tex-picking-up-the-pieces-5-years-after-hurricane-ike.html.

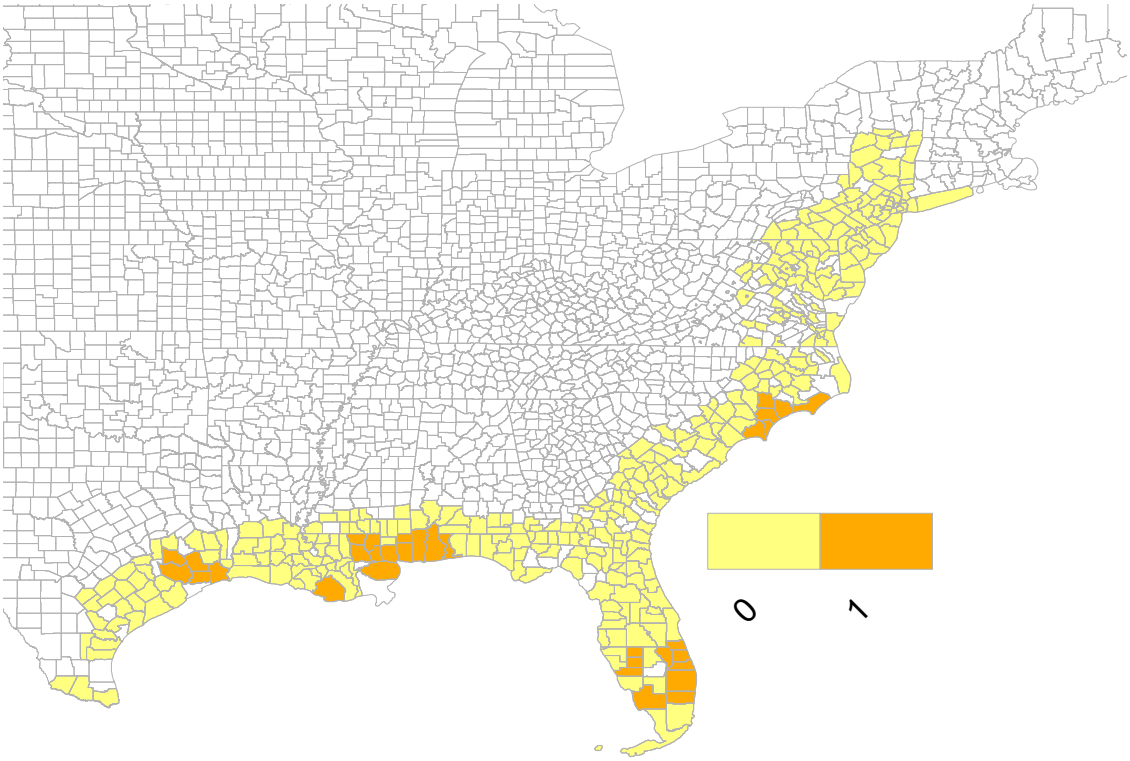
Figures

Figure 1: Sample of treated and control counties, all hurricanes



Notes: Map shows counties included in our sample (non-white counties) as well as the number of times they experienced a hurricane with wind speeds of at least 74 miles per hour. Yellow counties are counties that never experienced a hurricane, orange counties experienced one hurricane, red counties experienced 2 hurricanes, and brown counties experienced 3 hurricanes. Our sample includes coastal counties and counties 75 miles from coastal counties. Counties that had zero outpatient and inpatient claims did not enter our sample. New Orleans Parish and Galveston counties were excluded from our treatment sample.

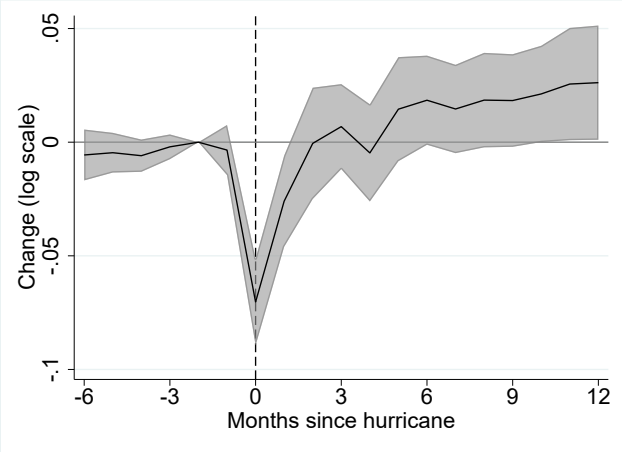
Figure 2: Sample of treated and control counties, strong hurricanes



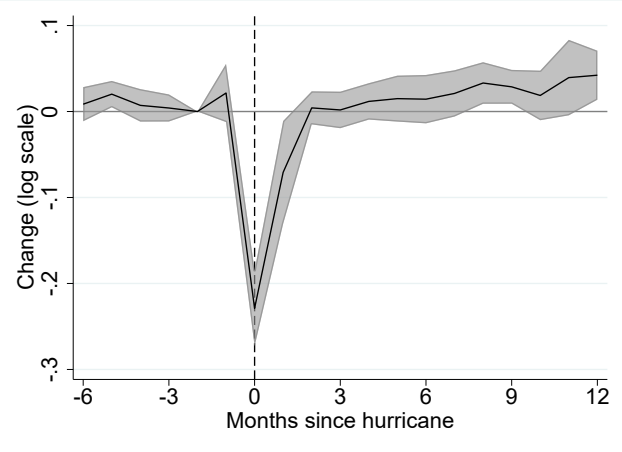
Notes: Map shows counties included in our sample (non-white counties) as well as the number of times they experienced a hurricane with wind speeds of at least 100 miles per hour. Yellow counties are counties that never experienced a hurricane and orange counties experienced one hurricane. Our sample includes coastal counties and counties 75 miles from coastal counties. Counties that had zero outpatient and inpatient claims did not enter our sample. New Orleans Parish and Galveston counties were excluded from our treatment sample.

Figure 3: Impact of hurricanes on elective care

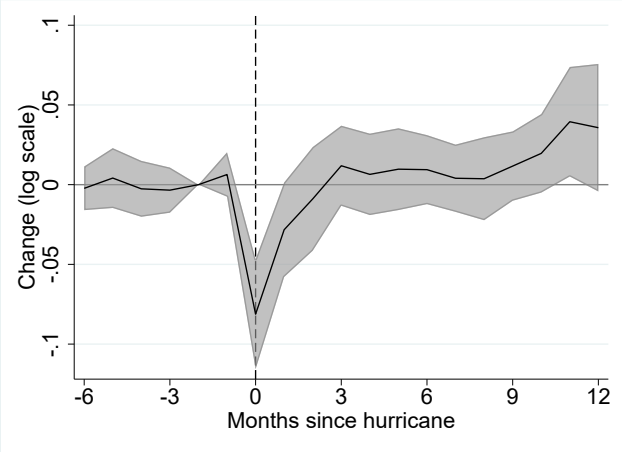
(a) Impact of all hurricanes on elective visits



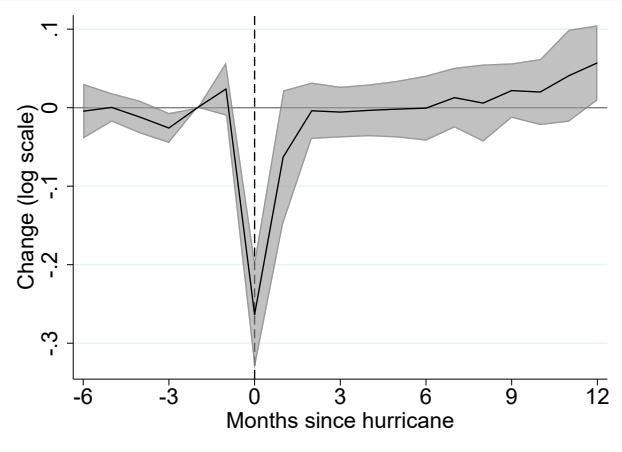
(b) Impact of strong hurricanes on elective visits



