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 16.5% increase in overall evictions after hurricane natural disaster events that increases to 19.7% when excluding ZIP codes that 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 critical questions over both the individual and government role in pre-disaster mitigation and post-disaster response, in particular through their shortcomings. 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 often 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.

[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 forecast cones for all hurricane and tropical storm events and includes the following characteristics: the forecast date, hurricane category, and the forecast time of impact. We use these cones to construct a hurricane time-of-impact and path dataset by examining all the cones for all hurricane and tropical storm events that traverse the state of Florida

However, the forecast cones are only available as far back as 2008. For storm events prior to 2008, we utilize NHC's data on the storm's realized path to reconstruct the forecast cone for each storm using the same properties as the forecast cones provided by the NHC in the period after 2008.[2] 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.

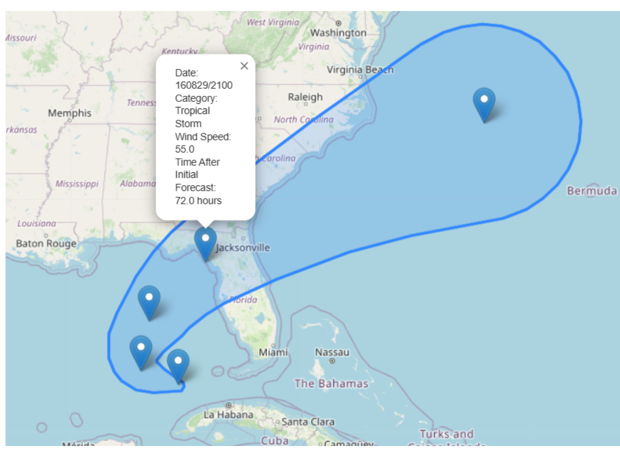


Figure 1: 5-Day Track Forecast Cone

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

2.1.4 FEMA Data

Since 1979, the Federal Emergency Management Agency (FEMA) has served as the federal government'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 applications, 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.

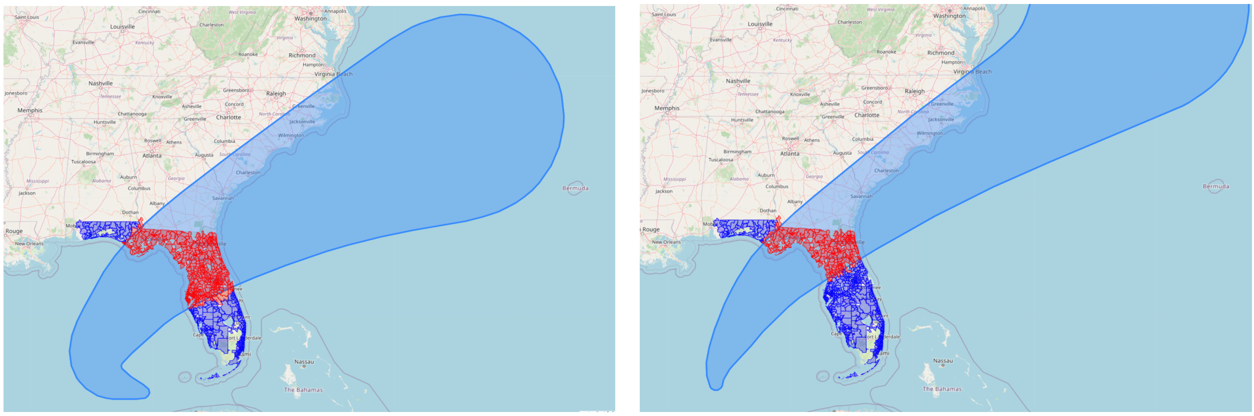
In the following three sections, we will explain how the treated and control groups were constructed and provide a detailed explanation of how the event study and difference-in-differences models were conducted.

2.2.1 Construction of treatment and control groups

To measure the impact of hurricanes on households, we construct two groups: treatment and control. The treated group consists of ZIP codes (or census tracts) that were within the forecast cone at any point for the entire path of the storm event, from the first prediction to the storm's dissipation. These areas appear in the forecast cone and are likely to experience some direct or/and indirect effects from the hurricane.

In contrast, our control group includes all ZIP codes (census tracts) that remain completely outside the forecast cone throughout the storm's progression. This ensures that the behavior and outcomes in these areas were more likely to not be influenced by the forecast or the storm itself, allowing us to isolate the impact of the disaster.

