Keeping in Place After the Storm — Emergency Assistance and Evictions

Bilal Islah* Ahmed Zoulati†

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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 a 8% increase in overall evictions after hurricane natural disaster events that is largely driven by hurricane events that do not receive FEMA aid. Furthermore, we also show that FEMA aid acts as a substitute to other forms of emergency credit, specifically we find an increase of 12% in the volume of transactions and an increase of 19% defaults in payday loans during hurricane events in locations that do not receive FEMA aid, an effect that largely reverses in areas that do FEMA aid. 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.

*Africa Business School, University Mohammed VI Polytechnic, Morocco. e-mail: bilal.islah@um6p.ma
†Africa Business School, University Mohammed VI Polytechnic, Morocco. e-mail: ahmed.zoulati@um6p.ma

1 Introduction

The loss of structures and in particularly housing in the wake of natural disasters is often among the notable images of large natural disasters. Historical catastrophes such as the Lisbon earthquake of 1755 or the Great Fire of Chicago in 1871 are still referenced to today because of the context of their wide spread destruction of buildings and neighborhoods. While the response to such events may yield positive silver linings in the resultant reemergence at the macroeconomic level such as via learned adaptation or in providing an opportunity to update regulatory frictions, at the micro level, the loss born by individuals can be large and has been documented in various forms in the literature.

Historical instances in which neighborhoods that have been rebuilt do not necessarily resemble their former composition as a result of the immediate loss of housing in such events. 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.

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 assistance and furthermore that the demand for emergency credit is substituted away from higher cost credit as we document in the case of payday loans.

[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 on household finances has more generally 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.

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 broader dynamics of financial distress, eviction risks, and 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 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 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	`Census Tract`	`evict`	`filing`	`atrisk`
Observations	498,793	498,793	498,793	498,793
Unique	3980	–	–	–
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

Table 1: Summary Statistics for Eviction data

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 loan-level observations. We are able to observe the loan date, due date, transaction amount, and any related fees. 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, even though the hurricane's path is available for all the periods of our primary datasets. So, for hurricanes and tropical storms before 2008, we used the data on the storm path provided from the NHC and reconstruct a forecast cone for each storm with the same properties as the forecast cones provided by the NHC in the period after 2008. 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.

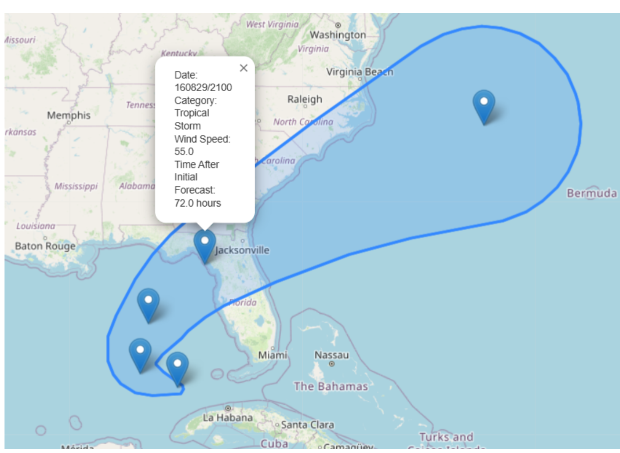


Figure 1: 5-Day Track Forecast Cone

2.1.4 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 (non-PII) 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 child-care), 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. FEMA aid is available only to U.S. citizens, non-citizen nationals, and qualifying non-citizens. Applicants must verify their identity with a valid social security number, and FEMA must confirm that the disaster-damaged home is their primary residence. FEMA cannot provide assistance for disaster-related needs already covered by another source, such as insurance or other programs. However, if those sources do not fully cover disaster-related costs, individuals may still qualify for FEMA assistance. When applying for FEMA aid, applicants must disclose any insurance coverage that may address disaster-related needs. If they 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.

For our purposes, we utilized two FEMA datasets: the FEMA Web Disaster Declarations and the Housing Assistance Program Data - Renters - v2. 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 extracting relevant data from the second dataset, which provides detailed information about housing assistance but does not include disaster names. 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 a summary statistics of key variables for the Housing Assistance Program - 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
2005-10-24	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	Valid Registrations*	Approved Ihp Amount in $ (Average)	Rental Amount in $ (Average)
Tropical Storm Bonnie and Hurricane Charley	50136	112,583.23	41,836.76
Hurricane Frances	114540	104,167.44	30,683.00
Hurricane Ivan	35961	89,149.65	19,905.15
Hurricane Jeanne	89278	135,649.48	34,465.50
Hurricane Dennis	9131	32,941.83	8,249.41
Hurricane Wilma	150501	76,758.15	19,882.96
Tropical Storm Fay	5463	10,678.00	6,598.96
Tropical Storm Debby	4455	15,135.29	9,207.61
Hurricane Hermine	1643	11,895.06	5,350.96
Hurricane Irma	1420062	106,985.30	65,693.42

** refers to individuals within any ZIP code affected by the disaster whose registration was validated by FEMA.*

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-difference model to confirm the results from the event study. Finally, we also then study the existence of federal aid assistance in an interacted difference-in-difference setting to measure the role of FEMA aid.

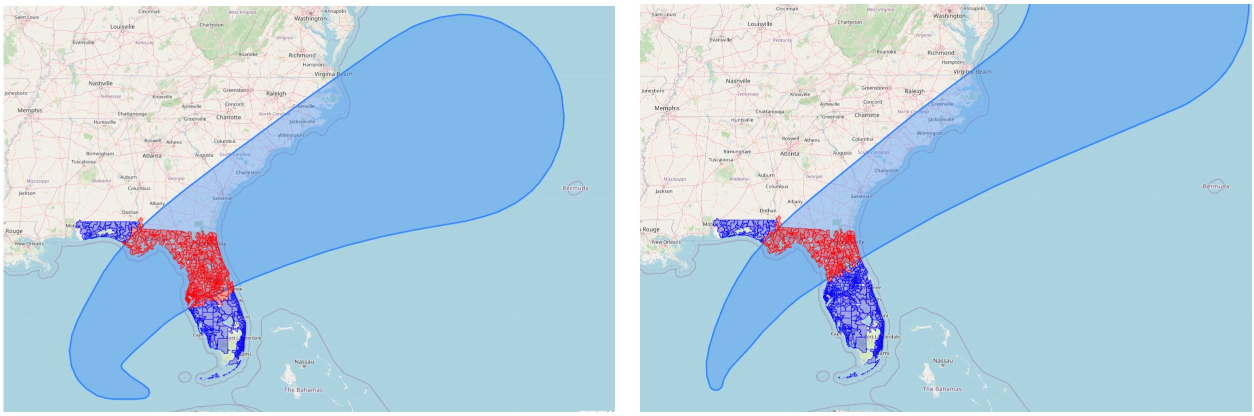
In the following three sections, we will explain how the treated and control groups were constructed and provide a detailed explanation of how the event study and difference-in-difference models were conducted.

