Keeping in Place After the Storm—Emergency Assistance and Evictions[*]

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Abstract

We offer evidence that federal emergency assistance (FEMA) in the days following natural disasters mitigate evictions in comparison to similar emergency scenarios where FEMA aid is not provided. We find an approximate 10.9% increase in overall evictions after hurricane natural disaster events driven in large part by areas in close proximity of the hurricane path that do not receive FEMA rental assistance. Furthermore, we also show that FEMA aid acts as a liquidity buffer to other forms of emergency credit, specifically we find that both transactions volumes and defaults decrease during hurricane events in locations that do receive FEMA aid. This effect largely reverses in areas that do not receive FEMA aid, where the magnitude of transaction volumes drop by less and default rates remain similar relative to the baseline. Overall, this suggests that the availability of emergency liquidity during natural disaster events is indeed a binding constraint with real household financial consequences, in particular through our documented channel of evictions and in usage of high-cost credit.

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1 Introduction

The loss of structures and in particularly housing is often among the notable and lasting images of in the wake of natural disasters. The resulting financial loss and displacement highlight the importance of both the individual and government role in pre-disaster mitigation and post-disaster response. At the micro level, the loss born by households can be large and has been documented in various forms in the literature.

Historically, the destruction of housing in such events has led to rebuilt neighborhoods that differ significantly from their original form and community composition. The Boston fire of 1871 (Hornbeck and Keniston, 2017) and the San Francisco 1906 earthquake (Siodla, 2015) provide specific historical moments of migration and reconstruction where entire neighborhoods were rebuilt but also with a notable change in the former population to which (Boustan et al., 2020) find systematic evidence of out-migration following disaster events in the United States. To contrast, in our work, we study instances of assistance in preserving housing access. That is, we examine the existence of federal assistance households to maintain their ability to make housing payments due to potential disruptions and damages directly related to the natural disaster.

Prior to the creation of the Federal Emergency Management Agency under the Carter administration in 1979, many natural disasters that have marked the history of the United States have required federal emergency funding through ad-hoc legislation in the aftermath of their occurrence. One form of disaster relief has been the need for emergency housing in the wake of damage and destruction to housing property. This has further expanded to include rental assistance starting initially under the Stafford Act of 1988 and then further expanded under the Individuals and Households Program in 2002[1] that aim to recognize disruption in household financial ability due to uninsured or under-insured emergency expenses.

In the same vein, we study the availability of emergency rental assistance through FEMA in the wake of hurricane disaster events and their impact on rental evictions in the state of Florida. We find that notably the rate of eviction is mitigated via the availability of FEMA rental assistance and furthermore we document, in the case of payday loans, that the demand for emergency credit is substituted away from higher cost credit.

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[1](Webster, 2022)

1.1 Literature Review

The household financial impacts of natural disasters have been increasingly studied, with significant attention given to household resilience and recovery mechanisms. The intersection of disasters and eviction risks has also garnered attention. (Brennan et al., 2022) explore the heightened vulnerability of renters in disaster-affected areas, showing that disasters exacerbate eviction rates, particularly for vulnerable populations. (Raymond et al., 2022) examine the legal and policy dimensions of eviction laws, emphasizing the gaps in tenant protections in states such as Florida. These findings are particularly relevant to our work, underscoring the cascading effects of disasters on eviction, financial distress, and reliance on high-cost credit.

Furthermore, the consequences of hurricane events has notably received attention in the literature. (Gallagher and Hartley, 2017) analyze the financial consequences of hurricane Katrina, highlighting the crucial role of federal aid in stabilizing household finances. (Deryugina et al., 2018) corroborate these findings, using tax return data to show long-term income declines and wealth disruptions. (Del Valle et al., 2024) extend this analysis to hurricane Harvey, examining household decision-making in the aftermath of a disaster. They identify shifts in financial behavior, including increased reliance on savings and external credit. Similarly, (Collier et al., 2024) demonstrates that FEMA assistance mitigates financial distress, using credit files data they show a reduction in delinquencies and defaults in affected regions. Our study complements this result by focusing on evictions and on substitution effects with higher cost credit, particularly how households resort to alternative financial lenders like payday loans when formal aid is absent or insufficient.

The literature on payday loans has highlighted the dual nature of high-cost credit, as both a financial lifeline and a debt trap. We similarly contrast its availability in the context of natural disasters.(Bhutta et al., 2015) describe how payday loans exacerbate financial strain for vulnerable borrowers, while (Morse, 2011) offers a contrasting view, emphasizing their utility during emergencies. (Gathergood et al., 2019) shows that payday loans increase financial distress, especially for low-income borrowers, but regulatory interventions can mitigate harmful effects. In the same vein, (Dobridge, 2016) finds mixed effects, while access to high-cost credit aids short-term liquidity, it negatively affects long-term financial outcomes. Extending this debate, our findings suggest that payday loans act as a substitute for formal disaster relief, especially in regions excluded from

FEMA's coverage. This substitution underscores the dual-edged nature of payday lending in disaster recovery contexts, offering immediate relief but also amplifying financial fragility as we observe a difference in subsequent default rates.

Beyond individual outcomes, the broader economic implications of disasters have been extensively analyzed. (Bernstein et al., 2019) highlight the long-term economic vulnerabilities of disaster-prone areas, particularly the impact of rising sea levels on property prices. The interplay between financial aid and alternative credit sources offers another dimension to understanding recovery dynamics. (Collier et al., 2024) analyze demand for disaster recovery loans, illustrating how credit availability shapes household recovery trajectories. (Lane, 2024) underscores the importance of guaranteed credit programs in building resilience, particularly for lower-income households. (Malmin, 2023) explores the role of federal credit in shaping future wealth trajectories, emphasizing the need for equitable and targeted recovery programs.

Finally, recent studies on disaster aid distribution and its long-term effects highlight systemic inequalities. (Billings et al., 2022) document the inequities in financial aid distribution during Hurricane Harvey, revealing gaps in support for vulnerable populations. (Bufe et al., 2021) explores how financial shocks impact lower-income households, identifying key factors that contribute to financial resilience, such as savings, credit access, and social support networks. (Ratnadiwakara and Venugopal, 2020) finds that flood-prone areas increasingly attract lower-income and less creditworthy populations due to declining property values and housing costs.

Using Florida as a case study, our research extends prior work by integrating multiple granular datasets to examine the dynamics of financial distress through eviction risks and high-cost credit during the recovery following disasters. Our granular spatial and temporal analysis reveals how gaps in disaster aid exacerbate loss of housing via increased evictions, driving households to substitute formal aid with high-cost credit options. This approach reinforces the importance of inclusive disaster recovery programs that address the nuanced needs of vulnerable populations, ultimately potentially mitigating long-term financial harm and fostering resilience.

The rest of the paper is as follows. In section 2, we describe the various data used and our spatial-temporal approach. In section 3 ,we present our main result linking eviction outcomes and access to emergency financial assistance. And then in section 4, we further extend this analysis to understand the interdependence with access to high-cost credit via payday loans.

2 Data and Methodology

2.1 Data

Our data comes from several administrative sources. Our access to evictions data comes from the Evictions Lab at Princeton, which sources their data via county level court records on evictions. Our access to payday loans data comes via a freedom of information request to the state of Florida's Office of Financial Regulation. We also utilize several federal level datasets. Specifically we retrieve FEMA's (Federal Emergency Management Agency) Web Disaster Declarations and Housing Assistance Program Data for Renters, as well as publicly available data from NOAA (the National Oceanic and Atmospheric Administration) and the NHC (National Hurricane Center). Finally, estimates of urban and rural population, housing units, and characteristics at the census level come from the American Community Survey.

2.1.1 Eviction Data

Princeton's Eviction Lab data provides Census-Tract level information at a weekly level, including eviction, filing, and at-risk outcome variables Desmond et al. (2018). Covering the period from 2003 to 2017. Table 1 shows summary statistics. The evict variable describes the number of evictions aggregated at the weekly-census tract level. The filing variable describes the number of court filings for eviction and the atrisk variable adjusts this for the number of individuals living in the household at risk of being evicted.

Statistic	evict	filing	atrisk
25th Perc.	1	1	1
Median	1	1	1
Mean	1.219	1.770	1.676
75th Perc.	1	2	2
Std. Dev.	1.26	1.59	1.49
Observations: 498793		Unique Census Tracts: 3980	

Table 1: Summary Statistics: Evictions dataset, measures per weekly-census tract.

2.1.2 Payday Loan Data

Our dataset on payday loans includes loan-level transactions from 2002 to 2018 in the state of Florida, totaling 101 million daily loan-level observations. We are able to observe the loan date, due

date, transaction amount, and any related fees. We also observe the date of repayment or whether the loan is outstanding. Furthermore, each loan observation has information on the retailer and borrower's ZIP code.

2.1.3 Hurricane Forecast Cone

The National Hurricane Center (NHC) provides authoritative information on the timing, location, and progression of tropical storms and hurricanes affecting the United States. In our study, this data is critical for reconstructing the geographic footprint of storms that impacted Florida between 2004 and 2018. However, the forecast cones are only available as far back as 2008.