(c) Impact of all hurricanes on elective charges



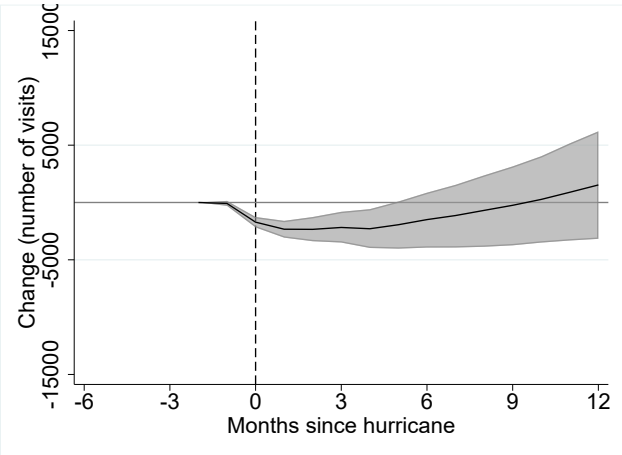
(d) Impact of strong hurricanes on elective charges



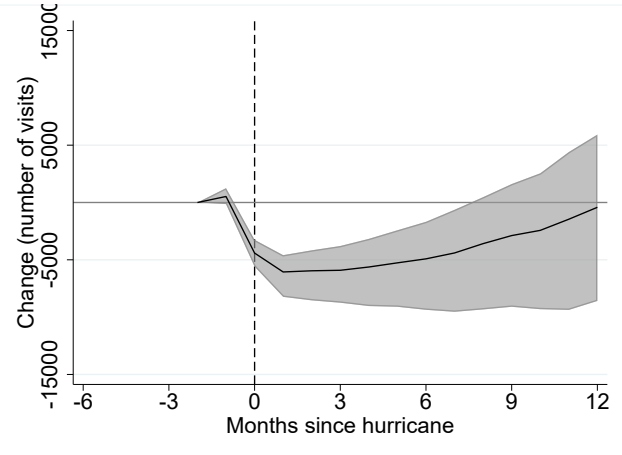
Notes: Event study graphs plot the monthly change in elective visits using a log scale. The specification is outlined in Section 3. The x-axis contains the relative number of months since the hurricane occurred in $t = 0$. Regressions are at the county-month level, cluster at the county level, and contain county-by-month and month-by-year fixed effects. See Table 3 for point estimates.

Figure 4: Cumulative impact of hurricanes on elective care

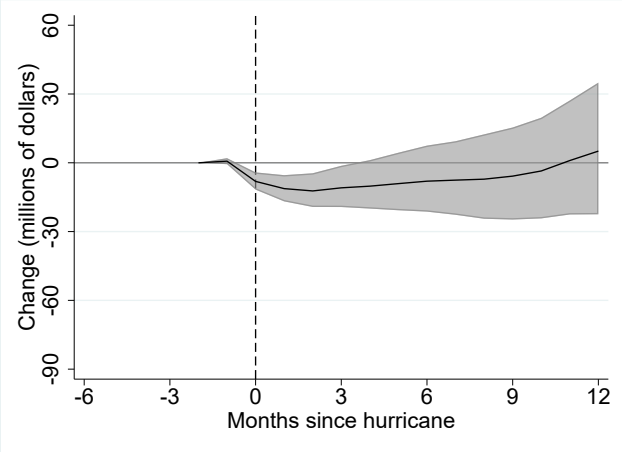
(a) Cumulative impact of all hurricanes on elective visits



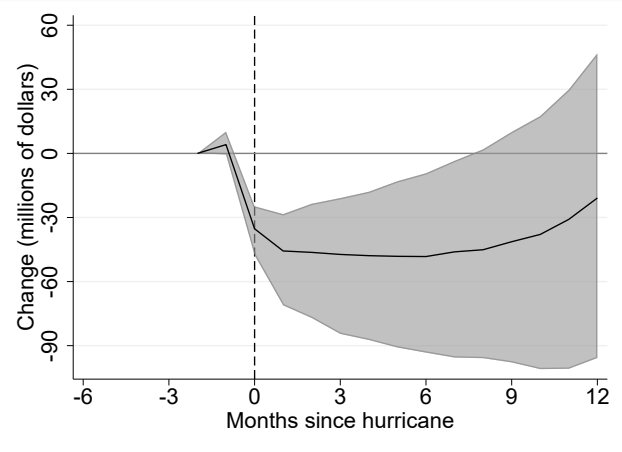
(b) Cumulative impact of strong hurricanes on elective visits



(c) Cumulative impact of all hurricanes on elective charges



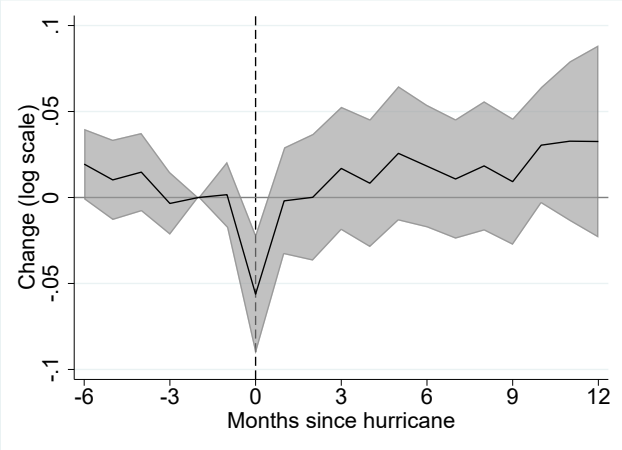
(d) Cumulative impact of strong hurricanes on elective charges



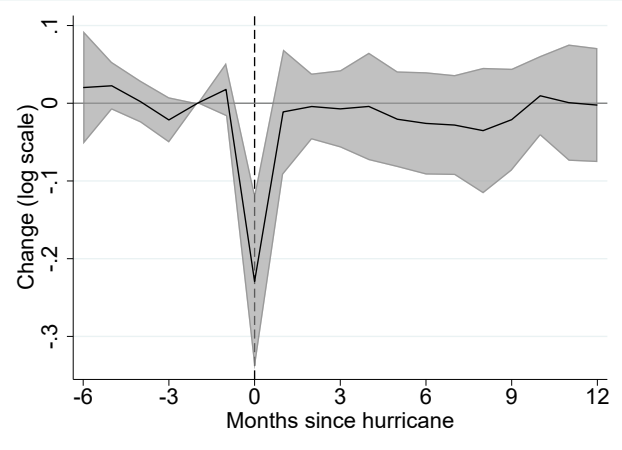
Notes: Graphs plot the cumulative change in the outcome of interest. The specification is outlined in Section 3. The x-axis contains the relative number of months since the hurricane occurred in $t = 0$. Regressions are at the county-month level, cluster at the county level, and contain county-by-month and month-by-year fixed effects.