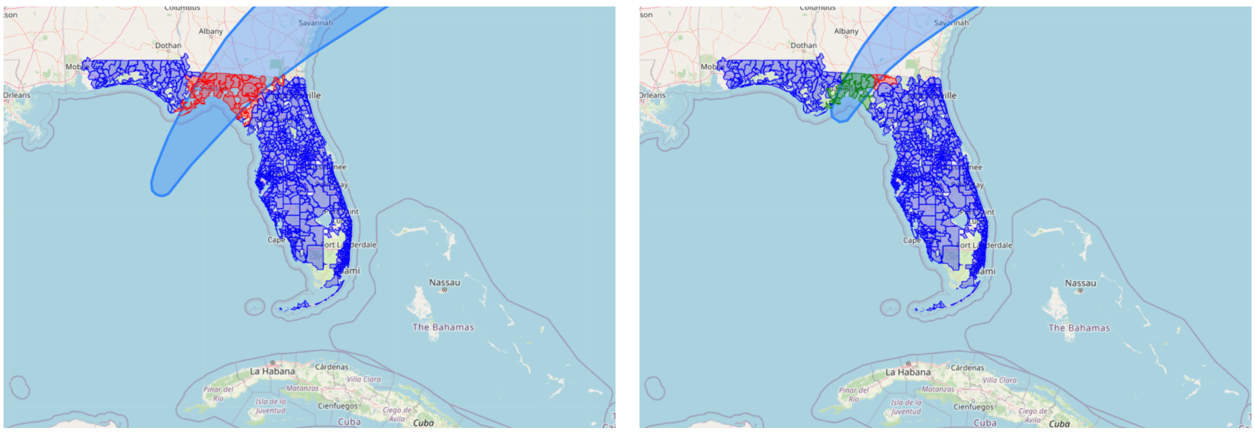
Figures 2 and 3 provide insight into our strategy. They show the evolution of four forecast cones for hurricane Hermine in 2016. The treated group is the green area, whereas the control group is the intersection between all blue areas, as demonstrated in Figure 4.



(a) 5th forecast cone

(b) 10th forecast cone

Figure 2: Forecast cones: distinguish between areas inside and outside the cone



(a) 17th forecast cone

(b) 19th forecast cone

Figure 3: Forecast cones: Evolution of forecast cones during the path of the storm with an example of the treated group (green area)

Figure 4 provides insight into how we constructed the treatment and control groups.

Control group (Blue): This group includes ZIP codes (census tracts) that are entirely outside of any given forecast cone, meaning that these areas were not expected to be affected by a hurricane at any point in time. By focusing on areas not under the forecast at any point, we construct a control group whose behavior and outcomes are assumed to be unaffected directly by storm warnings or the storm itself.

Treated Group (Green): This group includes ZIP codes (census tracts) located within the hurricane forecast cone. However, only areas that remained in the forecast cone up until the closest forecast cone (3 hours prior to impact) are included. That way, we include areas that were eventually either directly in or very close to the realized hurricane path.

In this setup, we compare two groups that likely have very differential impact. We compare the regions that were actually affected (the green area) to the regions (the blue area) that were consistently outside any potential threat of impact. The areas in red were excluded as they were previously in the forecast path but did not eventually remain in the realized path of the storm.

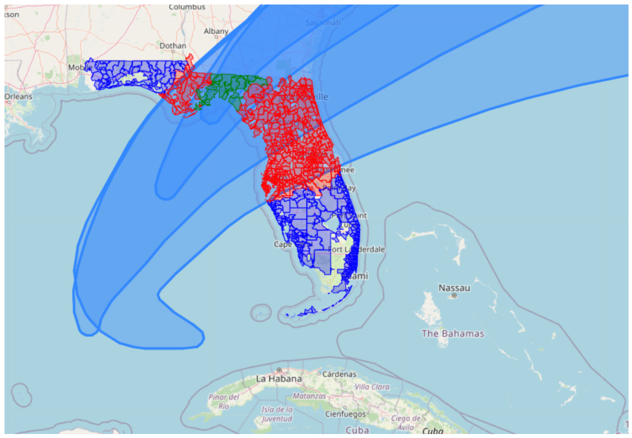


Figure 4: Dynamic 5-Day Forecast Cone

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 census tract 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 census tract and merge with the observed week in the eviction dataset. In the control group, since the geographies were constructed to not intersect with the storm forecast, we assign a pseudo-date, in particular, we use the median storm date. 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.

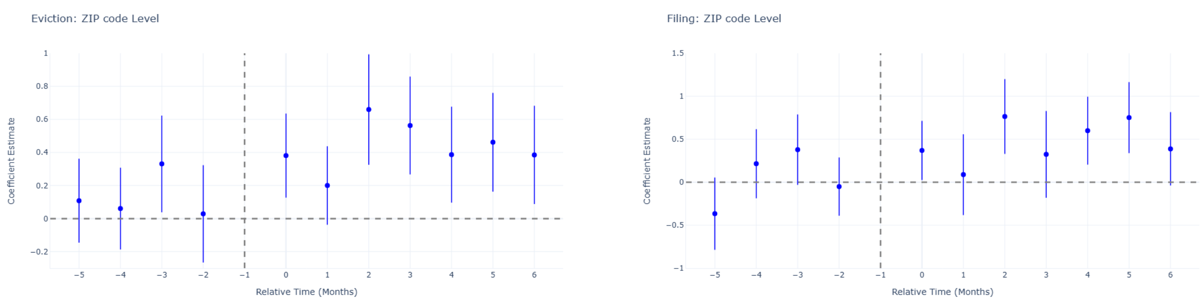
3 Results

3.1 Evictions

3.1.1 Hurricanes

Using our evictions dataset we find that ZIP codes that experienced hurricanes saw a monthly average increase of evictions of 0.525 per month per 1000 renters[3] Table 4. This represents a monthly increase of 16% evictions per month compared to the baseline. The event study in Figure 5 shows that this effect persists up to 6 months after the initial hurricane. The event study also shows a gradual increase in the initial two months up to a peak around months 3-5, 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 evaluate the change in the number of filings, in which we find an increase of 0.928 in the number of filings per month per 1000 renters, in the 6 month that follow the hurricane event. This represents a 28.7% increase relative to the baseline rate of filings per month.