2.2.1 Construction of treatment and control groups

To measure the impact of hurricanes on households, we created two groups: treatment and control. The treated group consists of ZIP codes (or Census Tracts) that were within the forecast cone at any point, from the first prediction to the storm's dissipation. These areas were under forecasted threat and were likely to experience direct or/and indirect effects from the hurricane.

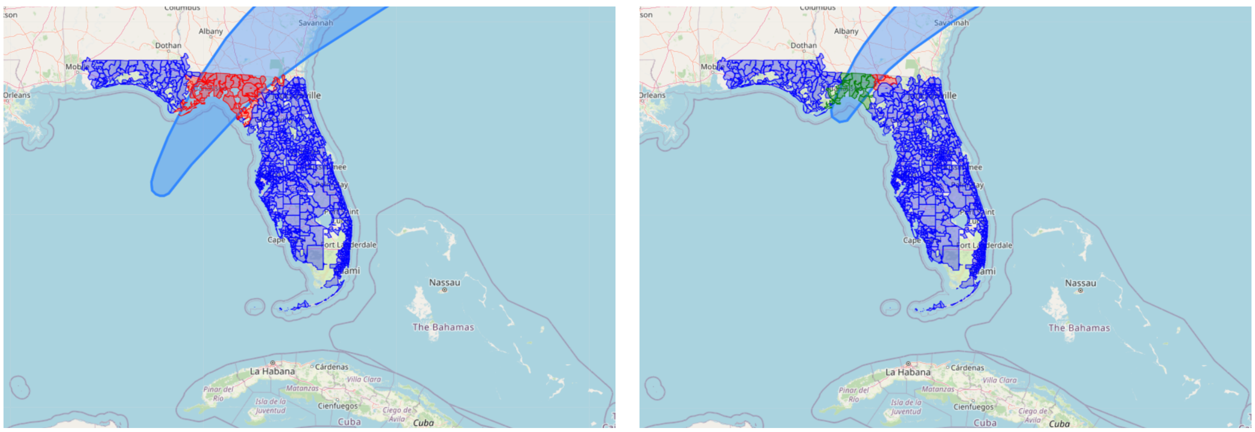
In contrast, the control group includes all ZIP codes (Census Tracts) that remained completely outside the forecast cone throughout the storm's progression. This ensures that the behavior and outcomes in these areas were far more likely not to be influenced by the forecast or the storm itself, allowing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

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



(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 Tract) 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 threat, we created a control group whose behavior and outcomes were assumed to be unaffected by hurricane warnings or the storm itself. Treated Group (Green): This group inlcudes ZIP codes (Census Tract) located within the hurricane forecast cone. However, only areas that remained in the forecast cone up until the closes forecast cone (3 hours prior to impact) are included.

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.

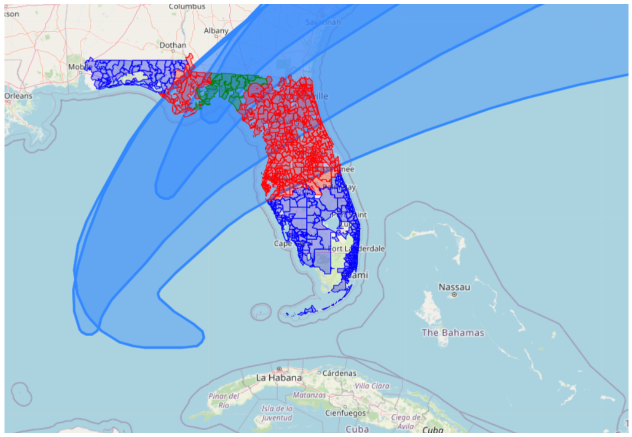


Figure 4: Dynamic 5-Day Forecast Cone

Unfortunately, the forecast cone is only available starting from 2008. However, hurricane paths are available, and some of the most significant hurricanes occurred in 2004 and 2005. To address this limitation, we extracted the hurricane paths from the NHC website and reconstruct the forecast cone, mirroring the cone shape at the initial forecast point. This approach allows us to estimate the impacted locations effectively.

2.2.2 Event Study Framework

To construct the data for the event study, we treat each hurricane and tropical storm as a separate case. We merge the treated group with evictions data at the census tract level for six months before and six months after the event. For the treated group, we use the exact storm date for each census tract to calculate the relative event date as the eviction date minus the storm date. In the control group, since there is no storm date, we assign a pseudo-date: for long-duration storms, we use the median storm date, and for storms lasting only one day, we use the same storm date as the treated group. To capture the difference between the eviction date and the storm date, we calculate the relative event date in weeks and also in months. 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:

$$y_{it} = \left(\sum_{j=-m,\ldots,0,\ldots,n} \gamma_j \cdot D_{i,t-j} \right) + \alpha_i + \delta_t + \beta \cdot X_{it} + \epsilon_{it} \tag{1}$$

In this equation, y_{it} represents the outcome variable for unit i at time t. The term $D_{i,t-j}$ is an indicator variable that equals 1 if the event occurred j periods before the observation's time t, and 0 otherwise. The coefficients γ_j capture the dynamic effects of the event over time. For $j > 0$, these coefficients show the post-event impact, while for $j < 0$, they provide a measure for pre-event trends. The summation term $\sum_{j=-m,\ldots,0,\ldots,n} \gamma_j \cdot D_{i,t-j}$ thus captures the event study terms over all pre- and post-event periods.

The model also includes α_i, which denotes unit-specific fixed effects to account for time-invariant heterogeneity across units, and δ_t, which represents time fixed effects to control for time-specific shocks common to all units. Additionally, $\beta \cdot X_{it}$ is an optional term incorporating control variables X_{it}, and ϵ_{it} is the error term. Together, these terms ensure the model effectively isolates the impact of the event while accounting for confounding factors and unobserved heterogeneity.

In our setup, we conducted multiple event studies focusing on evictions, filings, households at risk, transaction volumes, and default rates for both treated and control groups. These models incorporate geographic and time fixed effects to account for unobserved heterogeneity.