Figure 5: Impact of hurricanes on inpatient elective care

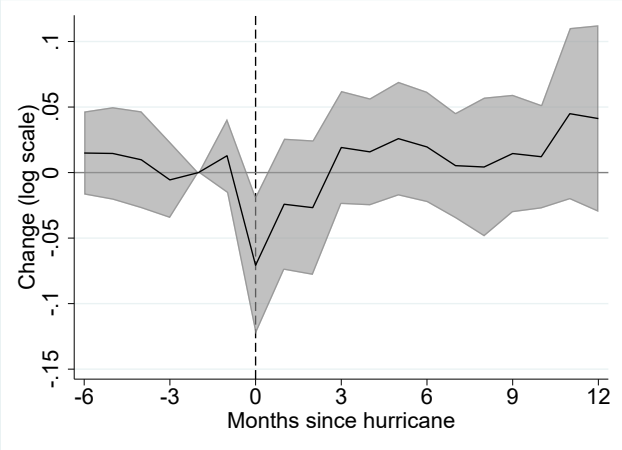
(a) Impact of all hurricanes on inpatient elective visits



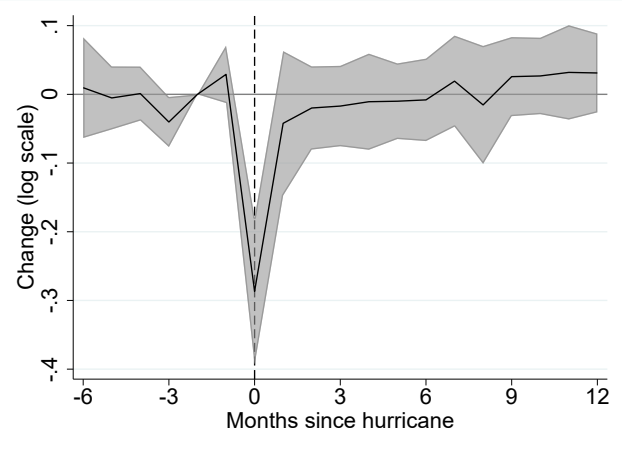
(b) Impact of strong hurricanes on inpatient elective visits



(c) Impact of all hurricanes on inpatient elective charges



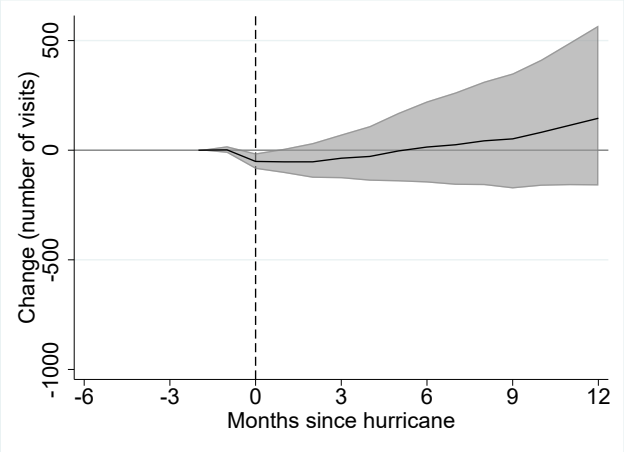
(d) Impact of strong hurricanes on inpatient elective charges



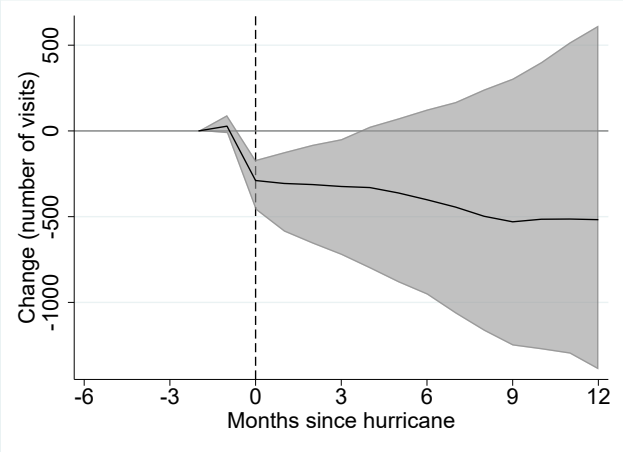
Notes: Event study graphs plot the monthly change in elective visits using a log scale. The specification is outlined in Section 3. The x-axis contains the relative number of months since the hurricane occurred in $t = 0$. Regressions are at the county-month level, cluster at the county level, and contain county-by-month and month-by-year fixed effects. See Table 4 for point estimates.

Figure 6: Cumulative impact of hurricanes on inpatient elective care

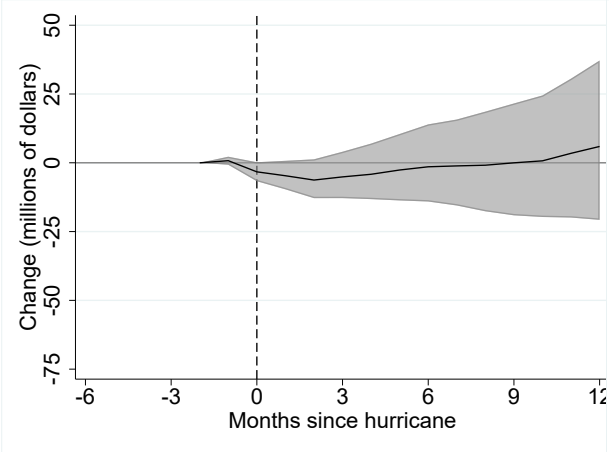
(a) Cumulative impact of all hurricanes on inpatient elective visits



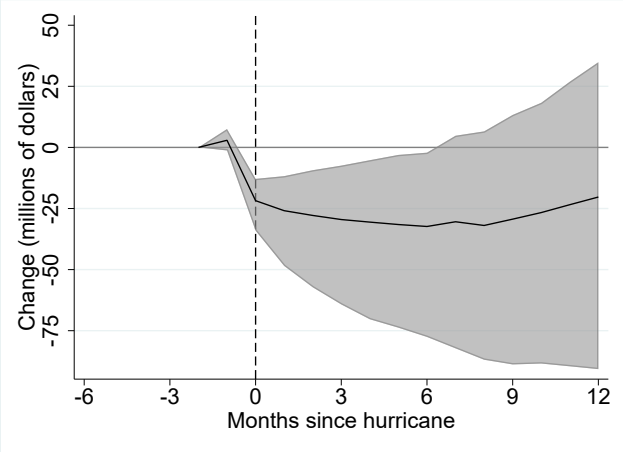
(b) Cumulative impact of strong hurricanes on inpatient elective visits



(c) Cumulative impact of all hurricanes on inpatient elective charges



(d) Cumulative impact of strong hurricanes on inpatient elective charges

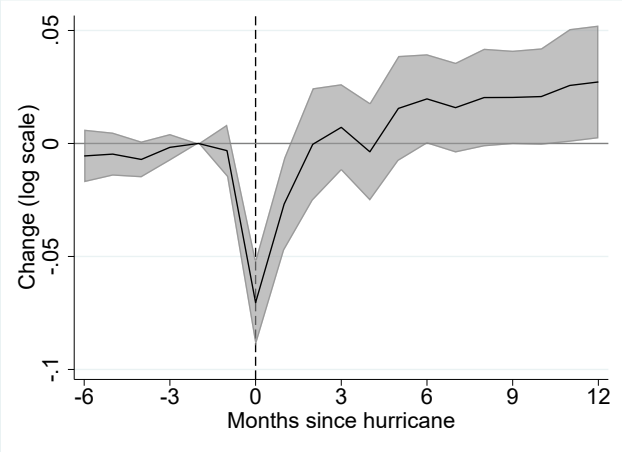


s

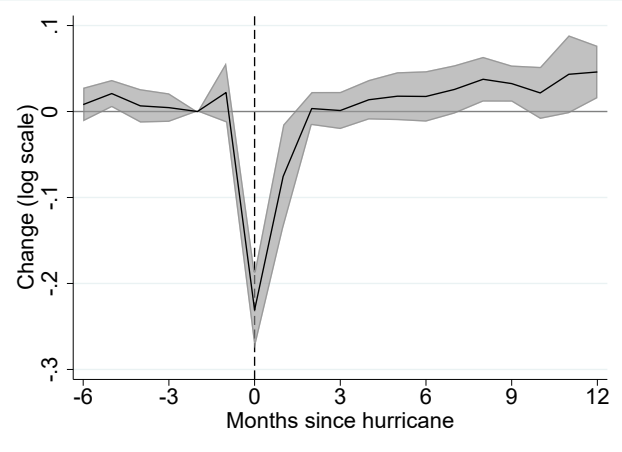
Notes: Graphs plot the cumulative change in the outcome of interest. The specification is outlined in Section 3. The x-axis contains the relative number of months since the hurricane occurred in $t = 0$. Regressions are at the county-month level, cluster at the county level, and contain county-by-month and month-by-year fixed effects.