(a) Eviction: ZIP Code - Monthly

(b) Filing: ZIP Code - Monthly

Figure 5: The figure provides the estimated coefficients from an event study examining the effect of hurricane exposure on monthly eviction-related outcomes at the ZIP code level. The analysis covers a window from five months before to six months after the hurricane 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. Vertical lines indicate 95% confidence intervals, constructed using standard errors clustered at the ZIP code level.

[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.

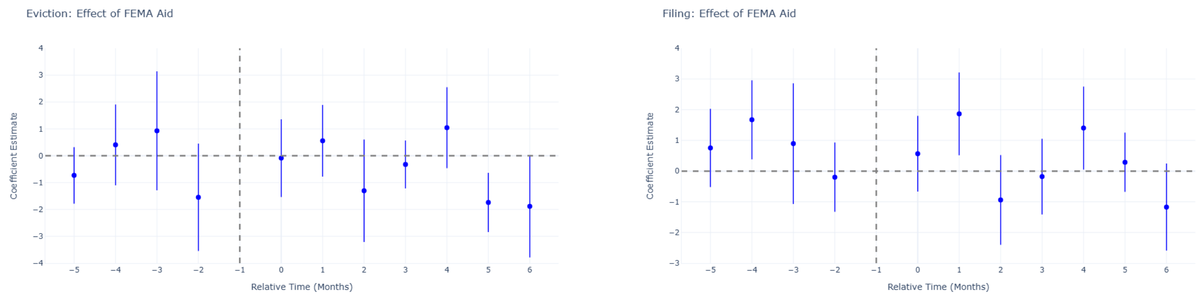
Dependent Variable	Eviction	Filing
Period	Monthly	Monthly
Window	[-5 ; 6]	[-5 ; 6]
Treated×Post	0.331***	0.428***
	[0.089]	[0.110]
Event-specific ZIP Code FE	Y	Y
Event-specific Time FE	Y	Y
Observations	18501	18501

Table 4: Difference-in-Differences results for monthly eviction and filing outcomes at the ZIP code level. The estimation window spans 5 months before the event to 6 months after the event, capturing both pre-event and post-event outcomes. the coefficient of 0.331 for evictions represents an approximate 16.5% increase relative to the treated group's pre-event average. Similarly, the 0.428 increase in filings corresponds to about a 13.3% rise from the treated group's pre-event average. 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.

Variable	Control Group	Treated Group
Eviction Rate	2.403	2.002
Filing Rate	3.601	3.203

Table 5: Baseline average monthly level per 1000 renters per ZIP code in the pre-event period.

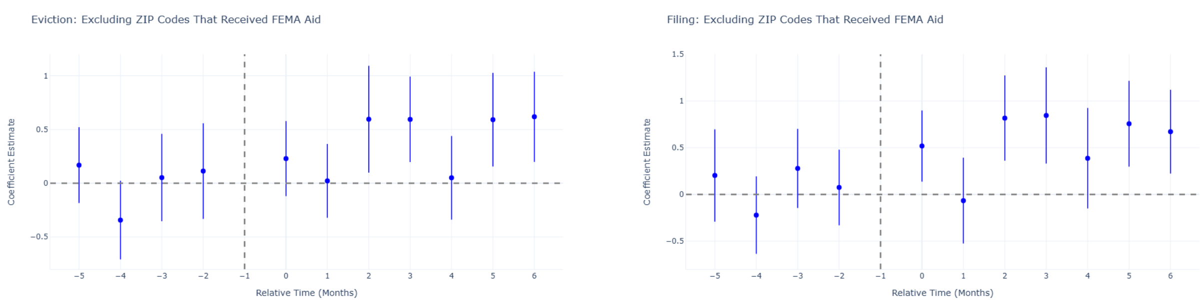
We then investigate the role of FEMA, in particular hurricane events in which FEMA made renter assistance available in impacted ZIP codes. Our results indicate a possible bifurcation in the resultant filings and evictions in the period following the hurricane event. Both the event-study and difference-in-differences regression results illuminate the decrease rate of filings and evictions for hurricane events where FEMA assistance is made available. In particular, we firstly find a decrease in the monthly average of 0.418 and 0.445, for evictions and filings per month, respectively **??** when restricting to the event study just within treated units. These represent a 20.9% and 13.9% decrease, respectively, for hurricanes that did not receive FEMA aid. Although both results are not statistically significant, we also show a larger estimate for evictions and filings when excluding ZIP codes that included FEMA assistance in the difference-in-differences results relative to the baseline. Comparatively, evictions increased by a statistically significant 0.392 when excluding FEMA receiving ZIP codes relative to the control group, a larger coefficient than 0.331 result when including all ZIP codes. Similarly, filings increased by a statistically significant 0.502 when excluding FEMA assistance, larger than the 0.428 coefficient when including all ZIP codes.