For storm events prior to 2008, we relied on NHC forecast cone archives,[2] which record the storm's position and projected path at successive forecast times. From these records, we extracted the initial forecast points that represent the best estimate of the storm's current location, thereby tracing the realized path of each hurricane. Figure 1 shows an example of a forecast cone. The first point represents the actual location of the hurricane, and as we move away from the initial point, the cone covers a larger area with increasing uncertainty, a method of construction chosen by the NHC based on the prediction error over the past five years.

For storm events prior to 2008, we complemented NHC records with storm track data from NOAA's Historical Hurricane Tracks database. By combining these sources, we were able to build a consistent dataset of storm paths across the full study period. This provided the foundation for identifying geographic areas affected by each hurricane and for distinguishing treated from control communities in the empirical analysis.

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[2]`https://www.nhc.noaa.gov/aboutcone.shtml` provides details on how the forecast cone is constructed.

IRMA (2017) — 5-Day Forecast Cone & Points

DATE: 5:00 PM Thu Sep 07 2017
STORMNAME: Hurricane Irma
MAXWIND: 80.0 kt
STORMTYPE: HU
TAU: 96.0 h

DATE: 5:00 PM Thu Sep 07 2017
STORMNAME: Hurricane Irma
MAXWIND: 135.0 kt
STORMTYPE: MH
TAU: 48.0 h

DATE: 5:00 PM Thu Sep 07 2017
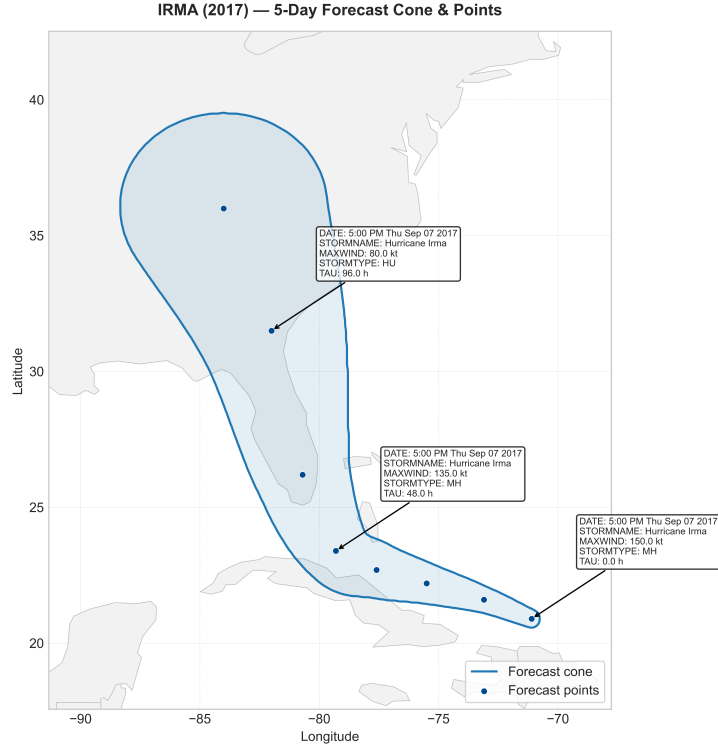STORMNAME: Hurricane Irma
MAXWIND: 150.0 kt
STORMTYPE: MH
TAU: 0.0 h

Figure 1: 5-Day Track Forecast Cone

2.1.4   FEMA Data

Since 1979, the Federal Emergency Management Agency (FEMA) has served as the federal gov-
ernment's lead agency in responding to and facilitating recovery from most significant crises. To
provide insight into FEMA's Housing Assistance Program for renters, the Individual Assistance
(IA) reporting team created a dataset beginning with disaster declaration DR1439 (2002). This
dataset includes aggregated, non-personally identifiable information such as the number of applica-
tions, inspections, the extent of damages, aid provided, and other relevant metrics, broken down by
state, county, and ZIP code where registrations were made. FEMA's Housing Assistance Program
for renters, a component of the Individuals and Households Program (IHP), offers critical financial
support to those impacted by federally declared disasters. Assistance includes temporary rental
aid, Other Needs Assistance (ONA) for uninsured expenses (e.g., personal property or childcare),
and Direct Housing Assistance (e.g., transportable housing units or repaired multi-family homes)
for cases where rental housing is unavailable.

Before an individual can receive FEMA aid, they must meet specific general eligibility criteria.

Applicants are required by FEMA to confirm that the disaster-damaged home is their primary residence that their disaster-related needs are not already covered by another source, such as insurance or other programs. If applicants have insurance, FEMA will require proof of the settlement or a letter explaining why coverage was denied before determining the assistance they are eligible to receive.

We utilize two FEMA datasets: the FEMA Web Disaster Declarations and the Housing Assistance Program Data on Renters. The first dataset includes information on all declared hurricanes and tropical storms affecting Florida, including the disaster name and its corresponding Disaster Number (a sequentially assigned identifier for declared disasters). The Disaster Number is essential for linking to the second dataset, which provides detailed information about housing assistance. We then identify ZIP codes where at least one individual has received rental disaster assistance.

Table 2 presents a list of all major disasters in Florida that were approved for the Individuals and Households Program (IHP). Table 3 provides summary statistics of key variables for the Housing Assistance Program on Renters.

Declaration Date	Disaster Name	Declaration Type
2004-08-13	Tropical Storm Bonnie and Hurricane Charley	Major Disaster
2004-09-04	Hurricane Frances	Major Disaster
2004-09-16	Hurricane Ivan	Major Disaster
2004-09-26	Hurricane Jeanne	Major Disaster
2005-07-10	Hurricane Dennis	Major Disaster
2005-08-28	Hurricane Katrina	Major Disaster
2005-10-24	Hurricane Wilma	Major Disaster
2008-08-24	Tropical Storm Fay	Major Disaster
2012-07-03	Tropical Storm Debby	Major Disaster
2016-09-28	Hurricane Hermine	Major Disaster
2017-09-10	Hurricane Irma	Major Disaster

Table 2: Major Disasters and Declaration Types

Disaster Name	Registered for FEMA Aid	Approved for FEMA Aid	Total Rental Assistance Disbursed ($)	Average Rental Assistance per Recipient ($)
Tropical Storm Bonnie and Hurricane Charley	50,136	28,945	26,273,487	912
Hurricane Frances	114,540	66,784	46,208,593	695
Hurricane Ivan	35,961	21,203	11,684,323	554
Hurricane Jeanne	89,278	57075	39,083,876	687
Hurricane Dennis	9,131	4238	1,006,428	242
Hurricane Wilma	150,501	57,542	23,939,083	418
Tropical Storm Fay	5,463	1,622	2,098,470	1,342
Tropical Storm Debby	4,455	1,752	2,771,489	1,638
Hurricane Hermine	1,643	585	797,293	1,442
Hurricane Irma	1,420,062	444,735	304,094,846	685

Table 3: Summary Statistics by Disaster Name

2.2 Methodology

We analyze our eviction and payday loan datasets to measure the impact of hurricanes and tropical storms on households. Our focus is on renters, and since our eviction data is at the census tract level, we weighted the outcome variables (evictions, filings, and at-risk individuals) based on the number of renters in each census tract. For the payday loan dataset, we aggregate defaults and number of transactions that we observe at the ZIP code level per day.

We use two models to measure the impact of natural disasters on households. First, we plot event studys to visually analyze the different outcome variables for both the treated and control groups. Then, we used a difference-in-differences model to confirm our results from the event study. Finally, we also then study the existence of federal aid assistance in an interacted difference-in-differences setting to measure the role of FEMA aid.

In the following three sections, we will explain how the treated and control groups were constructed and provide a detailed explanation of how the event study and difference-in-differences models were conducted.

2.2.1 Construction of treatment and control group

To assess the impact of hurricanes on households, we classify communities into treatment and control groups based on their geographic proximity to the storm path. The treated group consists of ZIP codes whose boundaries intersect the realized hurricane track, extended by a buffer. This buffer reflects the forecast uncertainty at the initial advisory position, as defined by the National

Hurricane Center (NHC) when constructing its cones of uncertainty. It captures not only areas directly along the storm's path but also nearby regions likely to experience significant effects. In this way, the treated group represents communities most plausibly exposed to wind, rainfall, and other storm-related disruptions.

By contrast, the control group includes ZIP codes in Florida that did not intersect the buffered storm path. These areas lie outside the spatial footprint of the hurricane and thus provide a counterfactual for how outcomes would have evolved in the absence of storm exposure. This distinction ensures that observed differences between the treated and control groups can be more directly attributed to hurricane impacts rather than broader regional dynamics.

Figure 2 illustrates our spatial treatment assignment strategy using Hurricane Charley (2004) as an example. The map shows how ZIP Code Tabulation Areas (ZCTAs) intersecting the storm's path are classified as treated, while those outside the exposure zone serve as controls.