For the evictions data, which is weekly and at the census tract level, we used census tracts as the geographic fixed effect. Considering the eviction process spans several weeks, we included calendar months and years as time fixed effects to account for seasonality and year specific impacts. Conversely, for the payday loans data, which is daily and at the ZIP code level, we used ZIP codes as the geographic fixed effect and days of the week and years as the time fixed effects.

Given the occurrence of many hurricanes and storms, some of which occurred in the same year, we took some steps to mitigate potential biases in the analysis. For events that occurred within the same year, we sorted them by date and chose the first occurrence as the event start date. This approach helps mitigate biases that may arise from applying Two-Way Fixed Effects (TWFE) models to multiple treatments within the same year.

A similar approach was applied to the control group. Since each event has both treated and control groups, combining them may result in overlap—for example, the control group for one event could include locations that are part of the treated group for another event in the same year. To confirm that the treatment impact was isolated, we remove any control group locations that matched treated group locations from previous events in the same year. This ensures that any control group is untouched by treatment from other events.

2.2.3 Difference-in-Differences Framework

To confirm the event study results, we conducted 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:

$$Y_{it} = \alpha + \beta \cdot \text{Group}_i + \gamma \cdot \text{Post}_t + \delta \cdot (\text{Group}_i \times \text{Post}_t) + \mu_i + \lambda_t + \eta_t + \epsilon_{it} \tag{2}$$

where Y_{it} denotes the dependent variable, representing (Evictions, filing, atrisk, transaction volume, defaults) observation i at time t. Group_i indicator variable for the treatment group, Post_t indicator variable for the post-treatment period. And μ_i, λ_t, η_t denotes the fixed effects of zip code (or Census Tract), month, and year, respectively.

The group is a binary variable in this setup, taking 1 for the treated group and zero for control. The Post variable takes 1 in the post-event and zero otherwise.

Finally, to shed light on the FEMA aid role, we conduct an interacted difference-in-difference comparison of three groups: control, treated without FEMA, and treated with FEMA. For this approach, the control group is the same as the control group in the earlier difference-in-difference; in contrast, we divide the last treated group into two groups. The treated group is ZIP codes impacted by hurricanes or tropical storms but didn't receive FEMA aid, whereas the FEMA group is ZIP codes impacted by hurricanes and tropical storms that received FEMA aid.

In the next section, we present the findings from the eviction and payday loan datasets analysis, focusing on the impact of hurricanes and FEMA aid on eviction, transactions and defaults. The results are consistent with prior findings in the literature, particularly on eviction trends, which also showed significant effects before financial transactions and defaults. Event study models were first employed to examine temporal trends, followed by Difference-in-Differences (DID) and interacted Difference-in-Differences models to estimate causal effects. These models control for census tract and/or ZIP code-level variations, as well as month and year fixed effects. The results provide insights into the interplay between hurricane exposure, FEMA aid, and payday loan outcomes, highlighting the broader economic impact of hurricanes and tropical storms.

3 Results

To set the baseline for the event-study and difference-in-difference results we present, we report the pre-event weekly averages from both the evictions and payday loans datasets. Table 4 shows the pre-event weekly average for each dependent variable used in the difference-in-difference. And table 5 shows the pre-event weekly average for each dependent variable used when further split by ZIP codes that received FEMA rental assistance and those that did not.

Variable	**Control Group**	**Treated Group**
Eviction Rate (Renters)	1.540	1.354
Filing Rate (Renters)	2.280	2.200
At-Risk Rate (Renters)	2.151	2.048
Number of Transactions	46.100	44.383
Default Rate	1.424	1.645

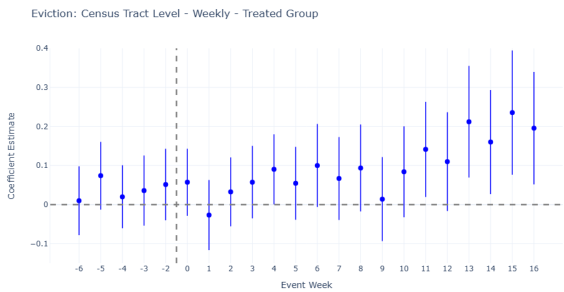
Table 4: Summary Statistics for Pre-Event Period used in difference-in-difference

Variable	**Control**	**Treated - No FEMA**	**Treated FEMA**
Eviction Rate (Renters)	1.540	1.366	1.328
Filing Rate (Renters)	2.280	2.230	2.134
At-Risk Rate (Renters)	2.151	2.070	2.000
Number of Transactions	46.100	36.619	48.919
Default Rate	1.424	1.118	1.954

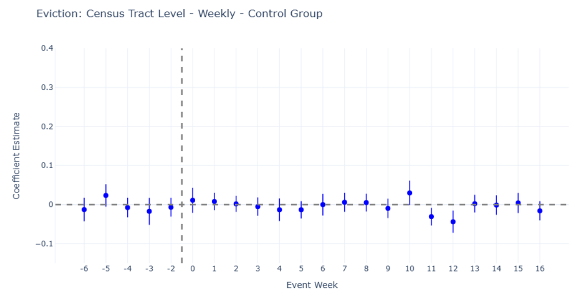
Table 5: Summary Statistics for Pre-Event Period used in interacted difference-in-difference

3.1 Eviction Analysis

The event study at the census tract level was conducted at both weekly and monthly frequencies to capture the immediate and cumulative impacts of hurricanes on evictions, filings, and at-risk households. The weekly analysis reveals a significant increase in eviction rates starting from week eleven post-event, as shown in figure 5 (a). At the monthly level, eviction rates show an upward trend during the fourth and fifth months following the hurricane, with a decline observed in the sixth month, as shown in 6 (a). In contrast, the control group shows no trend at either the weekly level figure 5 (b) or the monthly level 6 (b). Filing and at-risk households also exhibit an increasing trend in the post-event period, but earlier than the eviction variable, with both starting from week four at the weekly level figure 7 and month two at the monthly level figure 8.