(a) Eviction: ZIP Code - Monthly

(b) Filing: ZIP Code - Monthly

Figure 6: The figure provides the estimated coefficients from an event study evaluating the effect of hurricane exposure on monthly eviction and filing rates at the ZIP code level on the treated. The analysis spans a window from five months before to six months after the hurricane event, with the month preceding the event (month -1) serving as the reference period. Panel (a) presents the interacted monthly eviction estimates for ZIP codes that received FEMA aid versus those that did not for the treated group, while Panel (b) shows monthly interacted filing estimates for ZIP codes that received FEMA aid. Standard errors are clustered at the ZIP code level.



(a) Eviction: ZIP Code - Monthly

(b) Filing: ZIP Code - Monthly

Figure 7: The figure provides the estimated coefficients from an event study evaluating the effect of hurricane exposure on monthly eviction and filing rates at the ZIP code level with the entire set of control ZIP codes but excluding the treated ZIP codes that do not receive FEMA assistance. The analysis spans a window from five months before to six months after the hurricane event, with the month preceding the event (month -1) serving as the reference period. Panel (a) presents the interacted monthly eviction estimates for ZIP codes that do not receive FEMA assistance versus the control group, while Panel (b) shows monthly interacted filing estimates for ZIP codes that do not receive FEMA assistance versus the control group. Standard errors are clustered at the ZIP code level.

Dependent Variable	**Eviction**	**Filing**
Period	**Monthly**	**Monthly**
Window	**[-5 ; 6]**	**[-5 ; 6]**
FEMA×Post	-0.418	-0.445
	[0.291]	[0.303]
Event-specific ZIP Code FE	Y	Y
Event-specific Time FE	Y	Y
Observations	2729	2729

Table 6: Results for monthly eviction and filing outcomes at the ZIP code level on the treated group only, separated into ZIP codes that received FEMA assistance and those did not. this provides within storm event estimate comparisons for all ZIP codes that were within the storm path. The estimation window spans 5 months before the event to 6 months after the event, capturing both pre-event and post-event outcomes. For FEMA receiving ZIP codes, the coefficient of -0.418, for evictions, while not statistically significant, represents an approximate 20.9% decrease relative to the treated group's pre-event average (2.002), while the -0.445 decrease in filings corresponds to about a 13.9% decrease from the treated group's baseline (3.203).

Dependent Variable	**Eviction**	**Filing**
Period	**Monthly**	**Monthly**
Window	**[-5 ; 6]**	**[-5 ; 6]**
Treated×Post	0.392***	0.502***
	[0.092]	[0.116]
Event-specific ZIP Code FE	Y	Y
Event-specific Time FE	Y	Y
Observations	16647	16647

Table 7: Difference-in-difference results for monthly eviction and filing outcomes at the ZIP code level while excluding treated ZIP codes that received FEMA assistance. This provides a comparison with control group ZIP codes that for the same time period were not in the storm path. The estimation window spans 5 months before the event to 6 months after the event, capturing both pre-event and post-event outcomes. For non-FEMA receiving ZIP codes, the statistically significant coefficient of 0.392, for evictions, is larger than the 0.331 coefficient for all treated ZIP codes, represents an approximate 19.6% increase relative to the treated group's pre-event average (2.002), while the 0.502 increase in filings, larger than the 0.428 coefficient for all treated ZIP codes, corresponds to about a 15.6% increase from the treated group's baseline (3.203).

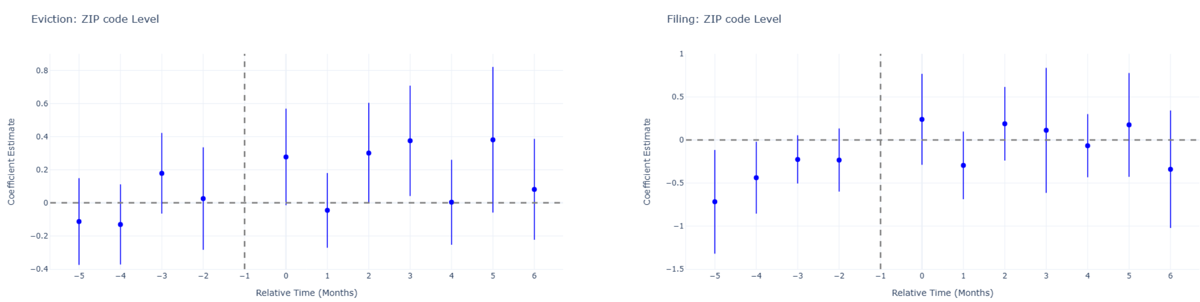
3.1.2 Hurricanes and Tropical Storms

Variable	Control Group	Treated Group
Eviction Rate	2.664	2.423
Filing Rate	3.950	3.829

Table 8: Baseline average monthly level per 1000 renters per ZIP code in the pre-event period.

We expand our baseline results to include tropical storms to show that the increase in observed evictions and filings still holds when lower intensity storms are included. Although, the comparative magnitudes decreases, we show that this is largely due to tropical storms seeing far lower post-storm eviction rates. 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.