Treated and Control ZIP Codes Relative to Hurricane Cone
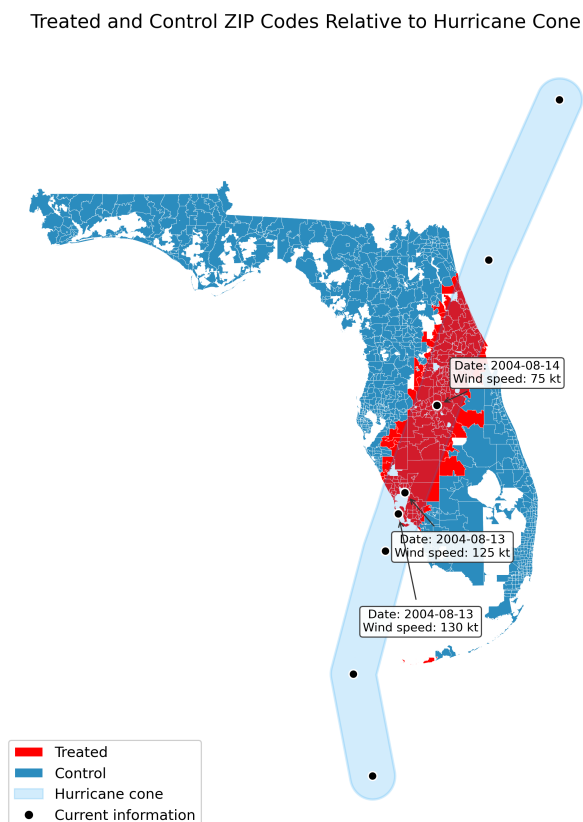
Figure 2: Treatment and Control ZIP Codes for Hurricane Charley (2004). The figure shows the hurricane's observed track (black points), the buffer zone used to define exposure (light blue), and ZIP Codes classified as treated (red) or control (blue).

2.2.2 Event Study Framework

To construct the data for the event study, we treat each hurricane and tropical storm as a separate event study. We merge the constructed treated and control group dataset of storm affected geographies with the evictions dataset at the ZIP code level for six months before and six months after the event. For the treated group, we use the exact date of the storm path for each ZIP code and merge with the observed week in the eviction dataset. For the control group, whose geographies were constructed to remain outside the storm's path, we assign a pseudo-date: when the storm event occurred on a single day, we assign that same day to all control ZIP codes, whereas for multi-day events, we randomly distribute the storm dates across control ZIP codes (e.g., if the storm lasted two days, some control ZIP codes are assigned the first day while others are assigned the second). Since our evictions dataset is at the weekly level, we calculate the relative event date in weeks and also in months to the storm date observed. We follow the same approach with payday loans, calculating the relative event date at the daily level since our payday loan data is recorded daily.

The estimating equation for our event study model is given by :

$$y_{h,i,\tau} = \left(\sum_{j=-m}^{n} \beta_j \cdot \mathbb{1}\{\tau = j\} \cdot D_{h,i} \right) + \alpha_{h,i} + \delta_{h,\tau} + \epsilon_{h,i,\tau} \tag{1}$$

In this equation, $y_{h,i,\tau}$ represents the outcome variable for unit i at relative time τ for hurricane event h. The term $\mathbb{1}\{\tau = j\} \cdot D_{h,i}$ is an indicator variable that equals 1 if the hurricane event h occurred at relative time to impact j in a treated ZIP code i, the unit of observation, and 0 otherwise. The coefficients β_j capture the dynamic effects of the event over time. For $\tau > 0$, these coefficients show the post-event impact, while for $\tau < 0$, they provide a measure for pre-event trends. The summation term thus captures the event study terms over all pre- and post-event periods.

The model also includes $\alpha_{h,i}$, which denotes event-by-unit fixed effects to account for event-specific and time-invariant heterogeneity across units, and $\delta_{h,\tau}$, which represents event-by-time fixed effects to control for event-specific time-specific shocks common to all units, ensuring that all the identification comes from within an event. Together, these terms ensure the model effectively isolates the impact of the event while accounting for unobserved heterogeneity.

As in (Cengiz et al., 2019) and Dube and Lindner (2024), this event study regression aligns

events based on event time rather than calendar time, making it comparable to a scenario where all events occur simultaneously. This approach aims to correct well documented challenges in the standard difference-in-differences approach (Baker et al., 2022).

To properly isolate both treated and control groups and to prevent overlap, we only consider a ZIP code as part of the treated group when it is the first event affecting each ZIP code during the event window. Essentially, we exclude ZIP codes that experience treatment of any other storm events during the construction of the event window of the control group. Similarly, for the control group, we only consider the never-treated during the event window.

In our setup, we conduct multiple event studies focusing on evictions, filings, households at risk, transaction volumes, and default rates for both treated and control groups.

For the evictions data, we used event-specific ZIP codes as the geographic fixed effect. Considering the eviction process spans potentially several months from initial notice, to filing, to eviction, we measured the effect spanning six months. For the payday loans data, we aggregated daily observations at the weekly level to account for within week seasonality, we used event-specific ZIP codes as the geographic fixed effect and event-specific relative weeks as the time fixed effects.

2.2.3 Difference-in-Differences Framework

We also present the event-study results in a difference-in-difference analysis comparing the treated and control groups in pre and post-event following each event study. The model is as follows:

$$y_{h,i,\tau} = \beta \cdot \mathbb{1}\{\tau \geq 0\} \cdot D_{h,i} + \alpha_{h,i} + \delta_{h,\tau} + \epsilon_{h,i,\tau} \tag{2}$$

where $y_{h,i,\tau}$ denotes the dependent variable, representing (evictions, filings, transaction volume, defaults) for observation of hurricane event h, unit i, at relative time τ. $D_{h,i}$ is an indicator variable for the treatment group, equals one for the treated ZIP code and zero otherwise for hurricane event h. The indicator variable $\mathbb{1}\{\tau \geq 0\}$ represents the post-treatment period. By constructing the panel based on relative time, we ensure a framework in which events are aligned to occur simultaneously. And $\alpha_{h,i}, \delta_{h,\tau}$ denotes the event specific fixed effects for unit and time (ZIP code and week/month), respectively.

Finally, to shed light on the role of FEMA aid, we conduct an interacted event study comparison

on the treated ZIP codes for hurricane events and resulted in ZIP codes having the availability of rental assistance. In addition we also conducted a difference-in-differences analysis while excluding treated units that received any FEMA assistance, therefore only on the non-FEMA receiving ZIP codes. For the difference-in-difference approach, the control group is the same as the event based matched control group in the earlier difference-in-difference; in contrast, for the FEMA event-study on the treated, we separated ZIP codes into those that received FEMA assistance and those do not within the same hurricane event.

In the next section, we present the findings from the eviction and payday loan analysis, focusing on the impact of hurricanes and FEMA aid on eviction, transactions and defaults.

3   Results

3.1   Evictions

3.1.1   Hurricanes

Using our evictions dataset we find that ZIP codes that experienced hurricanes saw a maximum monthly average increase of evictions of 0.201 per month per 1000 renters[3] as in Table 4. This represents a monthly increase of 10.9% evictions per month compared to the baseline. The event study in Figure 3 shows that this effect persists up to 6 months after the initial hurricane. The event study also shows a increase around months 2-5, reflecting the nature of the eviction process that may lag from the initial missed rental payment date, to the eviction filing, to the finally court approved eviction order.

We also show in Table 4 that including ZIP codes by broadening the size of the treatment group radius (in nautical miles) results in a decreasing effect size for evictions, as one might expect given the damage from the hurricane event correlates with distance. At 100 nautical miles the effect essentially disappears. This result is important as we later show that this effect does not hold when separating into FEMA receiving and non-FEMA receiving ZIP codes.