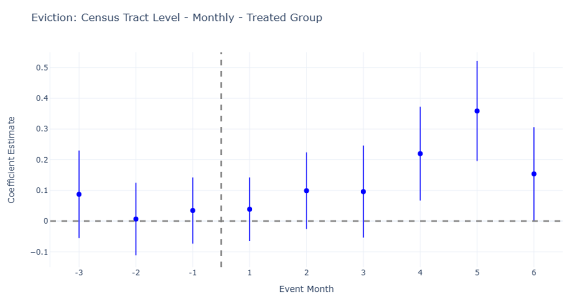


(a) Evictions: Treated - Weekly

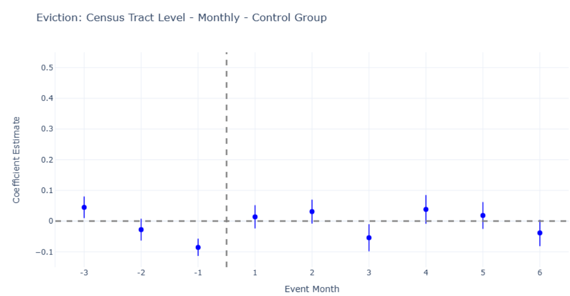


(b) Evictions: Control - Weekly

Figure 5: Event study plots at the census tract level, highlighting weekly trends for both treated and control groups. The reference variable is the week before the event (ref = -1). (a) Eviction Treated Group (Weekly): The plot displays a noticeable upward trend in eviction rates after the event, signaling significant post-event impacts in the treated group. (b) Eviction Control Group (Weekly): The plot indicates no substantial changes in eviction rates between pre-event and post-event periods. The trends remain steady, with variations well within the confidence intervals, suggesting an absence of event-driven effects in the control group.

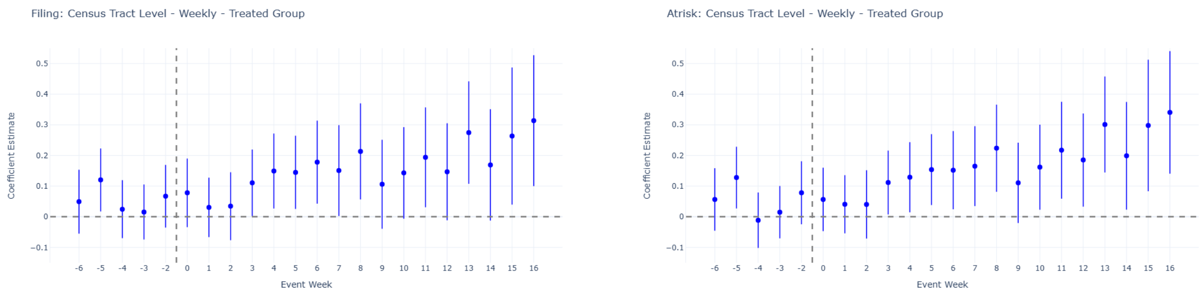


(a) Evictions: Treated - Monthly



(b) Evictions: Control - Monthly

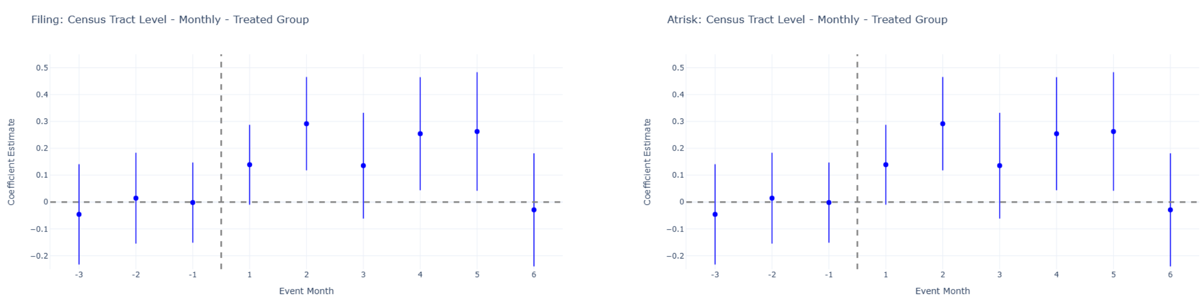
Figure 6: Event study plots at the census tract level, highlighting monthly trends for both treated and control groups. The reference variable is the month of the event (ref = 0). (a) Eviction Treated Group (Monthly): The plot reveals a clear upward trend in eviction rates following the event, with significant increases observed in months 4 and 5. A slight decline is noted at month 6. (b) Eviction Control Group (Monthly): The plot demonstrates a stable trend, with minor fluctuations and no substantial changes in eviction rates between the pre-event and post-event periods, suggesting no significant event-driven effects in the control group.



(a) Filings: Weekly

(b) At Risk: Weekly

Figure 7: Event study plots at the census tract level, highlighting weekly trends in both filing and at-risk in the treated group. The reference variable is the week before the event (ref = -1). (a) Filing Treated group (Weekly): The plot reveals a clear upward trend in filing rates after the event, with significant increases observed starting from week 4. (b) At risk Treated group (Weekly): The plot estimator shows almost the same pattern as filing.



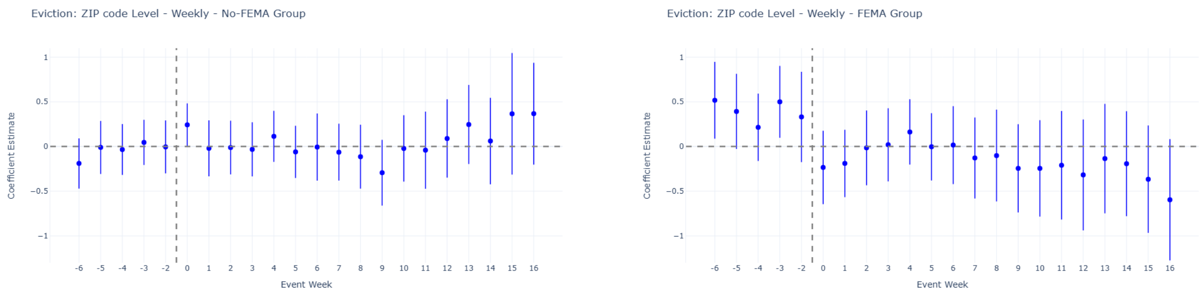
(a) Filings: Monthly

(b) At Risk: Monthly

Figure 8: Event study plots at the census tract level, highlighting monthly trends in both filing and at-risk in the treated group. The reference variable is the month of the event (ref = 0). (a) Filing Treated group (Monthly): The plot presents a clear upward trend in filing rates after the event, with large increases observed starting in month 2. A slight decline is observed in month 6. (b) At risk Treated group (Monthly): The at-risk plot shows the same pattern as filings.

3.1.1 Evictions and FEMA

We next investigate the resultant availability of FEMA aid for hurricanes and tropical storms that were declared FEMA eligible. We then conducted the same event study on both FEMA and NO-FEMA groups. We observe that the FEMA group figure 9 (b) shows a decreasing trend, whereas the NO-FEMA group figure 9 (a) exhibits an increasing trend. To confirm these results, we performed difference-in-difference and FEMA interacted difference-in-difference analyses to supplement our event-study results.