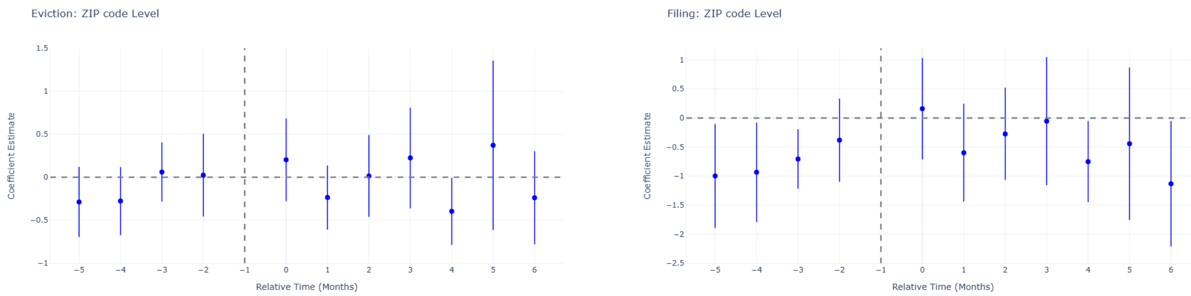
Figure 8 and Table 9 shows the baseline result even when including the greater number of tropical storm events still holds (note the three times increase in sample size). The decrease is largely driven by the inclusion of tropical storms, noting the treatment post-period coefficient drop from 0.371 to 0.128 for evictions when only tropical storms are included, although the decrease itself is not statistically significant.



(a) Eviction: ZIP Code - Monthly

(b) Filing: ZIP Code - Monthly

Figure 8: The figure provides the estimated coefficients from an event study examining the 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. Vertical lines indicate 95% confidence intervals, constructed using standard errors clustered at the ZIP code level.



(a) Eviction: ZIP Code - Monthly

(b) Filing: ZIP Code - Monthly

Figure 9: The figure provides the estimated coefficients from an event study examining the impact of tropical storm exposure on monthly eviction-related outcomes at the ZIP code level. The analysis spans 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) reports estimates for monthly eviction rates, while Panel (b) shows estimates for monthly filing rates. Vertical lines represent 95% confidence intervals, calculated using standard errors clustered at the ZIP code level. The results suggest no statistically significant change in either eviction or filing rates following a tropical storm event.

Dependent Variable	**Eviction**	**Filing**	**Eviction**	**Filing**
Period	**Monthly**	**Monthly**	**Monthly**	**Monthly**
Window	**[-5 ; 6]**	**[-5 ; 6]**	**[-5 ; 6]**	**[-5 ; 6]**
Treated×Post	0.209***	0.336***	0.103	0.255
	[0.070]	[0.125]	[0.105]	[0.200]
Event-specific ZIP Code FE	Y	Y	Y	Y
Event-specific Time FE	Y	Y	Y	Y
Hurricanes	Y	Y	N	N
Observations	62209	62209	43708	43708

Table 9: Difference-in-Differences results for monthly eviction and filing outcomes at the ZIP code level, combining both hurricanes and tropical storms. The analysis includes two specifications: one with all storms and another excluding hurricane events. The estimation window spans from 5 months before to 6 months after the event. In the full specification including hurricanes and tropical storms, the coefficient on *Treated×Post* indicates a statistically significant increase of 0.209 evictions and 0.336 filings in treated ZIP codes. These correspond to approximately 8.6% and 8.7% increases relative to the treated group's pre-event averages of 2.423 and 3.829, respectively. When hurricanes are excluded, the estimated effects are smaller and not statistically significant.

Dependent Variable	Eviction	Filing
Period	**Monthly**	**Monthly**
Window	**[-5 ; 6]**	**[-5 ; 6]**
Treated×Post	0.331***	0.428***
	[0.089]	[0.110]
Treated×Post×Storm	-0.228*	-0.173
	[0.137]	[0.212]
Event-specific ZIP Code FE	Y	Y
Event-specific Time FE	Y	Y
Observations	62209	62209

Table 10: Triple Difference-in-Differences results for monthly eviction and filing outcomes at the ZIP code level, combining both hurricanes and tropical storms. The analysis evaluates the differential effects of the tropical storm event across treated and control groups, with an estimation window spanning from 5 months before to 6 months after the event. The coefficient of 0.331 for evictions and 0.428 for filings in the *Treated×Post* interaction term suggests a significant increase in both outcomes in the treated ZIP codes, corresponding to approximately 13.6% and 11.1% increases relative to the pre-event averages of 2.423 and 3.829, respectively. The triple interaction *Treated×Post×Storm* is negative and marginally significant (-0.228, significant at the 10%) for Eviction, suggesting that the treatment effect after tropical storms is somewhat lower than after hurricanes. In other words, tropical storms appear to have a weaker impact on evictions compared to hurricanes. However, for eviction filings, the triple interaction (-0.173) is negative but not statistically significant.