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[3]We normalize the raw number of evictions and filings using census data on the number of renters present in a ZIP code to account for heterogeneity in the percentage of renters and in the population per ZIP code.
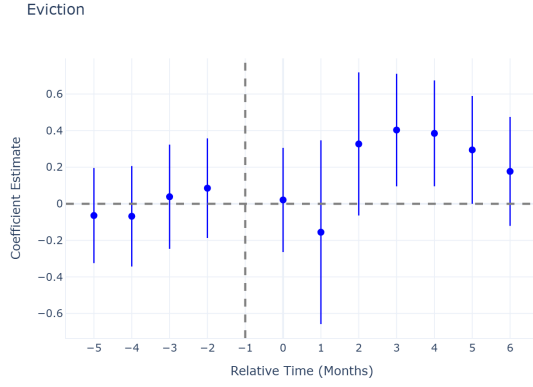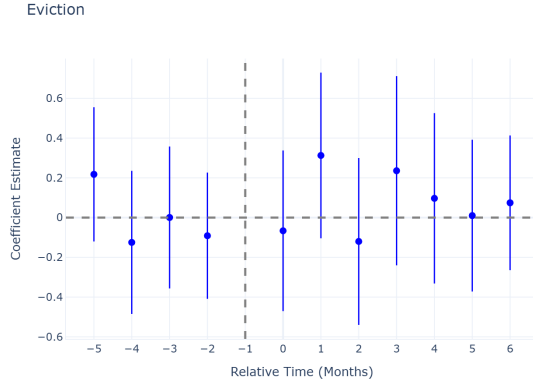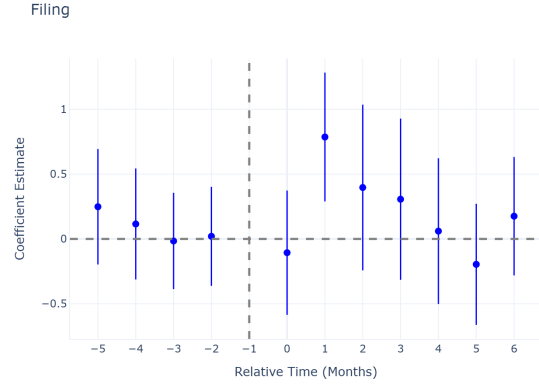
(a) Eviction: ZIP Code - Monthly
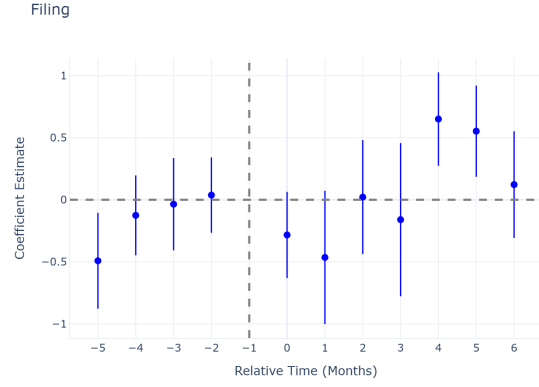
(b) Filing: ZIP Code - Monthly

Figure 3: Estimated coefficients from an event study model evaluating the impact of hurricane exposure on monthly eviction and filing rates at the ZIP code level with a treatment radius of 21 nautical miles. The event window spans from five months before to six months after landfall, with the month immediately preceding the hurricane (month -1) serving as the reference period. Standard errors are clustered at the ZIP code level.

(a) Eviction: ZIP Code - Monthly

(b) Filing: ZIP Code - Monthly

Figure 4: Estimated coefficients from an event study model evaluating the impact of hurricane exposure on monthly eviction and filing rates at the ZIP code level with a treatment radius of 50 nautical miles. The event window spans from five months before to six months after landfall, with the month immediately preceding the hurricane (month -1) serving as the reference period. Standard errors are clustered at the ZIP code level.

	Treatment Radius					
	10	15	21	26	50	100
Panel A: Eviction						
Treated×Post	0.142	0.172*	0.201*	0.169	0.073	-0.049
	[0.100]	[0.097]	[0.103]	[0.114]	[0.114]	[0.084]
Panel B: Filing						
Treated×Post	0.143	0.164	0.167	0.142	0.133	0.193
	[0.132]	[0.126]	[0.125]	[0.137]	[0.150]	[0.149]
Event-specific ZIP Code FE	Y	Y	Y	Y	Y	Y
Event-specific Time FE	Y	Y	Y	Y	Y	Y
Observations	22,638	21,617	20,383	19,360	16,939	15,894

Table 4: Difference-in-Differences results for monthly eviction and filing outcomes at the ZIP code level by treatment radius. The estimation window spans 5 months before the event to 6 months after the event, capturing both pre-event and post-event outcomes. Standard errors clustered at the ZIP code level are reported in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Treatment Radius					
	10	15	21	26	50	100
Panel A: Evictions						
Control	2.096	2.112	2.189	2.239	2.302	2.201
Treated	1.956	1.974	1.842	1.782	1.782	1.824
Panel B: Filings						
Control	3.129	3.164	3.291	3.372	3.515	3.535
Treated	3.058	3.041	2.811	2.740	2.746	2.693

Table 5: Baseline averages by group (pre-hurricane period) for each treatment radius. Control and treated ZIP codes are compared across radii of 10, 15, 21, 26, 50, and 100 miles.
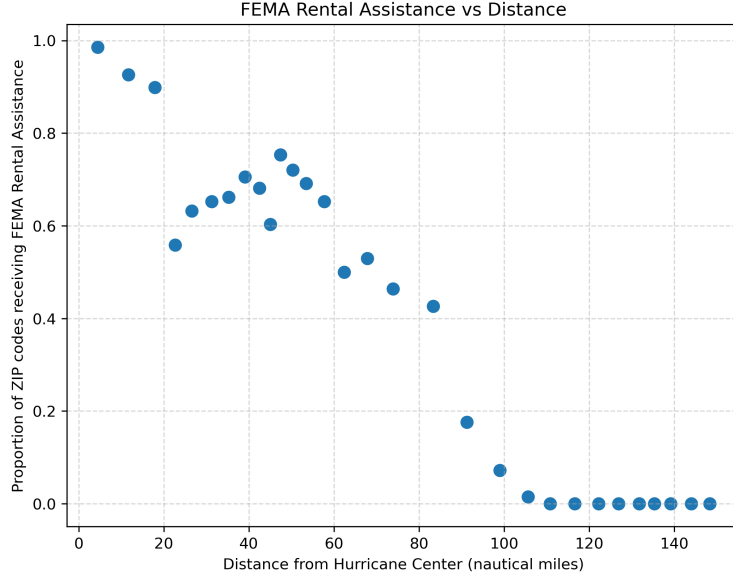
Figure 5: A bin scatter plot of the proportion of ZIP codes at increasing distances from the hurricane path that had recipients of FEMA rental assistance. The plot shows a decreasing in the proportion with a notable jump at the 20 nautical mile mark.

We then investigate the role of FEMA, in particular hurricane events in which FEMA made renter assistance available in impacted ZIP codes. Eligibility for assistance through FEMA depends on a geography being declared FEMA eligible[4], as well as individual assessments of damage and hardship which correlate with proximity to the path of the hurricane event. Figure 6 shows the ZIP codes that received assistance via FEMA and their distance to the hurricane event. We observe that the intersection of ZIP code boundaries, storm damage intensity and receiving FEMA assistance correlate and vary in relation to distance. Figure 5 shows the proportion of ZIP codes with individuals receiving FEMA assistance and the distance from the path of the hurricane during FEMA declared hurricanes.

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[4]FEMA provides a web page for individuals to lookup whether their ZIP code lies in a FEMA disaster declared county https://www.fema.gov/node/how-do-i-know-if-my-area-eligible-assistance?
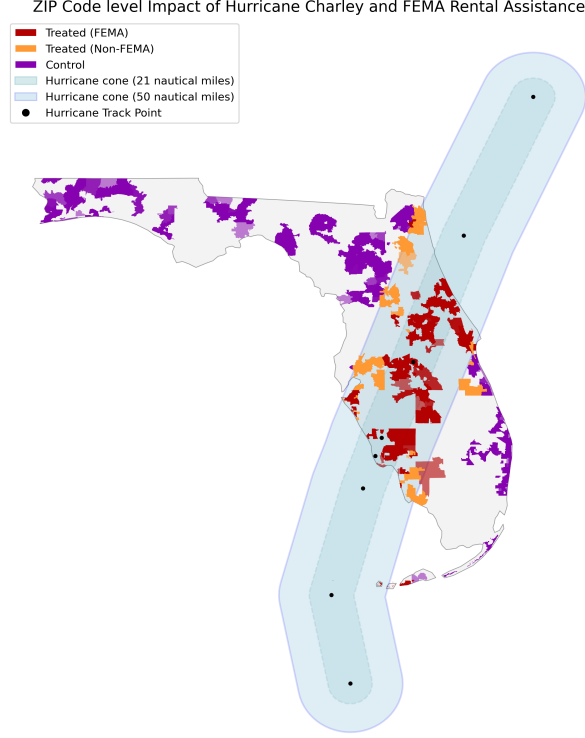
Figure 6: A map of ZIP codes that received FEMA rental assistance in red during Hurricane Charley. The orange non-FEMA treated ZIP codes are those that fall within the hurricane cone but did not receive FEMA rental assistance. The map displays two cone sizes, 21 nautical miles and 50 nautical miles, illustrating the sensitivity of the proportion of ZIP codes receiving FEMA rental assistance at different distances.