(a) Evictions: No FEMA

(b) Evictions: FEMA

Figure 9

3.1.2 Difference-in-differences

Dependent Var.	**Eviction**	**Filing**	**At-risk**
Group	-0.1685***	0.0307	0.0086
	[0.029]	[0.036]	[0.035]
Post	-0.0320	-0.0172	-0.0192
	[0.020]	[0.026]	[0.025]
Group:Post	0.1073**	0.1575**	0.1727***
	[0.048]	[0.061]	[0.059]
ZIP Code Fixed Effect	Y	Y	Y
Time Fixed Effect	Y	Y	Y

Table 6: Difference-in-Differences Analysis of Eviction Outcomes at the ZIP Code Level

Importantly, the interaction term Group:Post (Table 6) has a positive and significant coefficient of 0.1073 ($p \leq 0.05$), indicating that treated ZIP codes experienced a 0.1073 per 1000 renters increase in the number of weekly evictions in the post-event period relative to control ZIP codes. When compared to their pre-event baseline, this represents a 7.93% relative increase in the rate of evictions, where the weekly pre-event average across ZIP codes of 1.3537 weekly evictions per 1000 renters. Similarly, both weekly filings and individuals labeled as at-risk saw a marked increase post disaster event.

Dependent Var.	Eviction	Filing	At-Risk
Treated Group (Baseline)	-0.2329***	0.0073	-0.0188
	[0.034]	[0.043]	[0.041]
FEMA Group (Baseline)	-0.0468	0.0768	0.0622
	[0.045]	[0.057]	[0.055]
Post-Treatment	-0.0352*	-0.0178	-0.0200
	[0.020]	[0.026]	[0.025]
Treated Group × Post-Treatment	0.1135**	0.1916***	0.2078***
	[0.057]	[0.072]	[0.069]
FEMA Group × Post-Treatment	0.0973	0.0833	0.0965
	[0.082]	[0.104]	[0.101]
ZIP Code Fixed Effect	Y	Y	Y
Time Fixed Effect	Y	Y	Y

Table 7: Interacted DiD Analysis: Changes in Eviction Outcomes Across Groups

Table 7 presents the results of an interacted difference-in-differences analysis examining eviction outcomes across three groups: Control, Treated (no FEMA), and FEMA (treated with FEMA). As only treated ZIP codes (i.e. those that faced hurricane or storm events) are eligible for FEMA aid, we cannot conduct a triple DiD under our construction of a control group, so we instead compare both FEMA and non-FEMA eligible disaster events under the same specification to a single control group.

We observe that the interaction term Treated Group × Post-Treatment (0.1135, $p \leq 0.05$) indicates that treated ZIP codes experienced a relative increase in eviction rates after the event to the control group. This corresponds to 8.31% increase when compared to the pre-event average eviction rate in treated areas. In contrast, the interaction term for FEMA-aided ZIP codes (FEMA Group × Post-Treatment, 0.0973) is not statistically significant. This result is further validated in the coefficient reported for filings for eviction in non-FEMA treated ZIP codes (Treated Group × Post-Treatment, 0.1916, $p \leq 0.01$) and FEMA treated ZIP codes having lower magnitude and non statistically significant results (FEMA Group × Post-Treatment, 0.0833).

These findings underscore the disparate impacts of the hurricane on treated areas and FEMA-aided areas. The significant post-event increase in eviction rates in treated ZIP codes highlights the vulnerability of areas without federal assistance, whereas the absence of a significant effects observed in FEMA-aided ZIP codes suggests that federal aid may have helped mitigate the adverse effects of the hurricane on eviction rates. This suggests meaningful household outcomes into the role of disaster assistance programs in reducing evictions during the post-disaster recovery.

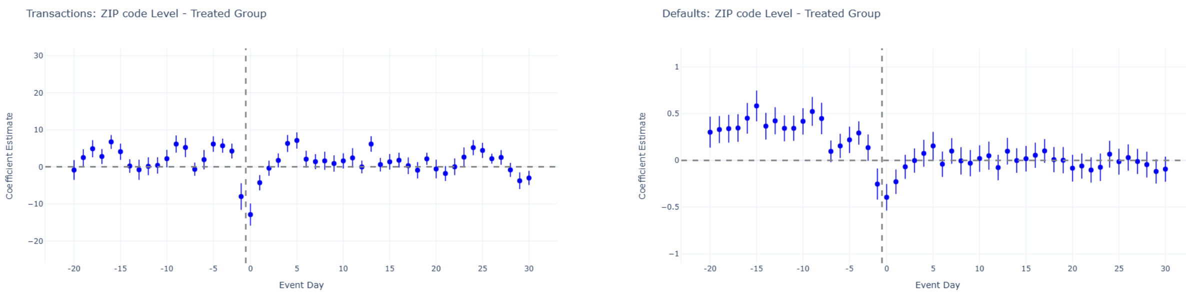
4 Payday Loans

Following the analysis of eviction outcomes, we examine the dynamics of household payday loan activity in the context of hurricane-affected areas. Payday loans often serve as a financial lifeline for households experiencing immediate cash flow constraints. By analyzing transaction volumes and default rates, we aim to uncover how financial distress evolves in disaster-stricken communities and its potential interplay with broader housing instability. The results shed light on the short-term reliance on payday loans and the subsequent financial challenges faced by households during the recovery period.

4.1 Event Study

The results reveal a significant impact on payday loan transaction volumes (figure 10a) and defaults (figure 10b) among the treated group. Before the hurricane event, in days prior (≤ -2), the volume of payday loan transactions remained relatively stable, exhibiting minor fluctuations. However, immediately following the hurricane, a sharp decline in transaction volume is observed, suggesting that the disaster disrupted typical borrowing patterns. This disruption could stem from reduced access to payday loan services. Over time, transaction volumes begin to stabilize.

Interestingly, the pattern for defaults diverges from expectations. Post-event, default rates are lower compared to pre-event levels, which may reflect the swift and effective intervention of FEMA in providing financial relief to the affected population. To better understand this dynamic, and following a similar approach used in eviction studies, we divided the treated group into two subgroups: ZIP codes that received FEMA aid and those who did not.