Figure 7: Impact of hurricanes on outpatient care

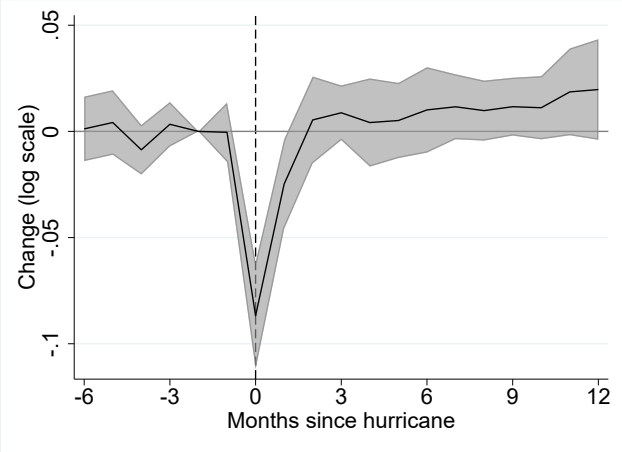
(a) Impact of all hurricanes on outpatient visits



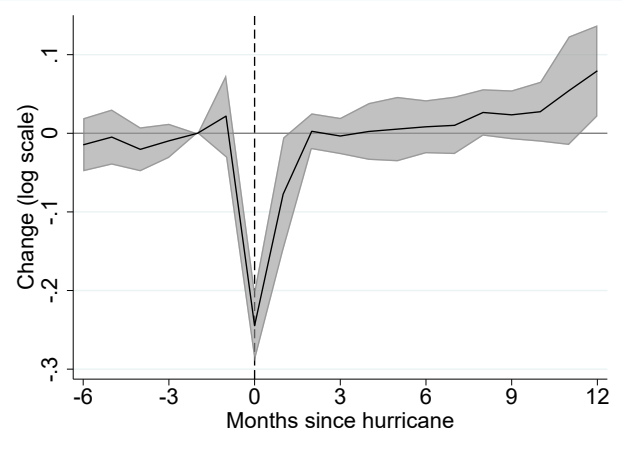
(b) Impact of strong hurricanes on outpatient visits



(c) Impact of all hurricanes on outpatient charges



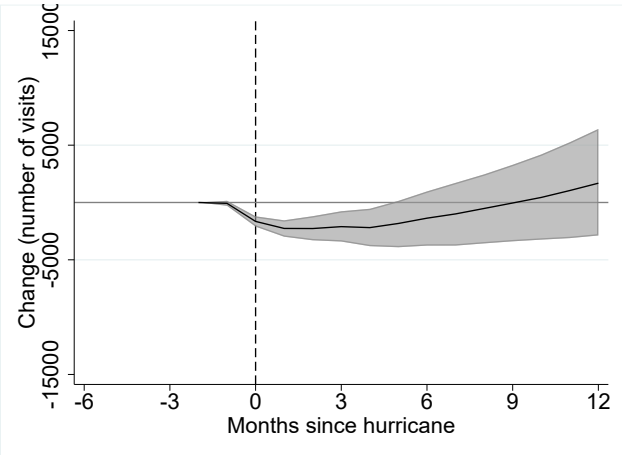
(d) Impact of strong hurricanes on outpatient charges



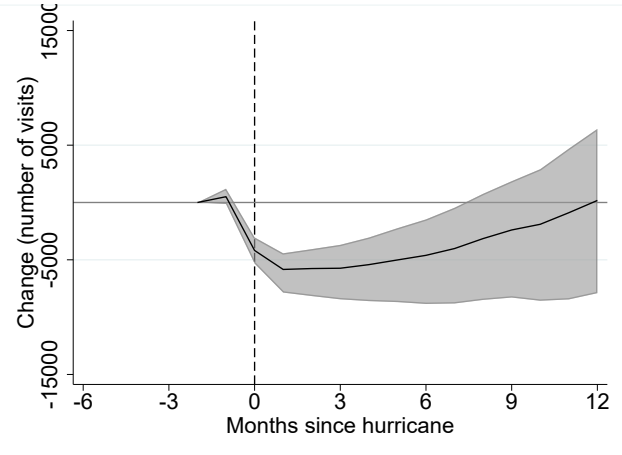
Notes: Event study graphs plot the monthly change in elective visits using a log scale. The specification is outlined in Section 3. The x-axis contains the relative number of months since the hurricane occurred in $t = 0$. Regressions are at the county-month level, cluster at the county level, and contain county-by-month and month-by-year fixed effects. See Table 5 for point estimates.

Figure 8: Cumulative impact of hurricanes on outpatient care

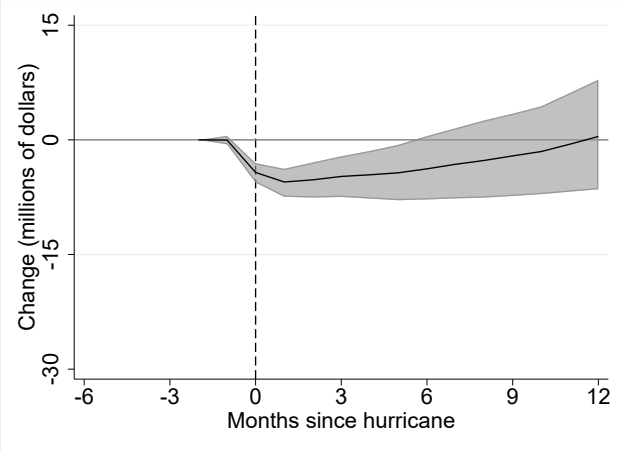
(a) Cumulative impact of all hurricanes on outpatient visits



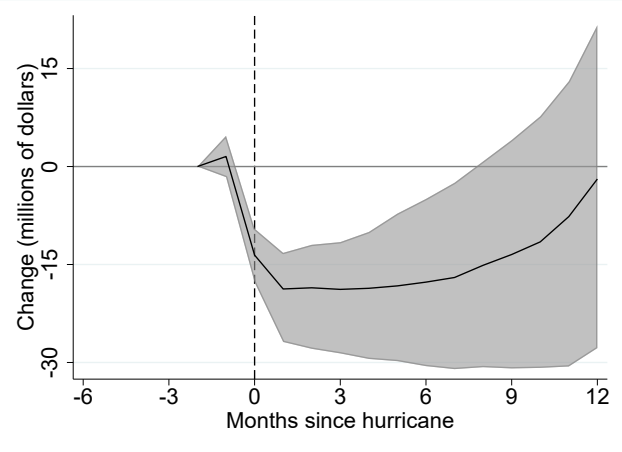
(b) Cumulative impact of strong hurricanes on outpatient visits