Building on our baseline eviction and filings results we observe a bifurcation in the resultant filings and evictions in the period following the hurricane event that varies with FEMA assistance. Both the event-study and difference-in-differences regression results illuminate the decrease rate of filings and evictions for hurricane events where FEMA assistance is made available. In particular, from Table 6 we find a maximal bifurcation in the monthly average evictions with an increase of 0.561 in non-FEMA receiving ZIP codes and a 0.541 increase in filings at the 50 nautical mile radius of inclusion of ZIP codes.
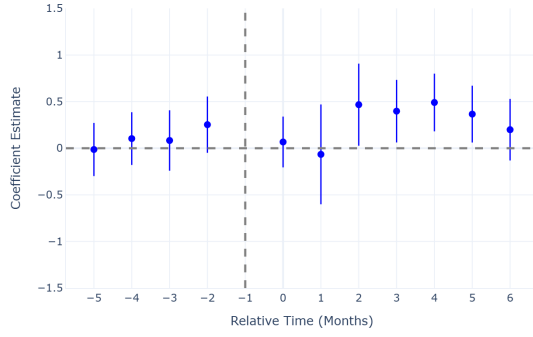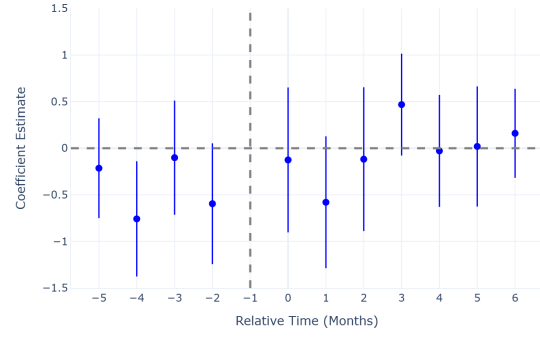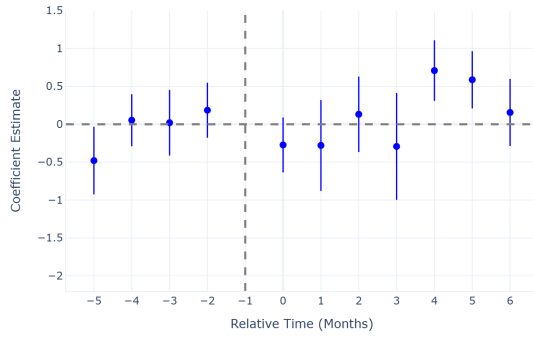
(a) Eviction: FEMA

(b) Eviction: Non-FEMA

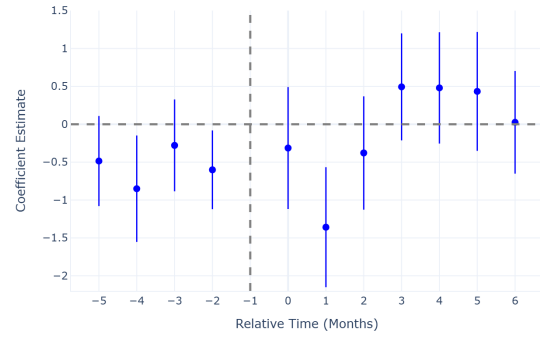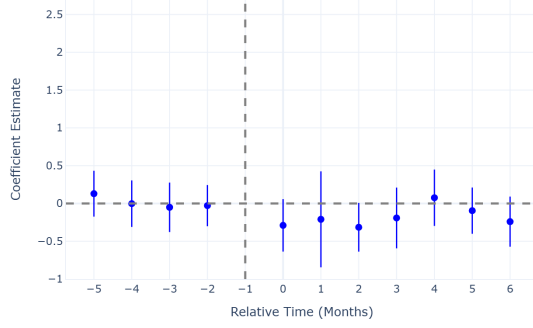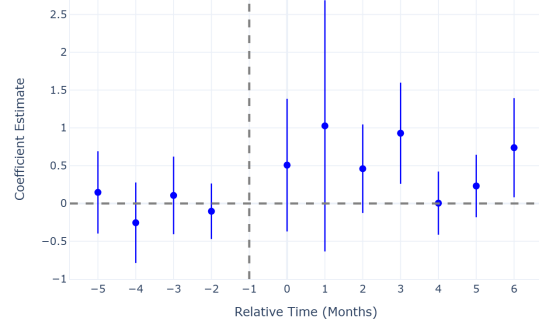(c) Filing: FEMA

(d) Filing: Non-FEMA

Figure 7: Estimated coefficients from an event study model evaluating the impact of hurricane exposure on monthly eviction rates at the ZIP code level with a treatment radius of 21 nautical miles. The event window spans from five months before to six months after landfall, with the month immediately preceding the hurricane (month -1) serving as the reference period. The treated group is divided based on FEMA rental assistance availability. Standard errors are clustered at the ZIP code level.
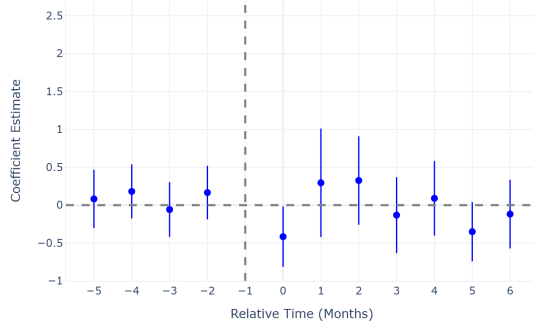
(a) Eviction: FEMA

(b) Eviction: Non-FEMA

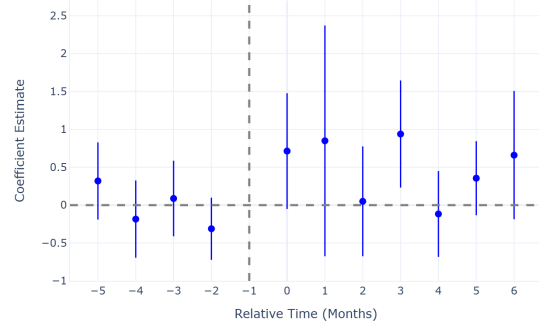(c) Filing: FEMA

(d) Filing: Non-FEMA

Figure 8: Estimated coefficients from an event study model evaluating the impact of hurricane exposure on monthly eviction rates at the ZIP code level with a treatment radius of 50 nautical miles. The event window spans from five months before to six months after landfall, with the month immediately preceding the hurricane (month -1) serving as the reference period. The treated group is divided based on FEMA rental assistance availability. Standard errors are clustered at the ZIP code level.

	Treatment Radius					
	10	15	21	26	50	100
Panel A: Eviction						
Post×Non-FEMA	0.200	0.232	0.285*	0.364**	0.561**	0.167
	[0.159]	[0.156]	[0.164]	[0.164]	[0.218]	[0.141]
Post×FEMA	0.130	0.160	0.182*	0.125	-0.042	-0.084
	[0.106]	[0.099]	[0.100]	[0.111]	[0.107]	[0.088]
Panel B: Filing						
Post×Non-FEMA	0.251	0.301*	0.298	0.299	0.541**	0.390*
	[0.162]	[0.174]	[0.186]	[0.217]	[0.247]	[0.215]
Post×FEMA	0.122	0.136	0.137	0.107	0.037	0.161
	[0.140]	[0.132]	[0.125]	[0.131]	[0.148]	[0.146]
Event-specific ZIP Code FE	Y	Y	Y	Y	Y	Y
Event-specific Time FE	Y	Y	Y	Y	Y	Y
Observations	22,638	21,617	20,383	19,360	16,939	15,894

Table 6: Difference-in-Differences estimates of post-event eviction and filing outcomes by FEMA-designated and non-FEMA-designated areas across treatment radii. Standard errors clustered at the ZIP code level are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.
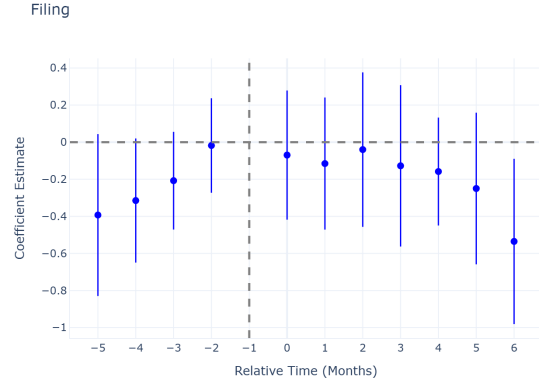
3.1.2 Hurricanes and Tropical Storms

We expand our baseline results to include tropical storms to show that the increase in observed evictions and filings when lower intensity storms are included no longer holds. We view this as a way to gauge the extent that potential damage severity maybe driving our results, suggesting that the sensitivity to the impact of availability for FEMA assistance matters more within event as opposed to across events. In other words, the relative damage of being on the peripheral distances and demand for assistance has observable impacts on evictions relative to any location for lower intensity storms that do not have FEMA assistance at all. Hence, our result is likely to be robust from other temporal patterns that may have coincided in our analysis with the comparatively fewer hurricane events. Adding additional storm events ensures the increased evictions and filings results are likely due to coinciding with intense hurricane events and the additional absence of FEMA assistance for some geographies.