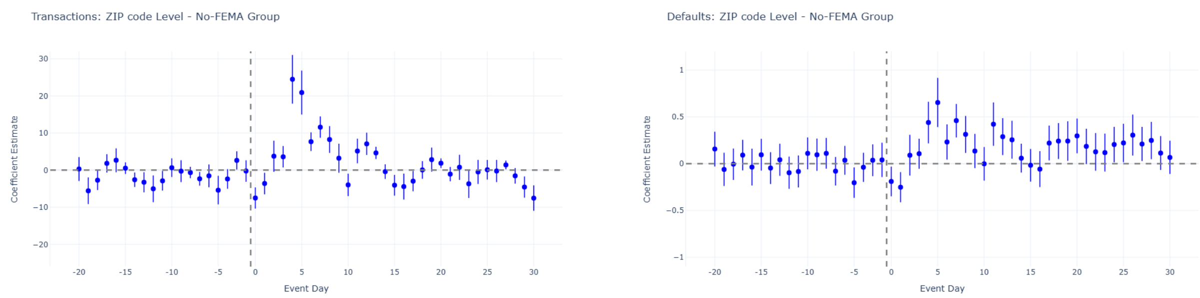
(a) Transaction Volume (b) Defaults

Figure 10

The results for payday loan transactions in ZIP codes that did not receive FEMA aid (figure 11a) reveal a distinct pattern in borrowing behavior following the hurricane. Prior to the hurricane (days ≤ -1), the volume of payday loan transactions was stable, with minor fluctuations reflecting typical variability in financial activity. However, immediately after the hurricane, there is a notable spike in transaction volumes, which peaks shortly thereafter. This sudden increase suggests that individuals in areas without FEMA aid may have relied more heavily on payday loans to address urgent financial needs caused by the disaster.

Over time, transaction volumes begin to decline but remain elevated compared to pre-hurricane levels for several periods, indicating a prolonged dependence on short-term financial solutions in the absence of external aid. This pattern underscores the critical role that financial assistance programs, such as FEMA, play in mitigating the immediate and long-term financial hardship faced by disaster-affected populations. The reliance on payday loans in these ZIP codes highlights the financial vulnerability of individuals in regions lacking additional liquidity, emphasizing the importance of targeted disaster relief to alleviate financial strain.

Similarly, the default rates (figure 11b) exhibit a significant disruption. Before the hurricane, default rates followed a relatively consistent pattern. However, post-hurricane, there is a noticeable increase in default rates, peaking shortly after the event. This rise suggests that the hurricane imposed substantial financial stress on borrowers, making it challenging for them to meet repayment obligations. Although default rates eventually stabilize, they remain slightly higher than pre-hurricane levels, indicating a sustained financial strain on the affected population. These findings highlight the dual impact of hurricanes on financial behavior, marked by increased financial distress and defaults, emphasizing the critical need for timely financial support and disaster relief measures to mitigate such challenges in the aftermath of natural disasters.

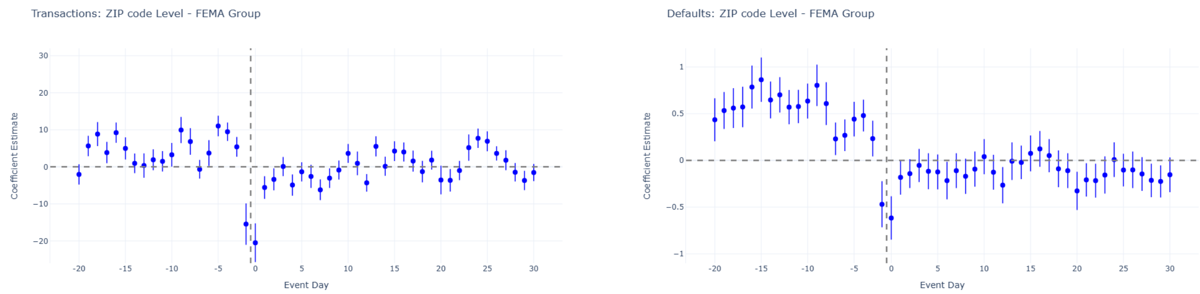


(a) Transaction Volume (b) Defaults

Figure 11: Event study plots demonstrating the impact of the hurricane on financial behavior in areas without FEMA aid. (a) Transaction volumes: There appears a significant increase in transaction volumes following the hurricane (event_date $\geq$ 0), peaking shortly after the event. This reflects heightened reliance on payday loans among households lacking FEMA support. (b) Default rates: The TWFE-estimator shows a notable increase in default rates immediately after the hurricane (event_date $\geq$ 0), indicating financial distress in areas without FEMA aid. Default rates remain elevated compared to pre-hurricane levels.

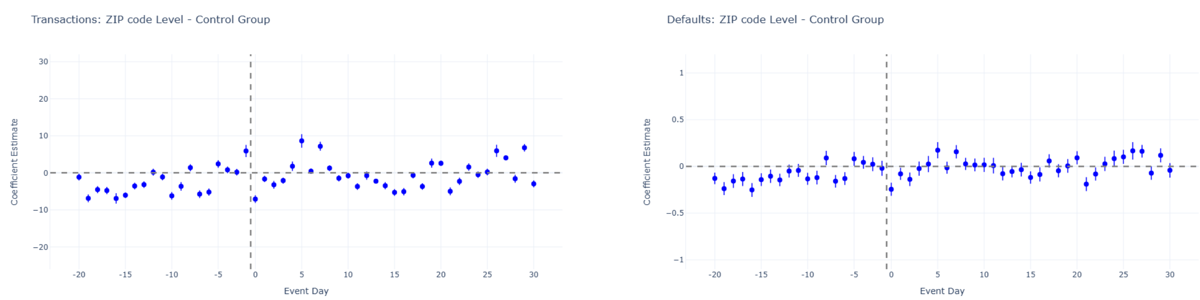
In areas that received FEMA aid (figure 12), there is no discernible increase in payday loan transactions or defaults following the hurricane. Default rates after the hurricane exhibit minor fluctuations; however, they remain lower than pre-hurricane levels. This pattern supports the hypothesis that FEMA's intervention effectively mitigated financial distress for households, providing critical relief and stability in the aftermath of the disaster.

These findings are further validated through an event study conducted for the control group, which shows no significant trends in either transactions figure 13 (a) or defaults figure 13 (b). This absence of substantial variation in the control group further suggests that the observed changes in the treated group are directly attributable to the case of hurricane events where FEMA aid plays a role in alleviating financial strain.