3.2 Payday Loans

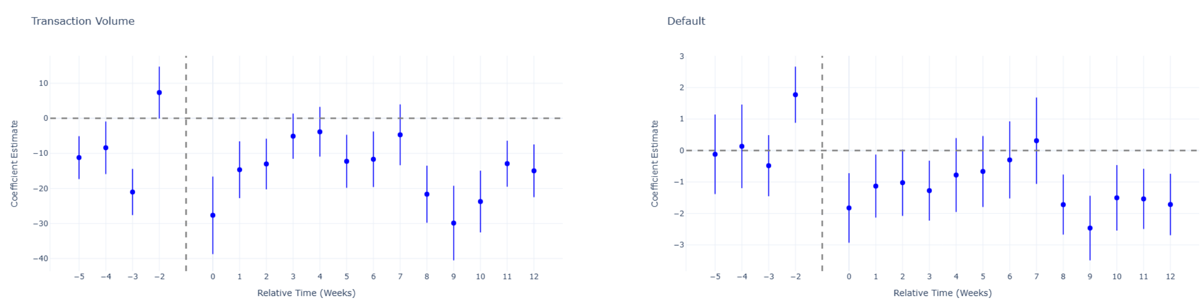
3.2.1 Hurricanes

We further compare the usage of high cost credit during hurricane events with the availability of FEMA rental assistance. We find that both transaction volumes and default rates are lower post storm and that when FEMA assistance is made available, transactions volumes and default rates decrease by greater magnitude compared to when it is not made available, reflecting a reduction in demand of payday credit when FEMA is available but also a decrease in precarity in making repayments. In particular, **??** we observe a decrease in defaults and reduction in transaction volumes (except a spike around 4,8 and 12 weeks, possibly reflecting a feature of payday loans that repeat customers often rollover their outstanding 30-day loans).

Specifically, in Table 12 we show that the volume of transactions reduces by 8.364 per week and a decrease in defaults by 1.458 per week on average per ZIP code. This reflects a 3.8% decrease in transactions per week relative to the baseline period and 14% decrease relative to the baseline period. Comparatively, when FEMA rental assistance is available, we find transactions volumes decrease by 12.597 per week relative to non-FEMA ZIP codes, a decline of 5.7% relative to the pre-event baseline. Furthermore, we find a decrease decrease in defaults by 3.318 per week, an approximately 31.8% relative to the pre-event baseline. While when ZIP codes receiving FEMA assistance are excluded, transaction volumes reduced by 8.538 per ZIP code per week relative to the baseline period, a decrease of 3.9% per week per ZIP code relative to the baseline period. Defaults, on the other hand, show a not statistically significant decrease of 0.433.

Variable	**Control Group**	**Treated Group**
Transaction Volume	228.833	221.300
Default	8.714	10.418

Table 11: Baseline average weekly level per ZIP code in the pre-event period.



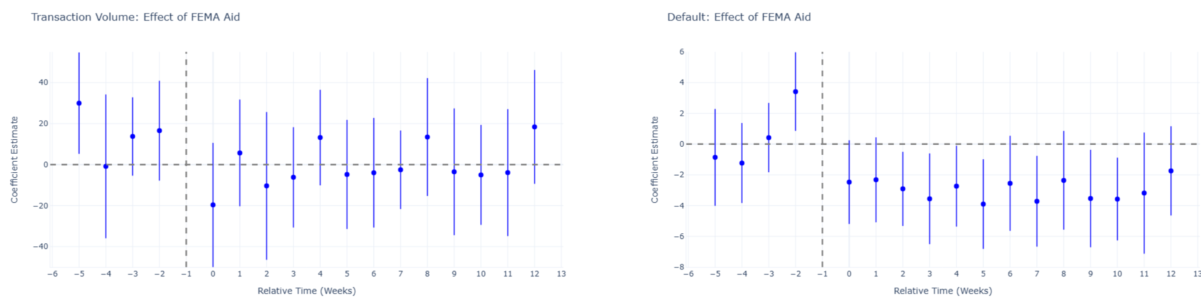
(a) Transaction Volume: Weekly

(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. The analysis spans a window from five weeks before to 12 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.

Weekly Window	[-5 ; 7]		[-5 ; 12]	
Dependent Variable	**Transaction**	**Default**	**Transaction**	**Default**
Treated×Post	-4.857**	-1.088***	-8.364***	-1.458***
	[2.040]	[0.403]	[2.121]	[0.416]
Event-specific ZIP Code FE	Y	Y	Y	Y
Event-specific Time FE	Y	Y	Y	Y
Observations	25856	25856	35912	35912

Table 12: Difference-in-Differences results for transaction volume and default rate outcomes at the ZIP code level for payday loan data. The analysis evaluates the impact of hurricane event across treated and control groups over two different weekly windows: from 5 weeks before to 7 weeks after the event ([-5 ; 7]) and from 5 weeks before to 12 weeks after the event ([-5 ; 12]). The coefficient of -4.857** for transaction volume in the [-5 ; 7] window suggests a significant decrease in transaction volume in the treated ZIP codes, corresponding to approximately 2.2% lower transaction volume relative to pre-event levels. The coefficient for default rate in the same window is -1.088***, indicating a significant reduction in the default rate, corresponding to approximately 10.4% lower default rates in treated ZIP codes. The longer window, [-5 ; 12], shows even stronger effects with a coefficient of -8.364*** for transaction volume, suggesting a 3.8% reduction in transactions, and -1.458*** for default rates, corresponding to a 14% reduction in defaults.