Figure 9 and Table 7 shows the baseline result when including the greater number of tropical storm events no longer holds (note the three times increase in sample size). Whereas separating the two, shows even a possible statistically significant decline in evictions along the path of tropical storms for radii under 26 nautical miles.
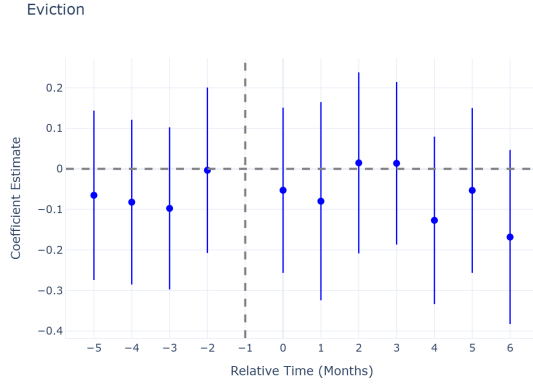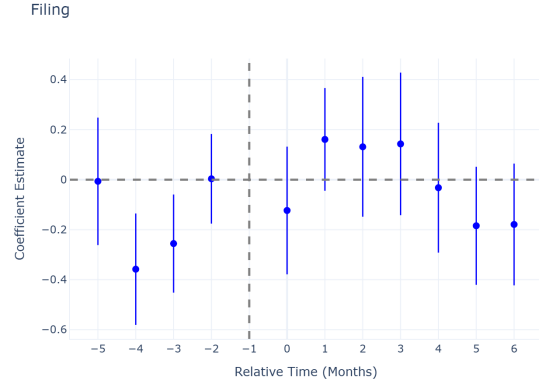
(a) Eviction: 21 nautical miles

(b) Filing: 21 nautical miles
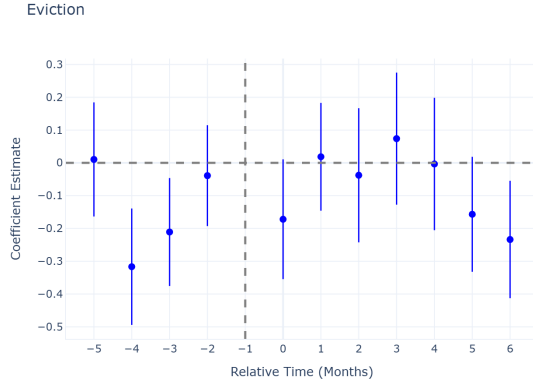
(c) Eviction: 50 nautical miles

(d) Filing: 50 nautical miles

Figure 9: The figure provides the estimated coefficients from an event study examining the combined effect of storm exposure, including hurricanes and tropical storms on monthly eviction-related outcomes at the ZIP code level. The analysis covers a window from five months before to six months after the storm event, with the month immediately preceding the event (month -1) serving as the reference period. Panel (a) displays estimates for monthly eviction rates, while Panel (b) shows estimates for monthly filing rates at the 21 nautical mile treatment radius, whereas Panel (c) displays estimates for monthly eviction rates, while Panel (d) shows estimates for monthly filing rates at the 50 nautical mile treatment radius. Vertical lines indicate 95% confidence intervals, constructed using standard errors clustered at the ZIP code level.

	Treatment Radius					
	10	15	21	26	50	100
Hurricanes and Tropical Storms						
Panel A: Eviction						
Treated×Post	-0.024	-0.042	-0.014	0.013	0.038	-0.005
	[0.061]	[0.059]	[0.054]	[0.057]	[0.051]	[0.043]
Panel B: Filing						
Treated×Post	0.020	-0.018	0.005	0.048	0.113	0.188***
	[0.105]	[0.099]	[0.090]	[0.079]	[0.072]	[0.058]
Separate Effects: Hurricane and Tropical Storms						
Panel C: Eviction						
Post×Hurricane	0.142	0.172*	0.201*	0.169	0.073	-0.049
	[0.100]	[0.097]	[0.103]	[0.114]	[0.114]	[0.084]
Post×Tropical Storm	-0.113	-0.157**	-0.121**	-0.061	0.028	0.001
	[0.075]	[0.071]	[0.060]	[0.060]	[0.052]	[0.048]
Panel D: Filing						
Post×Hurricane	0.143	0.164	0.167	0.142	0.133	0.193
	[0.132]	[0.126]	[0.125]	[0.137]	[0.150]	[0.149]
Post×Tropical Storm	-0.046	-0.116	-0.076	0.003	0.107	0.187***
	[0.114]	[0.110]	[0.095]	[0.078]	[0.069]	[0.062]
Event-specific ZIP Code FE	Y	Y	Y	Y	Y	Y
Event-specific Time FE	Y	Y	Y	Y	Y	Y
Observations	80,963	83,704	81,921	80,495	75,703	71,206

Table 7: Difference-in-Differences estimates of eviction and filing outcomes following hurricanes and tropical storms. The top panel reports combined treatment effects for all events, while the bottom panels separate effects for hurricanes and tropical storms. Standard errors clustered at the ZIP code level are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

3.2 Payday Loans

3.2.1 Hurricanes

We further compare the usage of high cost credit during hurricane events with the availability of FEMA rental assistance. In particular, as the individual rental assistance provided by FEMA is of similar magnitudes to the average loan amount available to households via payday loans[5]. We find that both transaction volumes and default rates are lower post hurricane event and that this decrease in usage and decrease in defaults is particularly driven when FEMA assistance is made available. Both transactions volumes and defaults decrease by greater magnitudes compared to when it is not made available, reflecting a reduction in demand of payday credit when FEMA is

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[5]The maximum amount in the state of Florida is $500 and often households borrow at the maximum

available but also a decrease in precarity in making repayments. In particular, Figure 11 we observe a decrease in defaults and reduction in transaction volumes.

Specifically, in Table 8 we show that the volume of transactions reduce by a maximal amount of 17.609 per week and a decrease in defaults by 2.414 per week on average per ZIP code. This reflects a 8.3% decrease in transactions per week relative to the baseline period and 22.6% decrease in defaults relative to the baseline period.

Comparatively, when FEMA rental assistance is available, we find transactions volumes decrease by 21.209 per week and that non-FEMA ZIP codes see an increase of 13.609 transactions per week at the most maximal, a decline of 10.4% for FEMA receiving ZIP codes and an increase of 6.3% for non-FEMA receiving ZIP codes relative to the pre-event baseline. Furthermore, we find FEMA receiving ZIP codes result in a decrease in defaults by 2.810 per week and that non-FEMA ZIP codes no statistically signficant change across almost all treatment radius. This represents approximately a 26.3% decrease in defaults relative to the pre-event baseline for FEMA receiving ZIP codes.

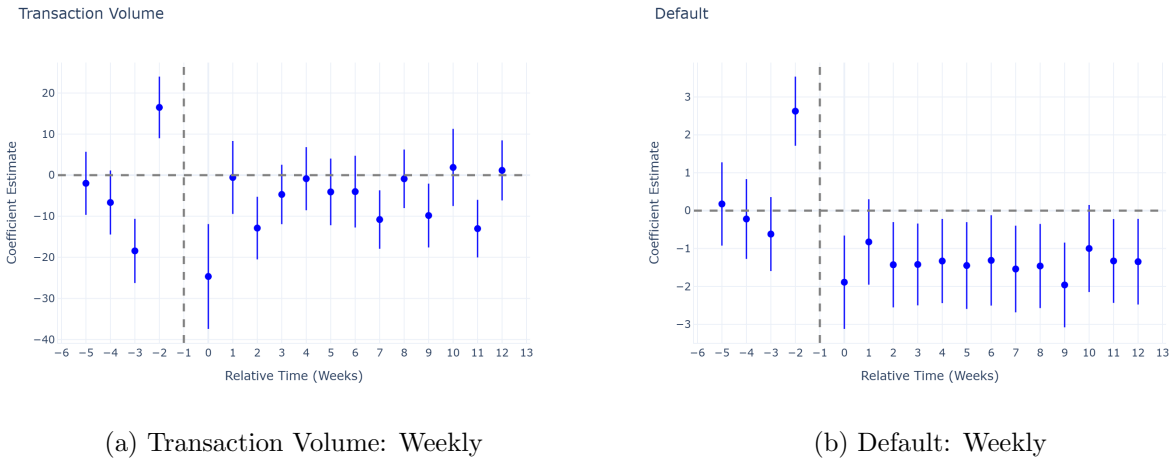(a) Transaction Volume: Weekly   (b) Default: Weekly

Figure 10: The figure provides the estimated coefficients from an event study examining the impact of hurricane exposure on weekly payday loan-related outcomes at the ZIP code level with a treatment radius of 21 nautical miles. The analysis spans a window from five weeks before to twelve weeks after the hurricane event, with the week immediately preceding the event (week -1) serving as the reference period. Panel (a) reports estimates for weekly transaction volume, while Panel (b) shows estimates for weekly default rates. Vertical lines represent 95% confidence intervals, calculated using standard errors clustered at the ZIP code level.