(a) Transaction volumes (b) Default rates

Figure 12: Event study plots illustrating the role of FEMA in the aftermath of a hurricane. (a) Transaction volumes: A significant increase is observed in the week leading up to the hurricane, likely driven by NOAA forecast information prompting preparedness behaviors among households. However, transaction volumes drop sharply on the day of the event and the day before, possibly due to store closures. In the days following the event, transaction volumes rebound and remain elevated with some fluctuations. (b) Default rates appear lower in the post-event period relative to the pre-period.



(a) Transaction volumes (b) Default rates

Figure 13: Event study plots for the control group. (a) Transaction volumes: The plot shows a stable demand for payday loans with minor fluctuations. (b) Default rates: No significant differences are observed between pre-event and post-event periods within the control group.

4.2 Difference-in-differences

We also conduct a difference-in-difference and an interacted difference-in-difference, between treated and control group, and between control, treated, FEMA groups, the same way as we did with evictions.

Table 8 presents the results of a difference-in-difference analysis on payday loan transaction volumes and default rates. In the post hurricane period, the positive and statistically significant coefficient for the interaction term Group × Post (2.4903, $p \leq 0.001$) indicates a relative increase in transaction volume in the treated group. This representing a 5.61% increase when compared to the pre-event average transaction volume in the treated group. This finding suggests a notable rise in payday loan demand in treated areas, possibly driven by financial strain following the event. After the hurricane, the negative and statistically significant coefficient for Group × Post (-0.1166, $p \leq 0.001$) highlights a reduction in default rates in treated areas relative to the control group. Specifically, this corresponds to approximately 7.09% decrease compared to the pre-hurricane average default rate in the treated group. While this suggests a reduction in defaults, our next analysis provides evidence that this is largely driven by FEMA assistance in alleviating financial strain in areas impacted by the hurricane.

Dependent Var.	**Transaction Volume**	**Defaults**
Group	-11.4203***	-0.1656***
	[0.382]	[0.019]
Post	-8.7649***	-0.2056***
	[0.246]	[0.013]
Group × Post	2.4903***	-0.1166***
	[0.418]	[0.021]
ZIP Code Fixed Effect	Y	Y
Time Fixed Effect	Y	Y

Table 8: Difference-in-Differences Analysis: Changes in Transaction and Default Outcomes Across Groups

To further explore the role of FEMA aid, we conducted an interacted difference-in-differences analysis, dividing the data into three categories: control, treated (areas without FEMA aid), and FEMA (areas with FEMA aid). This approach allows us to compare areas that received FEMA aid and those that did not to the baseline control group.

Table 9 illustrates the outcomes of the interacted difference-in-differences analysis on payday loan transaction volumes and defaults. In the post-event period, the coefficient for Treated Group × Post-Treatment (4.5395, $p \leq 0.01$) indicates a substantial relative increase of 12.38% in transaction volumes for the treated group compared to the control and the pre-event daily average. This suggests that areas without FEMA aid experienced increased financial stress, resulting in a greater reliance on payday loans. On the other hand, the FEMA Group × Post-Treatment coefficient (0.5376) was not statistically significant, indicating no meaningful change in transaction volumes for FEMA-aided areas. These results highlight the differential impact of FEMA assistance, with aided areas not experiencing the same surge in loan demand observed in areas that did not receive FEMA aid.

Additionally, in examining default rates and the role of FEMA aid in alleviating financial distress we find similar bifurcation. Post-hurricane, the coefficient for Treated Group × Post-Treatment (0.2115, $p \leq 0.01$), a 18.9% increase, which reveals a notable increase in defaults for the treated group. This reflects the financial strain faced by areas without FEMA assistance, as default rates increased relative to both the control and FEMA-aided groups. In contrast, the FEMA Group × Post-Treatment coefficient (-0.3669, $p \leq 0.01$), an 18.8% relative decrease to pre-event average, demonstrates a significant reduction in defaults for FEMA receiving areas compared to the control group. This finding underscores the effectiveness of FEMA aid in mitigating financial hardship and preventing defaults in hurricane-affected areas.

Overall, after the hurricane, the treated group saw a significant increase in payday loan transactions and default rates, reflecting heightened financial challenges. Conversely, FEMA aid helped mitigate these negative effects, stabilizing transaction volumes and substantially reducing defaults. These findings underscore the vital role of FEMA assistance in alleviating financial distress and fostering economic resilience in communities affected by disasters.

Dependent Var.	**Transaction Volume**	**Defaults**
Treated Group (Baseline)	-11.7407***	-0.3289***
	[0.493]	[0.025]
FEMA Group (Baseline)	-12.2832***	-0.0969***
	[0.517]	[0.026]
Post-Treatment	-8.6587***	-0.1891***
	[0.246]	[0.013]
Treated Group × Post-Treatment	4.5395***	0.2115***
	[0.599]	[0.031]
FEMA Group × Post-Treatment	0.5376	-0.3669***
	[0.520]	[0.027]
ZIP Code Fixed Effect	Y	Y
Time Fixed Effect	Y	Y

Table 9: Interacted Difference-in-Differences Analysis: Changes in Transaction and Default Outcomes Across Groups

5 Tropical Storms

We show that in addition to hurricane events that do not receive FEMA aid, that disaster events that reach the intensity of tropical storms but not hurricanes also have elevated eviction and payday loan usage. As tropical storms rarely receive FEMA aid, we believe this result to be consistent with our result documenting household economic hardship for hurricanes that do not receive FEMA aid. That is, not receiving FEMA aid is correlated with being less severe in disaster intensity, but this does not mean that this absolves households of economic hardship. In fact, we find that our result is largely similar to hurricanes that do not receive FEMA aid. This suggests that the counterfactual economic hardship for severe disasters had they not received FEMA aid would likely have been even larger.

We conducted the same analysis as we did in previous sections but focus solely on tropical storms. Eviction rates increase after tropical storms, and households turn to payday loans to cover their emergency needs and that default rates rise shortly after the tropical storm event.