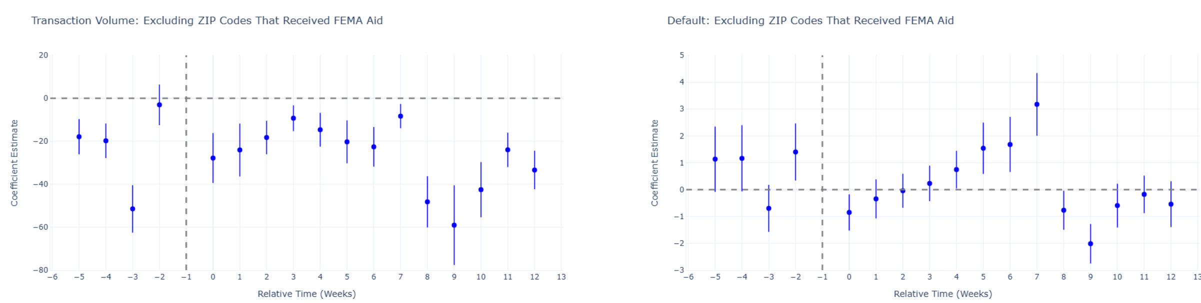
(a) Transaction Volume: Weekly

(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 for the treated only. The analysis spans a window from five weeks before to 12 weeks after the hurricane event, with the week immediately preceding the event (week -1) serving as the reference period. Panel (a) presents transaction estimates for ZIP codes that received FEMA aid and were in the storm path, while panel Panel (b) shows default estimates for ZIP codes that received FEMA aid and were in the storm path. Standard errors are clustered at the ZIP code level.

Dependent Variable	Transaction	Default
Period	**Weekly**	**Weekly**
Window	**[-5 ; 12]**	**[-5 ; 12]**
FEMA×Post	-12.597*	-3.316***
	[7.130]	[1.112]
Event-specific ZIP Code FE	Y	Y
Event-specific Time FE	Y	Y
Observations	7366	7366

Table 13: Results for transaction volume and default rate outcomes at the ZIP code level for the payday loan data. The analysis evaluates the impact of hurricane event across treated groups and interacted with receiving FEMA rental assistance over the weekly window: from 5 weeks before to 12 weeks after the event ([-5 ; 12]). The coefficient of -12.597* for transaction volume in the suggests a significant decrease in transaction volume in the treated ZIP codes that received FEMA assistance, corresponding to approximately 5.7% lower transaction volume relative to pre-event levels. The coefficient for default rate in the same window is -3.316***, indicating a significant reduction in the default rate, corresponding to approximately 31.8% lower default rates in treated ZIP codes that received FEMA assistance.



(a) Transaction Volume: Weekly

(b) Default: Weekly

Figure 12: 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 excluding ZIP codes that received FEMA assistance. The analysis spans a window from five weeks before to 12 weeks after the hurricane event, with the week immediately preceding the event (week -1) serving as the reference period. Panel (a) presents transaction volume estimates for ZIP codes relative to the control group excluding treated ZIP codes that received FEMA assistance, while panel Panel (b) shows default estimates for ZIP codes relative to the control group excluding treated ZIP codes that received FEMA assistance. Standard errors are clustered at the ZIP code level.

Dependent Variable	Transaction	Default
Period	**Weekly**	**Weekly**
Window	**[-5 ; 12]**	**[-5 ; 12]**
Treated×Post	-8.538***	-0.433
	[1.727]	[0.348]
Event-specific ZIP Code FE	Y	Y
Event-specific Time FE	Y	Y
Observations	31686	31686

Table 14: Difference-in-differences esults for transaction volume and default rate outcomes at the ZIP code level for the payday loan data. The analysis evaluates the impact of hurricane event relative to the control group excluding treated ZIP codes receiving FEMA rental assistance over the weekly window: from 5 weeks before to 12 weeks after the event ([-5 ; 12]). The coefficient of -8.538* for transaction volume in the suggests a significant decrease in transaction volume in the treated ZIP codes that did not receive FEMA assistance relative to the control group, corresponding to approximately 3.9% lower transaction volume relative to pre-event levels. The coefficient for default rate in the same window is -0.433, indicating a non statistically significant reduction in the default rate when excluding treated ZIP codes that received FEMA assistance.

3.2.2 Hurricanes and Tropical Storms Combined

Variable	Control Group	Treated Group
Transaction Volume	267.802	256.220
Default	8.681	9.537

Table 15: Baseline average weekly level per ZIP code in the pre-event period for hurricanes and tropical storms combined

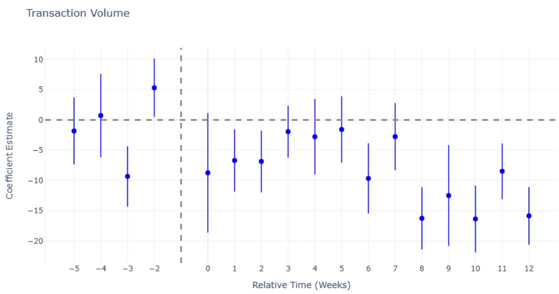
Variable	Control Group	Treated Group
Transaction Volume	286.228	291.139
Default	8.666	8.655

Table 16: Baseline average weekly level per ZIP code in the pre-event period for tropical storms

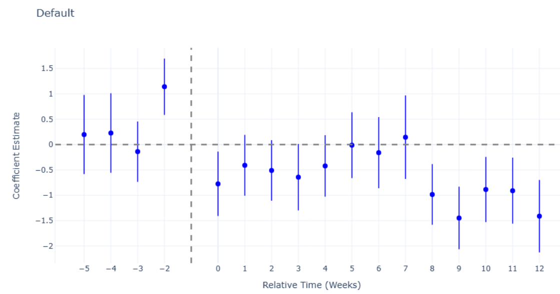
Adding lower intensity tropical storms once again does not overturn the results in comparing events that include FEMA assistance. We continue to observe a decrease in transaction volume and a comparative decrease in default rates for events that saw FEMA assistance. Hence, allowing us to control for possible additional temporal events and for differences possibly due to intensity of non-FEMA hurricane events.