(c) Cumulative impact of all hurricanes on outpatient charges



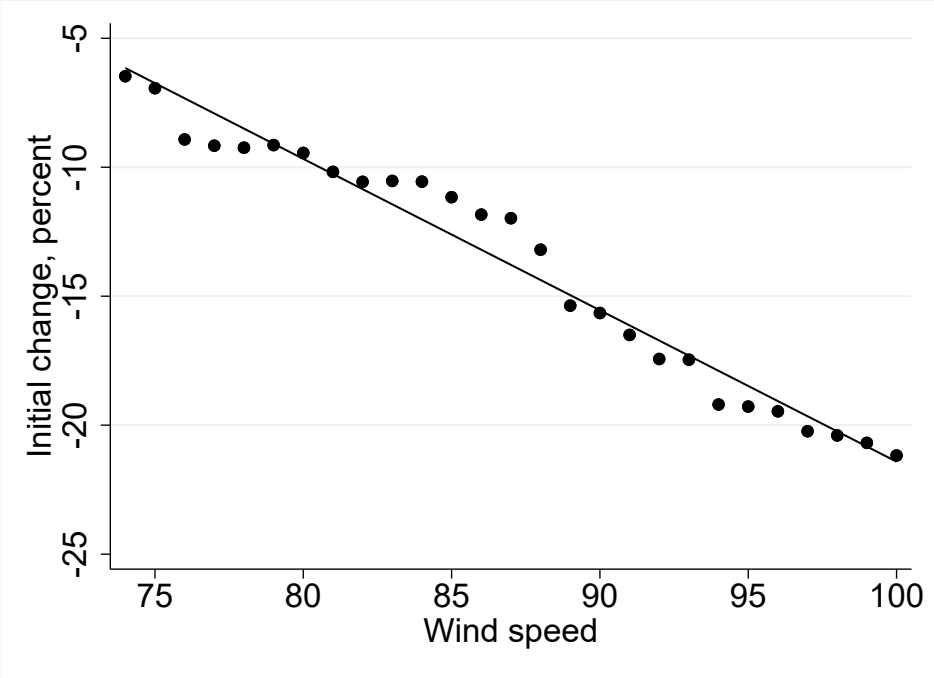
(d) Cumulative impact of strong hurricanes on outpatient charges



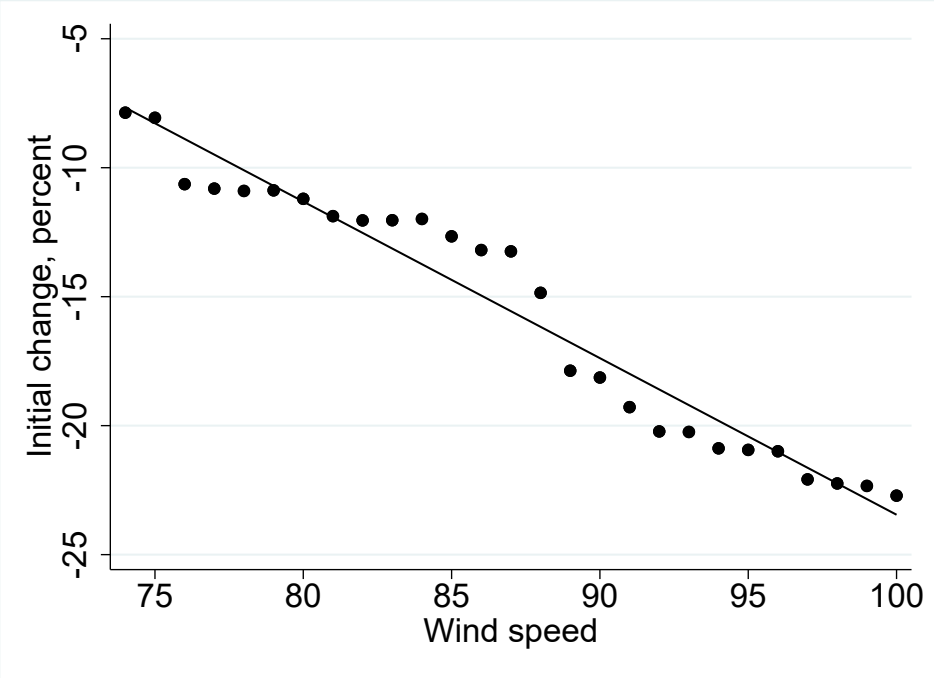
Notes: Graphs plot the cumulative change in the outcome of interest. The specification is outlined in Section 3. The x-axis contains the relative number of months since the hurricane occurred in $t = 0$. Regressions are at the county-month level, cluster at the county level, and contain county-by-month and month-by-year fixed effects.

Figure 9: Initial impact on elective services by wind speed

(a) Elective visits



(b) Elective charges



Notes: Graphs plot the estimated changes in elective care in the month of the hurricane for different definitions of treatment (black circles) and a linear fit line (black line).

Tables

Table 1: In-sample hurricanes

Hurricane name	Date formed	Affected states
Danny	Jul 16, 1997	LA
Bonnie	Aug 19, 1998	NC*, VA
Earl	Aug 31, 1998	AL, FL, GA
Georges	Sep 15, 1998	LA*, MS*
Bret	Aug 18, 1999	TX
Floyd	Sep 10, 1999	MD, NC, VA
Irene	Oct 12, 1999	FL
Lili	Sep 21, 2002	LA
Claudette	Jul 10, 2003	TX
Isabel	Sep 10, 2003	NC*, VA
Charley	Aug 10, 2004	FL*
Frances	Aug 25, 2004	FL*
Ivan	Sep 10, 2004	AL*
Jeanne	Sep 13, 2004	FL
Dennis	Jul 10, 2005	AL, FL*
Katrina	Aug 23, 2005	FL, LA*, MS*
Rita	Sep 18, 2005	TX*
Wilma	Oct 15, 2005	FL*
Humberto	Sep 12, 2007	TX
Dolly	Jul 20, 2008	TX
Gustav	Aug 25, 2008	LA*
Ike	Sep 1, 2008	TX*
Irene	Aug 21, 2011	DE, MD, NC, NJ, PA, VA
Isaac	Aug 20, 2012	LA
Sandy	Oct 21, 2012	MD, NJ, NY, PA

Notes: The table reports the names and formation dates of hurricanes in our estimation sample, as well as the states they affected. * indicates that at least one county within the state experienced winds of 100 miles per hour or greater.

Table 2: Characteristics for treated and control counties in 1997

	All hurricane counties			Strong hurricane counties		
	Treated	Control	P-value	Treated	Control	P-value
County characteristics						
Number of counties	169	205		33	341	
Size of over 65 population	29,779	15,825	p< 0.001	28,885	21,477	0.26
Number of providers	4	2	0.001	6	3	0.19
Community hospitals	3	2	p< 0.001	4	2	0.19
Large hospitals	2	1	p< 0.001	3	2	0.23
Visits						
Elective visits	20,417	10,352	0.02	18,651	16,476	0.71
Outpatient visits	19,439	9,937	0.02	17,328	15,777	0.77
Inpatient elective visits	1,151	517	0.04	1,494	818	0.28
Charges in dollars						
Elective charges	34,735,040	12,915,498	0.006	43,423,044	24,323,845	0.25
Outpatient charges	10,198,689	3,815,562	p< 0.001	13,201,245	7,078,497	0.09
Inpatient elective charges	25,487,154	9,288,393	0.01	30,739,235	17,978,464	0.33
Change in log visits						
Log elective visits	-0.0058	-0.0057	0.95	-0.011	-0.0051	0.08
Log outpatient visits	-0.0055	-0.0057	0.94	-0.011	-0.0049	0.08
Log inpatient elective visits	-0.014	-0.010	0.31	-0.013	-0.012	0.81
Change in log charges						
Log elective charges	-0.012	-0.0076	0.19	-0.013	-0.0098	0.42
Log outpatient charges	-0.0095	-0.0077	0.40	-0.014	-0.0079	0.03
Log inpatient elective charges	-0.014	-0.0097	0.37	-0.013	-0.012	0.78

Notes: "Control" counties did not experience a hurricane between 1997–2012. Unaffected counties are coastal counties or within 75 miles of coastal counties in states that experience hurricanes. Treated "All hurricane counties" experienced at least one hurricane with wind speeds over 74 miles per hour between 1997–2012. Treated "Strong hurricane counties" experienced at least one hurricane with wind speeds over 100 miles per hour between 1997–2012. We show the average of each category. Charges are in dollars.