(a) Transaction Volume: Weekly
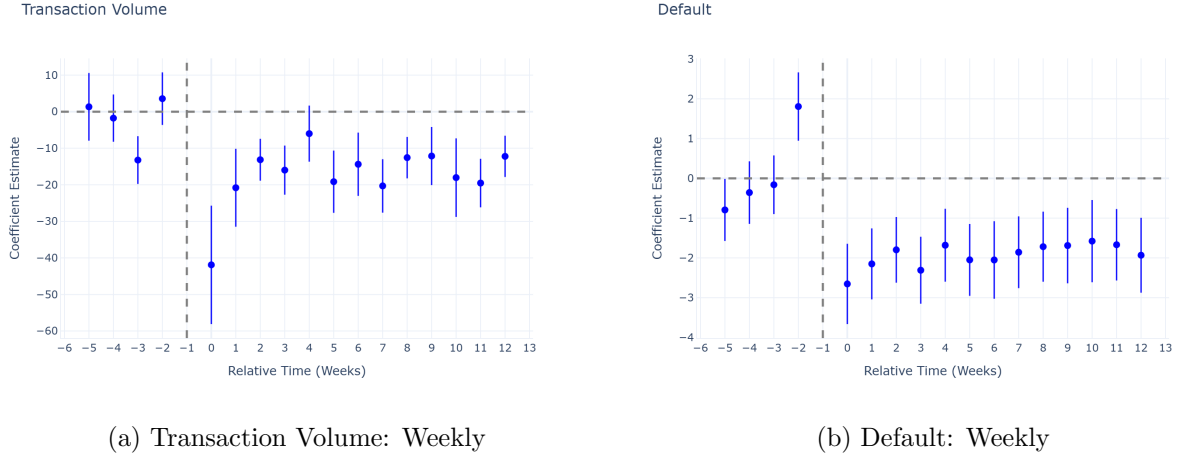
(b) Default: Weekly

Figure 11: The figure provides the estimated coefficients from an event study examining the impact of hurricane exposure on weekly payday loan-related outcomes at the ZIP code level with a treatment radius of 50 nautical miles. The analysis spans a window from five weeks before to twelve weeks after the hurricane event, with the week immediately preceding the event (week -1) serving as the reference period. Panel (a) reports estimates for weekly transaction volume, while Panel (b) shows estimates for weekly default rates. Vertical lines represent 95% confidence intervals, calculated using standard errors clustered at the ZIP code level.

	Treatment Radius					
	10	15	21	26	50	100
Panel A: Transaction Volume						
Treated×Post	-8.405***	-5.119**	-4.192*	-5.012**	-15.104***	-17.609***
	[2.962]	[2.497]	[2.404]	[2.228]	[2.021]	[2.535]
Panel B: Default						
Treated×Post	-2.322***	-1.560***	-1.798***	-1.548***	-2.026***	-2.414***
	[0.586]	[0.479]	[0.441]	[0.409]	[0.404]	[0.586]
Event-specific ZIP Code FE	Y	Y	Y	Y	Y	Y
Event-specific Time FE	Y	Y	Y	Y	Y	Y
Observations	45,526	41,821	38,920	36,613	31,904	29,527

Table 8: Difference-in-Differences estimates of post-event impacts on payday loan transaction volume and defaults across treatment radii. Standard errors clustered at the ZIP code level are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Treatment Radius					
	10	15	21	26	50	100
Panel A: Transaction Volume						
Control	251.098	259.797	263.990	271.601	291.747	296.754
Treated	247.778	226.742	227.980	217.360	204.819	212.644
Panel B: Default						
Control	9.697	9.821	9.713	9.881	10.185	10.085
Treated	12.010	11.146	11.243	10.566	10.298	10.678

Table 9: Baseline averages by group (pre-hurricane period) for each treatment radius. Control and treated ZIP codes are compared across radii of 10, 15, 21, 26, 50, and 100 miles.

(a) Transaction Volume: FEMA

(b) Transaction Volume: Non-FEMA
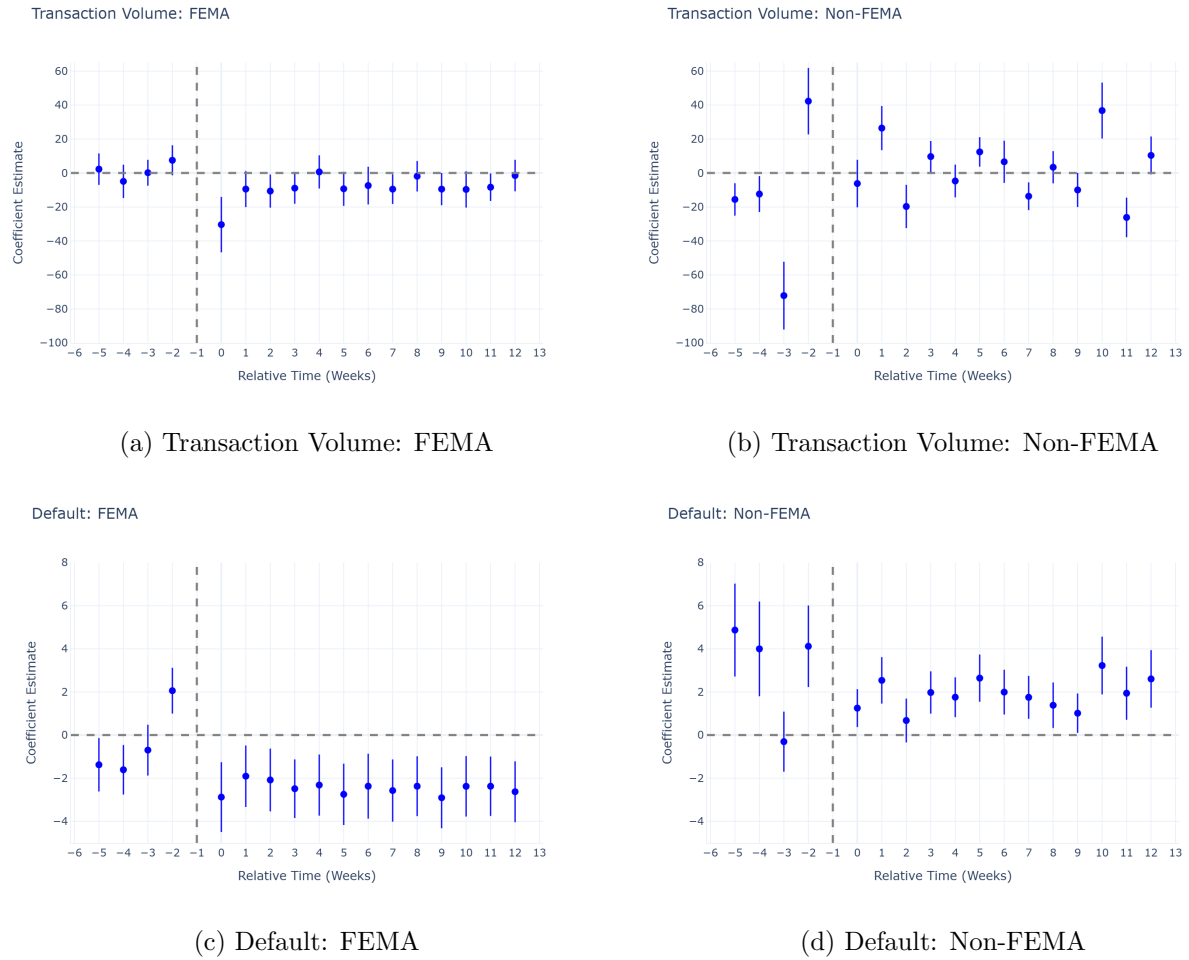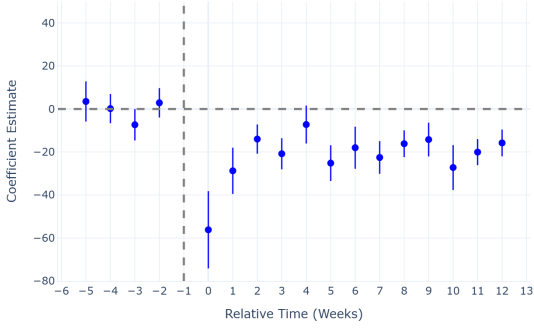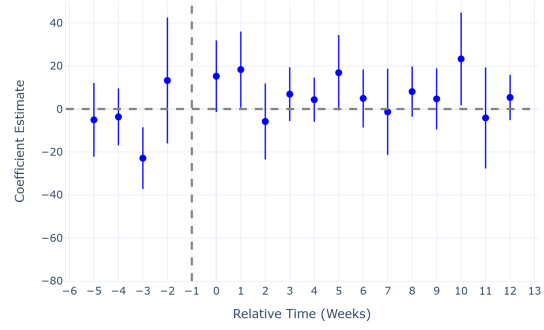
(c) Default: FEMA

(d) Default: Non-FEMA

Figure 12: Estimated coefficients from an event study model evaluating the impact of hurricane exposure on weekly payday loan transaction volume at the ZIP code level with a treatment radius of 21 nautical miles. The event window spans from five weeks before to twelve weeks after landfall, with the week immediately preceding the hurricane (week -1) serving as the reference period. The treated group is divided based on FEMA rental assistance availability. Standard errors are clustered at the ZIP code level.
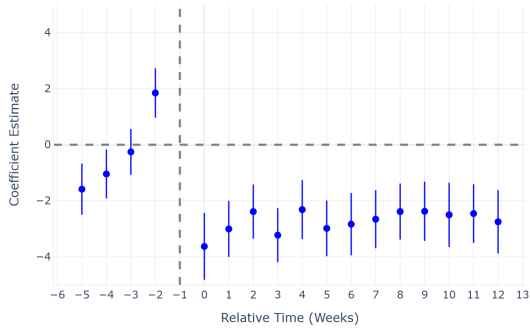
(a) Transaction Volume: FEMA

(b) Transaction Volume: Non-FEMA

(c) Default: FEMA
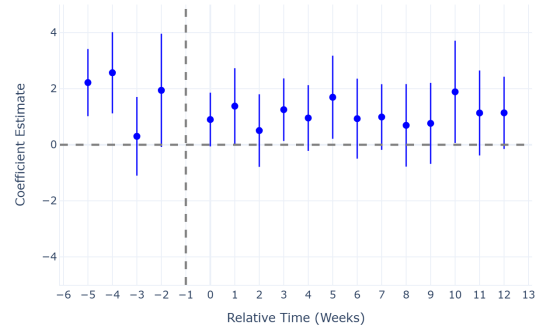
(d) Default: Non-FEMA

Figure 13: Estimated coefficients from an event study model evaluating the impact of hurricane exposure on weekly payday loan transaction volume at the ZIP code level with a treatment radius of 21 nautical miles. The event window spans from five weeks before to twelve weeks after landfall, with the week immediately preceding the hurricane (week -1) serving as the reference period. The treated group is divided based on FEMA rental assistance availability. Standard errors are clustered at the ZIP code level.