Table 17 and Table 18 show that overall transaction volumes decrease by 7.468 weekly transactions per ZIP code and that defaults decrease by 0.982 defaults per week on average relative to a statistically non-significant change in defaults when only including tropical storm events.

Most of the change in decreases in transaction volumes and in preservation of default rates is not attributed to non-FEMA events being possibly due to lower intensity storms relative to FEMA declared hurricane events as tropical storms show similar magnitudes of changes in transaction volumes and non-decrease in default rates to non-FEMA hurricanes as in Table 14.

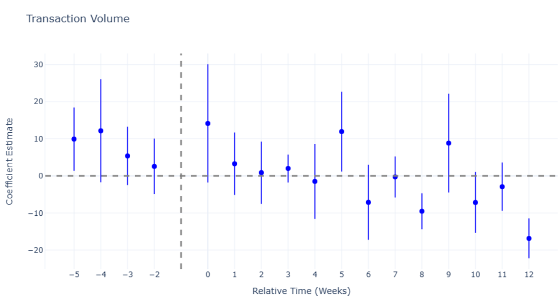


(a) Transaction Volume: Weekly

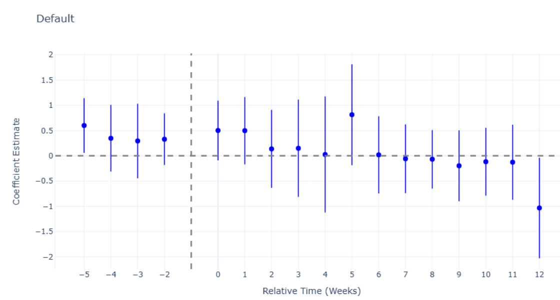


(b) Default: Weekly

Figure 13: The figure provides the estimated coefficients from an event study examining the impact of storm (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 12 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 14: The figure provides the estimated coefficients from an event study examining the impact of tropical storm exposure on weekly payday loan-related outcomes at the ZIP code level. The analysis spans a window from five weeks before to 12 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.

Weekly Window	**[-5 ; 12]**		**[-5 ; 12]**	
Dependent Variable	**Transaction**	**Default**	**Transaction**	**Default**
Treated×Post	-7.468***	-0.932***	-6.345***	-0.273
	[1.316]	[0.234]	[1.847]	[0.200]
Event-specific ZIP Code FE	Y	Y	Y	Y
Event-specific Time FE	Y	Y	Y	Y
Hurricanes	Y	Y	N	N
Observations	103,291	103,291	67,379	67,379

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 17: Difference-in-Differences results for weekly payday loan transaction volume and default rate outcomes at the ZIP code level, combining both hurricanes and tropical storms. The analysis includes two specifications: one with all storm events (hurricanes and tropical storms), and another excluding hurricane events. The estimation window spans from 5 weeks before to 12 weeks after the event. In the full specification including hurricanes and tropical storms, the coefficient on *Treated×Post* indicates a statistically significant decline of 7.468 transactions and 0.932 defaults in treated ZIP codes. These correspond to approximately 2.9% and 9.8% decreases relative to the treated group's pre-event averages of 256.220 transactions and 9.537 defaults, respectively. When hurricanes are excluded, the estimated effects are smaller: a 6.345 decrease in transactions (2.2%) and a non-significant 0.273 decrease in defaults (3.2%).

Weekly Window	**[-5 ; 12]**	
Dependent Variable	**Transaction**	**Default**
Treated×Post	-8.364***	-1.458***
	[2.040]	[0.403]
Treated×Post×Storm	2.019	1.185**
	[2.907]	[0.463]
Event-specific ZIP Code FE	Y	Y
Event-specific Time FE	Y	Y
Observations	103,291	103,291

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 18: Triple Difference-in-Differences results for weekly payday loan transaction volume and default rate outcomes at the ZIP code level, combining both hurricanes and tropical storms. The analysis investigates heterogeneity in the treatment effect by interacting the treatment indicator with a binary storm type indicator (1 = tropical storm, 0 = hurricane). The estimation window spans from 5 weeks before to 12 weeks after the event. The coefficient on *Treated×Post* indicates a statistically significant decrease of 8.364 transactions and 1.458 defaults in treated ZIP codes overall. The interaction term *Treated×Post×Storm* captures differential effects by storm type: default rates rise after tropical storms relative to hurricanes, potentially reflecting the role of FEMA assistance, which is less commonly triggered by tropical storms.

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 and the need to better understand their availability in a world subject to an increasing propensity of climate shock events.

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