Table 3: Difference-in-difference estimate for elective visits and charges

	(1)	(2)	(3)	(4)
	Elective visits (log)		Elective charges (log)	
	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
Month -1	-0.0000205	0.0125	0.00534	0.0304**
	(0.00480)	(0.0136)	(0.00668)	(0.0136)
Month 0	-0.0669***	-0.238***	-0.0819***	-0.258***
	(0.0104)	(0.0224)	(0.0155)	(0.0346)
Month 1	-0.0218**	-0.0786***	-0.0274**	-0.0546
	(0.00929)	(0.0296)	(0.0127)	(0.0420)
Month 2	0.00373	-0.00363	-0.00806	0.00449
	(0.0114)	(0.00807)	(0.0136)	(0.0149)
Months 3 to 12	0.0201**	0.0147*	0.0159*	0.0230*
	(0.00976)	(0.00841)	(0.00920)	(0.0129)
Outcome mean (weighted, levels)	19,819	19,819	77,176,584	77,176,584
Observations	75,082	75,082	75,082	75,082
Adjusted R-squared	0.961	0.961	0.976	0.976

Notes: The table reports estimates of Equation (2). Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Standard errors (in parentheses) are clustered by county. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4: Difference-in-difference estimate for all elective inpatient visits

	(1)	(2)	(3)	(4)
	Elective inpatient visits (log)		Elective inpatient charges (log)	
	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
Month -1	-0.00743	0.0118	0.00388	0.0346*
	(0.00935)	(0.0175)	(0.0136)	(0.0190)
Month 0	-0.0652***	-0.235***	-0.0794***	-0.281***
	(0.0175)	(0.0601)	(0.0217)	(0.0526)
Month 1	-0.0101	-0.0162	-0.0313	-0.0349
	(0.0139)	(0.0392)	(0.0201)	(0.0479)
Month 2	-0.00800	-0.00932	-0.0339*	-0.0126
	(0.0155)	(0.0175)	(0.0205)	(0.0223)
Months 3 to 12	0.0121	-0.0185	0.0131	0.0145
	(0.0154)	(0.0300)	(0.0171)	(0.0278)
Outcome mean (weighted, levels)	860	860	42,572,528	42,572,528
Observations	65,491	65,491	65,491	65,491
Adjusted R-squared	0.960	0.960	0.938	0.938

Notes: The table reports estimates of Equation (2). Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Standard errors (in parentheses) are clustered by county. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5: Difference-in-difference estimate for all outpatient visits

	(1)	(2)	(3)	(4)
	Outpatient visits (log)		Outpatient charges (log)	
	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
Month -1	0.000501	0.0130	-0.000893	0.0293
	(0.00501)	(0.0143)	(0.00722)	(0.0259)
Month 0	-0.0668***	-0.240***	-0.0873***	-0.238***
	(0.0105)	(0.0230)	(0.0126)	(0.0230)
Month 1	-0.0224**	-0.0834***	-0.0246**	-0.0676*
	(0.00939)	(0.0298)	(0.0107)	(0.0368)
Month 2	0.00404	-0.00436	0.00558	0.0124
	(0.0116)	(0.00839)	(0.0111)	(0.0129)
Months 3 to 12	0.0212**	0.0178*	0.0112	0.0331***
	(0.00989)	(0.00908)	(0.00726)	(0.0122)
Outcome mean (weighted, levels)	19,066	19,066	33,719,624	33,719,624
Observations	75,053	75,053	75,053	75,053
Adjusted R-squared	0.951	0.951	0.949	0.949

Notes: The table reports estimates of Equation (2). Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Standard errors (in parentheses) are clustered by county. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6: Difference-in-difference estimate for orthopedic procedures

	(1)	(2)	(3)	(4)
	Orthopedic procedures visits (log)		Orthopedic procedures charges (log)	
	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
Month 0	-0.0944***	-0.273***	-0.0379**	-0.122***
	(0.0158)	(0.0422)	(0.0159)	(0.0298)
Months 1 to 12	0.0171	-0.00888	-0.00690	-0.00552
	(0.0145)	(0.0176)	(0.00825)	(0.0174)
Outcome mean (weighted, levels)	275	275	17,912,266	17,912,266
Observations	61,663	61,663	69,724	69,724
Adjusted R-squared	0.950	0.950	0.939	0.939

Notes: The table reports estimates of a modified version of Equation (2). Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Standard errors (in parentheses) are clustered by county. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 7: Difference-in-difference estimate for hernia procedures

	(1)	(2)	(3)	(4)
	Hernia procedures visits (log)		Hernia procedures charges (log)	
	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
Month 0	-0.0713**	-0.395***	-0.0806	-0.403***
	(0.0348)	(0.0704)	(0.0557)	(0.133)
Months 1 to 12	-0.00132	-0.0256	0.0254	0.0416
	(0.0150)	(0.0252)	(0.0321)	(0.0745)
Outcome mean (weighted, levels)	37.3	37.3	1,882,255	1,882,255
Observations	60,957	60,957	65,641	65,641
Adjusted R-squared	0.912	0.912	0.790	0.790

Notes: The table reports estimates of a modified version of Equation (2). Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Standard errors (in parentheses) are clustered by county. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 8: Difference-in-difference estimate for chemotherapy

	(1)	(2)	(3)	(4)
	Chemotherapy visits (log)		Chemotherapy charges (log)	
	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
Month 0	-0.0329	-0.0894**	-0.0311	-0.0280
	(0.0205)	(0.0347)	(0.0456)	(0.0594)
Months 1 to 12	0.0238	0.0572	0.0548*	0.110*
	(0.0251)	(0.0785)	(0.0326)	(0.0600)
Outcome mean (weighted, levels)	615	615	8,840,696	8,840,696
Observations	45,000	45,000	46,778	46,778
Adjusted R-squared	0.926	0.926	0.841	0.841

Notes: The table reports estimates of a modified version of Equation (2). Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Standard errors (in parentheses) are clustered by county. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9: Difference-in-difference estimate for radiation therapy

	(1)	(2)	(3)	(4)
	Radiation therapy visits (log)		Radiation therapy charges (log)	
	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
Month 0	0.0298	-0.0300	-0.0302	-0.108*
	(0.0437)	(0.0389)	(0.0318)	(0.0561)
Months 1 to 12	0.0317	0.0139	-0.00623	0.00518
	(0.0514)	(0.0472)	(0.0229)	(0.0499)
Outcome mean (weighted, levels)	272	272	4,307,686	4,307,686
Observations	33,046	33,046	35,902	35,902
Adjusted R-squared	0.851	0.850	0.773	0.773

Notes: The table reports estimates of a modified version of Equation (2). Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Standard errors (in parentheses) are clustered by county. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix

Table A1: Difference-in-difference estimate for all visits and charges

	(1)	(2)	(3)	(4)
	All visits (log)		All charges (log)	
	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
Month -1	0.000303	0.0110	0.00535	0.0319***
	(0.00395)	(0.0107)	(0.00492)	(0.00908)
Month 0	-0.0456***	-0.162***	-0.0258***	-0.0999***
	(0.00792)	(0.0181)	(0.00872)	(0.0288)
Month 1	-0.0159**	-0.0616***	-0.00655	-0.0288
	(0.00774)	(0.0223)	(0.00924)	(0.0248)
Month 2	0.00201	-0.00641	-0.00124	-0.00441
	(0.00906)	(0.00630)	(0.00791)	(0.0113)
Months 3 to 12	0.0163**	0.0104	9.58e-06	0.00461
	(0.00804)	(0.00711)	(0.00538)	(0.0119)
Outcome mean (weighted, levels)	23,401	23,401	182,386,656	182,386,656
Observations	75,082	75,082	75,082	75,082
Adjusted R-squared	0.972	0.972	0.985	0.985

Notes: The table reports estimates of Equation (2). Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Standard errors (in parentheses) are clustered by county. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A2: Difference-in-difference estimate for emergency visits and charges