	Treatment Radius					
	10	15	21	26	50	100
Panel A: Transaction Volume						
Post×Non-FEMA	10.269**	10.234***	12.972***	13.609***	11.563***	-0.053
	[4.350]	[3.096]	[2.927]	[3.137]	[3.096]	[3.353]
Post×FEMA	-12.902***	-10.043***	-9.787***	-10.386***	-21.209***	-21.120***
	[3.412]	[3.002]	[2.879]	[2.525]	[2.240]	[2.597]
Panel B: Default						
Post×Non-FEMA	-2.116*	-0.194	-0.646	-0.412	0.204	-0.436
	[1.211]	[0.809]	[0.727]	[0.701]	[0.632]	[0.680]
Post×FEMA	-2.372***	-1.998***	-2.173***	-1.875***	-2.536***	-2.810***
	[0.654]	[0.553]	[0.509]	[0.458]	[0.440]	[0.608]
Event-specific ZIP Code FE	Y	Y	Y	Y	Y	Y
Event-specific Time FE	Y	Y	Y	Y	Y	Y
Observations	45,526	41,821	38,920	36,613	31,904	29,527

Table 10: Difference-in-Differences estimates of post-event transaction Volume and default outcomes by FEMA-designated and non-FEMA-designated areas across treatment radii. Standard errors clustered at the ZIP code level are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.
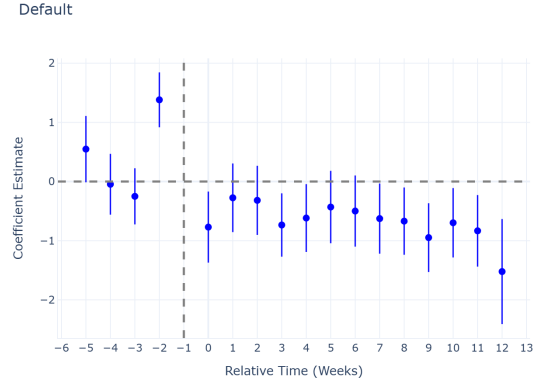
3.2.2 Hurricanes and Tropical Storms Combined

Adding lower intensity tropical storms for payday loans show a dampened effect for transaction volumes and defaults, unlike the case with evictions where the effect was non-significant. In this case, the results remain significant but the magnitudes decrease with treatment radii, which is in line with the a decrease in potential damage from the storm and the absence of FEMA intervention.
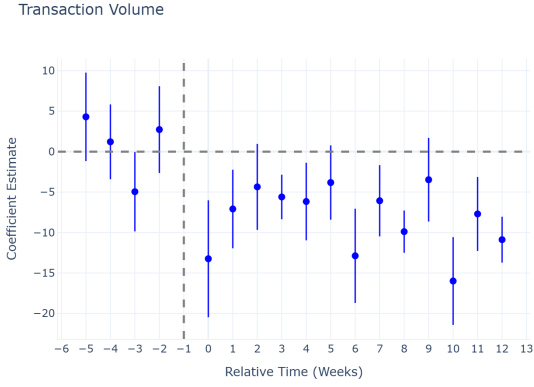
Figure 14 and Table 11 show that overall transaction volumes decrease by a maximal amount of 10.810 weekly transactions per ZIP code and that defaults decrease by 0.504 defaults per week on average.
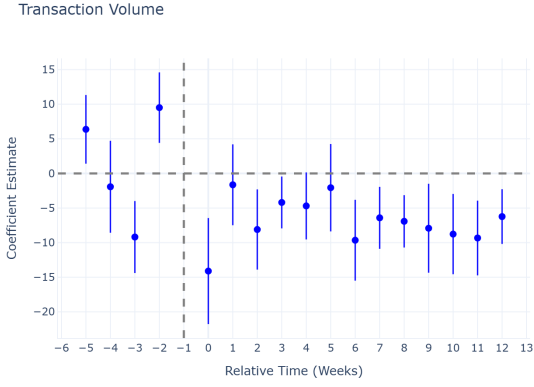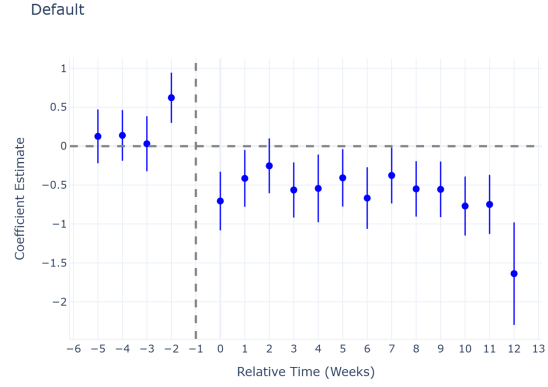
(a) Transaction Volume: 21 nautical miles

(b) Default: 21 nautical miles

(c) Transaction Volume: 50 nautical miles

(d) Default: 50 nautical miles

Figure 14: The figure provides the estimated coefficients from an event study examining the impact of combined hurricane and tropical storm exposure on weekly payday loan-related outcomes at the ZIP code level. The analysis spans a window from five weeks before to twelve weeks after the hurricane event, with the week immediately preceding the event (week -1) serving as the reference period. Panel (a) reports estimates for weekly transaction volume, while Panel (b) shows estimates for weekly default rates at 21 nautical miles. Panel (c) reports estimates for weekly transaction volume, while Panel (d) shows estimates for weekly default rates at 50 nautical miles. Vertical lines represent 95% confidence intervals, calculated using standard errors clustered at the ZIP code level.

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	Treatment Radius					
	10	15	21	26	50	100
Hurricanes and Tropical Storms						
Panel A: Transaction Volume						
Treated×Post	-9.454***	-8.097***	-7.860***	-7.755***	-8.879***	-7.916***
	[1.696]	[1.366]	[1.262]	[1.163]	[0.991]	[1.285]
Panel B: Default						
Treated×Post	-1.335***	-0.982***	-1.014***	-0.863***	-0.813***	-0.869***
	[0.304]	[0.246]	[0.214]	[0.187]	[0.146]	[0.183]
Separate Effects: Hurricane and Tropical Storms						
Panel C: Transaction Volume						
Post×Hurricane	-8.405***	-5.119**	-4.192*	-5.012**	-15.104***	-17.609***
	[2.962]	[2.496]	[2.404]	[2.228]	[2.021]	[2.535]
Post×Tropical Storm	-10.456***	-10.810***	-10.698***	-9.620***	-6.605***	-5.622***
	[1.886]	[1.721]	[1.519]	[1.447]	[1.251]	[1.468]
Panel D: Default						
Post×Hurricane	-2.322***	-1.560***	-1.798***	-1.548***	-2.026***	-2.414***
	[0.585]	[0.479]	[0.441]	[0.409]	[0.404]	[0.586]
Post×Tropical Storm	-0.392**	-0.455***	-0.407***	-0.398***	-0.369***	-0.504***
	[0.171]	[0.156]	[0.140]	[0.133]	[0.118]	[0.176]
Event-specific ZIP Code FE	Y	Y	Y	Y	Y	Y
Event-specific Time FE	Y	Y	Y	Y	Y	Y
Observations	133,020	128,028	131,732	128,489	121,955	116,037

Table 11: Difference-in-Differences estimates of payday loan outcomes following hurricanes and tropical storms. The top panels report combined treatment effects, while the bottom panels separate effects by hurricane and tropical storm exposure. Standard errors clustered at the ZIP code level are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4   Conclusion

Using granular data on evictions and loan-level data on payday loans, we provide evidence of disaster induced increase in evictions and reliance on high cost credit in the state of Florida following major storms and hurricanes. We find that the existence of federal assistance helps mitigate the rate of evictions while also allowing households to avoid defaulting when relying on higher cost credit. Overall, this suggests that major household level impacts such as access to housing are sensitive to the availability of emergency liquidity, suggesting the utility for such programs while highlighting the need to better understand administrative cutoffs to access.

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