	(1)	(2)	(3)	(4)
	Emergency visits (log)		Emergency charges (log)	
	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
Month -1	0.0000616	0.00222	0.00226	0.0331**
	(0.00323)	(0.00705)	(0.00723)	(0.0145)
Month 0	0.0205***	0.0391*	0.00192	-0.0163
	(0.00544)	(0.0215)	(0.00919)	(0.0342)
Month 1	0.00263	-0.0153	0.00208	-0.0141
	(0.00513)	(0.0105)	(0.00878)	(0.0169)
Month 2	-0.00532	-0.0200**	-0.000130	-0.00885
	(0.00491)	(0.00825)	(0.00877)	(0.0164)
Months 3 to 12	-0.00436	-0.00445	-0.0114	-0.0124
	(0.00374)	(0.0103)	(0.00777)	(0.0181)
Outcome mean (weighted, levels)	4,081	4,081	110,215,096	110,215,096
Observations	74,888	74,888	74,888	74,888
Adjusted R-squared	0.976	0.976	0.957	0.957

Notes: The table reports estimates of Equation (2). Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Standard errors (in parentheses) are clustered by county. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A3: Point estimates for Figure 3

	(1)	(2)	(3)	(4)
	Elective visits (log)		Elective charges (log)	
Event time	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
-6	-0.0056	0.0085	-0.0023	-0.0045
	(0.0057)	(0.010)	(0.0070)	(0.018)
-5	-0.0046	0.020***	0.0041	0.00031
	(0.0044)	(0.0078)	(0.0095)	(0.0093)
-4	-0.0059	0.0072	-0.0026	-0.012
	(0.0036)	(0.0096)	(0.0089)	(0.011)
-3	-0.0020	0.0041	-0.0034	-0.026***
	(0.0028)	(0.0080)	(0.0072)	(0.0098)
-1	-0.0035	0.022	0.0064	0.024
	(0.0056)	(0.017)	(0.0071)	(0.017)
0	-0.070***	-0.23***	-0.081***	-0.26***
	(0.0097)	(0.022)	(0.018)	(0.035)
1	-0.026**	-0.071**	-0.028*	-0.063
	(0.010)	(0.030)	(0.015)	(0.043)
2	-0.00052	0.0042	-0.0089	-0.0039
	(0.012)	(0.0098)	(0.017)	(0.018)
3	0.0069	0.0018	0.012	-0.0056
	(0.0095)	(0.011)	(0.013)	(0.016)
4	-0.0047	0.012	0.0065	-0.0034
	(0.011)	(0.011)	(0.013)	(0.017)
5	0.015	0.015	0.0097	-0.0018
	(0.012)	(0.014)	(0.013)	(0.018)
6	0.018*	0.014	0.0094	-0.00061
	(0.010)	(0.014)	(0.011)	(0.021)
7	0.015	0.021	0.0040	0.013
	(0.0099)	(0.014)	(0.011)	(0.019)
8	0.019*	0.033***	0.0037	0.0058
	(0.011)	(0.012)	(0.013)	(0.025)
9	0.018*	0.029***	0.012	0.022
	(0.010)	(0.010)	(0.011)	(0.018)
10	0.021**	0.019	0.020	0.020
	(0.011)	(0.015)	(0.013)	(0.021)
11	0.026**	0.039*	0.039**	0.041
	(0.013)	(0.022)	(0.017)	(0.030)
12	0.026**	0.042***	0.036*	0.057**
	(0.013)	(0.015)	(0.020)	(0.024)
Outcome mean (weighted, levels)	19,819	19,819	77,176,584	77,176,584
Observations	75,082	75,082	75,082	75,082
Adjusted R-squared	0.96	0.96	0.98	0.98

Notes: The table reports estimates of equations (1). Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Standard errors (in parentheses) are clustered by county. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A4: Point estimates for Figure 4

	(1)	(2)	(3)	(4)
	Elective visits		Elective charges (millions)	
Event time	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
-1	-83	525	0.72	4.1*
	[-295, 141]	[-140, 1,249]	[-0.61, 2.0]	[-0.52, 10]
0	-1,714***	-4,410***	-8.1***	-35***
	[-2,177, -1,262]	[-5,595, -3,256]	[-12, -4.2]	[-48, -25]
1	-2,330***	-6,059***	-11***	-46***
	[-3,067, -1,601]	[-8,232, -4,595]	[-17, -5.4]	[-71, -28]
2	-2,342***	-5,957***	-12***	-46***
	[-3,382, -1,267]	[-8,538, -4,173]	[-19, -4.6]	[-77, -24]
3	-2,177***	-5,913***	-11**	-47***
	[-3,497, -811]	[-8,743, -3,796]	[-19, -1.3]	[-85, -21]
4	-2,290**	-5,627***	-10*	-48***
	[-3,971, -580]	[-9,034, -3,173]	[-20, 1.2]	[-87, -18]
5	-1,938*	-5,263***	-9.1	-48**
	[-4,030, 87]	[-9,098, -2,422]	[-21, 4.4]	[-91, -13]
6	-1,491	-4,915***	-8.0	-48**
	[-3,937, 856]	[-9,363, -1,685]	[-21, 7.5]	[-93, -9.3]
7	-1,137	-4,402**	-7.6	-46**
	[-3,931, 1,541]	[-9,537, -639]	[-23, 9.4]	[-96, -3.5]
8	-689	-3,588*	-7.1	-45*
	[-3,867, 2,365]	[-9,328, 464]	[-24, 12]	[-96, 1.9]
9	-245	-2,885	-5.8	-41*
	[-3,739, 3,148]	[-9,099, 1,608]	[-25, 15]	[-98, 10]
10	271	-2,430	-3.6	-38
	[-3,500, 4,035]	[-9,309, 2,545]	[-24, 20]	[-101, 17]
11	893	-1,460	0.99	-31
	[-3,318, 5,160]	[-9,371, 4,398]	[-23, 27]	[-101, 30]
12	1,530	-419	5.1	-21
	[-3,171, 6,208]	[-8,590, 5,920]	[-22, 35]	[-96, 47]

Notes: The table reports estimates of cumulative treatment effects. Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Ninety-five percent confidence intervals (in brackets) are based on 1,000 bootstrap draws. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A5: Point estimates for Figure 5

	(1)	(2)	(3)	(4)
	Elective inpatient visits (log)		Elective inpatient charges (log)	
Event time	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
-6	0.019*	0.020	0.015	0.0097
	(0.010)	(0.037)	(0.016)	(0.037)
-5	0.010	0.022	0.015	-0.0052
	(0.012)	(0.016)	(0.018)	(0.023)
-4	0.015	0.0022	0.0098	0.0011
	(0.012)	(0.014)	(0.019)	(0.020)
-3	-0.0035	-0.021	-0.0056	-0.040**
	(0.0093)	(0.015)	(0.015)	(0.019)
-1	0.0016	0.018	0.013	0.029
	(0.0098)	(0.017)	(0.014)	(0.021)
0	-0.056***	-0.23***	-0.071***	-0.29***
	(0.018)	(0.058)	(0.027)	(0.054)
1	-0.0020	-0.011	-0.024	-0.042
	(0.016)	(0.041)	(0.025)	(0.053)
2	0.00011	-0.0042	-0.027	-0.020
	(0.019)	(0.022)	(0.026)	(0.031)
3	0.017	-0.0072	0.019	-0.017
	(0.018)	(0.025)	(0.022)	(0.030)
4	0.0083	-0.0041	0.016	-0.011
	(0.019)	(0.035)	(0.021)	(0.036)
5	0.026	-0.021	0.026	-0.010
	(0.020)	(0.031)	(0.022)	(0.028)
6	0.018	-0.026	0.020	-0.0080
	(0.018)	(0.033)	(0.021)	(0.030)
7	0.011	-0.028	0.0053	0.019
	(0.018)	(0.033)	(0.020)	(0.034)
8	0.018	-0.035	0.0043	-0.015
	(0.019)	(0.041)	(0.027)	(0.044)
9	0.0092	-0.021	0.015	0.026
	(0.019)	(0.033)	(0.023)	(0.029)
10	0.030*	0.0096	0.012	0.027
	(0.017)	(0.026)	(0.020)	(0.028)
11	0.033	0.00075	0.045	0.032
	(0.024)	(0.038)	(0.033)	(0.035)
12	0.033	-0.0024	0.041	0.031
	(0.028)	(0.037)	(0.036)	(0.029)
Outcome mean (weighted, levels)	860	860	42,572,528	42,572,528
Observations	65,491	65,491	65,491	65,491
Adjusted R-squared	0.96	0.96	0.94	0.94

Notes: The table reports estimates of equations (1). Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Standard errors (in parentheses) are clustered by county. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A6: Point estimates for Figure 6

	(1)	(2)	(3)	(4)
	Elective inpatient visits		Elective inpatient charges (millions)	
Event time	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
-1	1.6	28	0.77	2.9
	[-13, 18]	[-13, 92]	[-0.72, 2.2]	[-1.3, 7.5]
0	-51**	-289***	-3.3*	-22***
	[-86, -14]	[-459, -169]	[-6.7, 0.20]	[-34, -13]
1	-53*	-306***	-4.7*	-26***
	[-104, 6.7]	[-587, -124]	[-9.7, 0.72]	[-48, -12]
2	-53	-313**	-6.3*	-28***
	[-126, 33]	[-658, -80]	[-13, 1.3]	[-57, -9.3]
3	-37	-324**	-5.1	-30**
	[-128, 72]	[-723, -48]	[-13, 4.0]	[-64, -7.5]
4	-28	-330*	-4.2	-31**
	[-140, 110]	[-802, 25]	[-13, 7.0]	[-70, -5.2]
5	-3.3	-362*	-2.6	-32**
	[-143, 170]	[-883, 73]	[-14, 10]	[-74, -3.1]
6	14	-401*	-1.4	-32**
	[-148, 223]	[-954, 125]	[-14, 14]	[-78, -2.2]
7	25	-444	-1.1	-30*
	[-158, 264]	[-1,065, 169]	[-16, 16]	[-82, 4.8]
8	43	-498	-0.88	-32*
	[-160, 313]	[-1,166, 242]	[-18, 19]	[-87, 6.6]
9	52	-530	-0.0079	-29
	[-175, 350]	[-1,252, 305]	[-19, 22]	[-89, 13]
10	82	-515	0.71	-27
	[-163, 413]	[-1,274, 401]	[-20, 24]	[-88, 18]
11	114	-514	3.4	-23
	[-160, 491]	[-1,299, 517]	[-20, 31]	[-90, 27]
12	146	-517	5.9	-20
	[-161, 569]	[-1,391, 615]	[-21, 37]	[-91, 35]

Notes: The table reports estimates of cumulative treatment effects. Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Ninety-five percent confidence intervals (in brackets) are based on 1,000 bootstrap draws. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A7: Point estimates for Figure 7

	(1)	(2)	(3)	(4)
	Outpatient visits (log)		Outpatient charges (log)	
Event time	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
-6	-0.0055	0.0081	0.0012	-0.015
	(0.0059)	(0.010)	(0.0077)	(0.017)
-5	-0.0047	0.021***	0.0042	-0.0048
	(0.0049)	(0.0081)	(0.0077)	(0.018)
-4	-0.0071*	0.0066	-0.0087	-0.020
	(0.0040)	(0.0099)	(0.0059)	(0.014)
-3	-0.0017	0.0045	0.0034	-0.0096
	(0.0030)	(0.0085)	(0.0053)	(0.011)
-1	-0.0032	0.022	-0.00042	0.022
	(0.0059)	(0.018)	(0.0071)	(0.027)
0	-0.070***	-0.23***	-0.087***	-0.24***
	(0.0097)	(0.023)	(0.013)	(0.023)
1	-0.027**	-0.076**	-0.025**	-0.077**
	(0.010)	(0.031)	(0.011)	(0.037)
2	-0.00039	0.0035	0.0054	0.0026
	(0.013)	(0.0098)	(0.010)	(0.012)
3	0.0071	0.0012	0.0088	-0.0035
	(0.0097)	(0.011)	(0.0065)	(0.012)
4	-0.0037	0.014	0.0042	0.0023
	(0.011)	(0.012)	(0.011)	(0.018)
5	0.016	0.018	0.0051	0.0053
	(0.012)	(0.014)	(0.0090)	(0.021)
6	0.020*	0.018	0.010	0.0083
	(0.010)	(0.015)	(0.010)	(0.017)
7	0.016	0.026*	0.012	0.010
	(0.010)	(0.014)	(0.0078)	(0.019)
8	0.020*	0.038***	0.0098	0.026*
	(0.011)	(0.013)	(0.0072)	(0.015)
9	0.020*	0.032***	0.012*	0.023
	(0.011)	(0.011)	(0.0069)	(0.016)
10	0.021*	0.022	0.011	0.027
	(0.011)	(0.015)	(0.0076)	(0.019)
11	0.026**	0.043*	0.019*	0.054
	(0.013)	(0.023)	(0.010)	(0.035)
12	0.027**	0.046***	0.020	0.079***
	(0.013)	(0.016)	(0.012)	(0.029)
Outcome mean (weighted, levels)	19,066	19,066	33,719,624	33,719,624
Observations	75,053	75,053	75,053	75,053
Adjusted R-squared	0.95	0.95	0.95	0.95

Notes: The table reports estimates of equations (1). Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Standard errors (in parentheses) are clustered by county. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A8: Point estimates for Figure 8

	(1)	(2)	(3)	(4)
	Outpatient visits		Outpatient charges (millions)	
Event time	All hurricanes	Strong hurricanes	All hurricanes	Strong hurricanes
-1	-74	507	-0.022	1.5
	[-288, 148]	[-131, 1,203]	[-0.59, 0.52]	[-1.6, 4.7]
0	-1,649***	-4,184***	-4.3***	-14***
	[-2,106, -1,206]	[-5,329, -3,047]	[-5.6, -3.0]	[-18, -9.5]
1	-2,262***	-5,840***	-5.5***	-19***
	[-2,988, -1,553]	[-7,859, -4,432]	[-7.5, -3.8]	[-27, -13]
2	-2,271***	-5,761***	-5.2***	-19***
	[-3,302, -1,197]	[-8,163, -4,071]	[-7.6, -3.0]	[-28, -12]
3	-2,105***	-5,734***	-4.8***	-19***
	[-3,409, -764]	[-8,449, -3,695]	[-7.5, -2.2]	[-29, -12]
4	-2,191**	-5,421***	-4.6***	-19***
	[-3,814, -547]	[-8,604, -3,056]	[-7.7, -1.4]	[-29, -10]
5	-1,828*	-5,012***	-4.3**	-18***
	[-3,906, 142]	[-8,691, -2,243]	[-7.9, -0.64]	[-30, -7.2]
6	-1,367	-4,610***	-3.8*	-18**
	[-3,765, 966]	[-8,853, -1,475]	[-7.8, 0.50]	[-31, -5.0]
7	-996	-4,017**	-3.2	-17**
	[-3,762, 1,712]	[-8,812, -459]	[-7.7, 1.5]	[-31, -2.5]
8	-521	-3,147*	-2.7	-15*
	[-3,570, 2,453]	[-8,500, 757]	[-7.6, 2.5]	[-31, 0.78]
9	-44	-2,396	-2.1	-13*
	[-3,387, 3,290]	[-8,293, 1,857]	[-7.3, 3.4]	[-31, 4.1]
10	442	-1,899	-1.5	-12
	[-3,241, 4,188]	[-8,575, 2,904]	[-7.1, 4.4]	[-31, 7.7]
11	1,045	-892	-0.57	-7.7
	[-3,109, 5,256]	[-8,457, 4,694]	[-6.8, 6.1]	[-31, 13]
12	1,684	178	0.45	-1.9
	[-2,879, 6,416]	[-7,910, 6,417]	[-6.5, 7.9]	[-28, 22]

Notes: The table reports estimates of cumulative treatment effects. Outcome variables are indicated at top of each column. All regressions include county-by-month and month-by-year fixed effects. Ninety-five percent confidence intervals (in brackets) are based on 1,000 bootstrap draws. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.