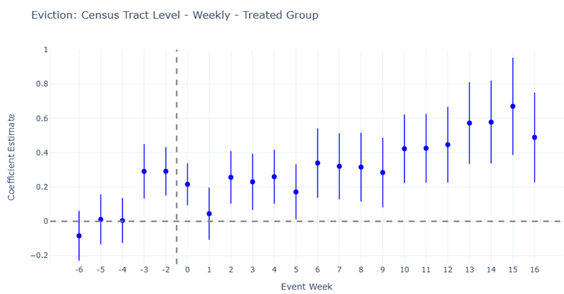
For tropical storms, FEMA aid only occurred from a single tropical storm event (FAY 2008). As a result for our analysis of tropical storm events, we do not include FAY except when we compare all hurricanes and tropical storms for the triple difference-in-differences (Table 17) analysis. w

Tropical Storm	**Year**	**Duration**
BONNIE	2004	Aug 03 – Aug 14
ALBERTO	2006	Jun 10 – Jun 19
FAY	2008	Aug 15 – Aug 28
CLAUDETTE	2009	Aug 16 – Aug 17
IDA	2009	Nov 04 – Nov 11
BONNIE	2010	Jul 22 – Jul 25
BERYL	2012	May 25 – Jun 02
DEBBY	2012	Jun 23 – Jun 27
ANDREA	2013	Jun 05 – Jun 08
COLIN	2016	Jun 05 – Jun 08
EMILY	2017	Jul 30 – Aug 02
ALBERTO	2018	May 25 – May 31

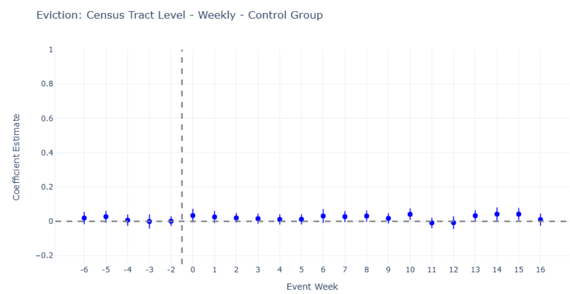
Table 10: Tropical Storms and Their Durations

5.1 Evictions

Figure 14 shows a noticeable increase in evictions post-event, whereas there is no significant change in the control group. Similar results were observed at the monthly level. Figure 15 shows a significant rise after the event lasting until the sixth month, whereas the control group exhibited minor fluctuations consistent with the normal eviction trend.

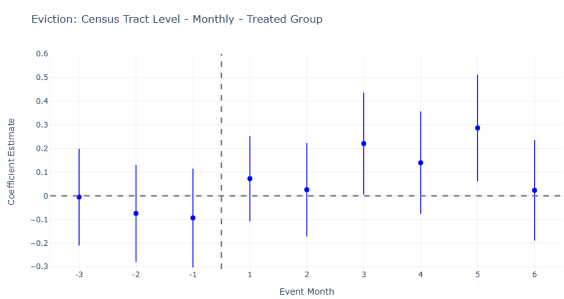


(a) Evictions: Treated - Weekly

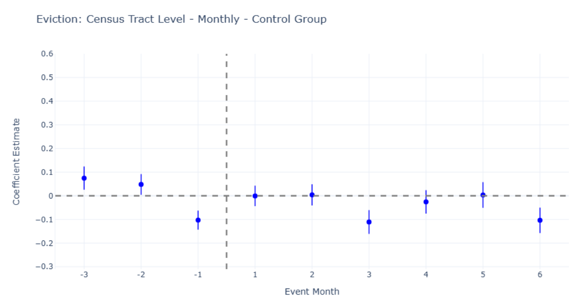


(b) Evictions: Control - Weekly

Figure 14

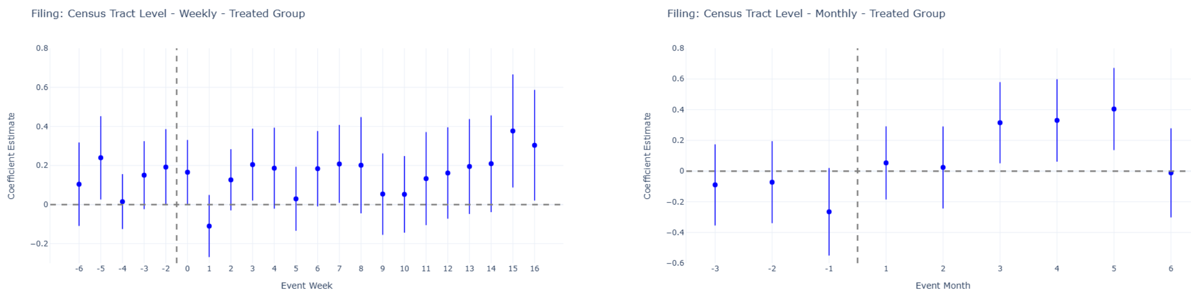


(a) Evictions: Treated - Monthly



(b) Evictions: Control - Monthly

Figure 15



(a) Filing: Treated - Weekly

(b) Filing: Treated - Monthly

Figure 16

5.1.1 Difference-in-Differences

To confirm the event study results and show causality, we conducted a difference-in-differences analysis. Table 11 presents the weekly difference-in-differences results, highlighting the increase in post-disaster outcomes with a significantly positive Group:Post coefficient. The coefficient becomes larger as the post period shifts from 0 weeks to 8, 10, and 11 weeks. Even when the window period is changed, the Group:Post coefficient remains significant. A similar observation is noted at the monthly level, as shown in Table 12. We find a similar effect directionally for eviction filings in table 14, but not as clearly statistically significant except at the monthly level, which can also be seen visually in the event-study plots 16.

Weekly-Window	**[-6 : +16]**	**[-6 : +16]**	**[-6 : +16]**	**[-6 : +16]**
Post-period	≥ 0	≥ 8	≥ 10	≥ 11
Dependent Var.	**Eviction**	**Eviction**	**Eviction**	**Eviction**
Group	-0.1759***	-0.1562***	-0.1639***	-0.1665***
	[0.029]	[0.021]	[0.020]	[0.020]
Post	0.0140	0.0003	-0.0047	-0.0174
	[0.010]	[0.009]	[0.009]	[0.009]
Group:Post	0.0579*	0.0581**	0.0983***	0.1237***
	[0.030]	[0.027]	[0.028]	[0.030]
Census Tract Fixed Effect	Y	Y	Y	Y
Time Fixed Effect	Y	Y	Y	Y

Table 11: Weekly Difference-in-Differences Analysis of Eviction Outcomes at the Census Tract Level

Monthly-Window	[-3 : +6]	[-3 : +6]	[-3 : +6]
Post-period	≥ 0	≥ 2	≥ 3
Dependent Var.	**Eviction**	**Eviction**	**Eviction**
Group	-0.3200***	-0.3237***	-0.3367***
	[0.044]	[0.037]	[0.035]
Post	-0.0006	-0.0515***	-0.0898***
	[0.017]	[0.017]	[0.016]
Group:Post	0.0628	0.0968**	0.1513***
	[0.046]	[0.043]	[0.045]
Census Tract Fixed Effect	Y	Y	Y
Time Fixed Effect	Y	Y	Y

Table 12: Monthly Difference-in-Differences Analysis of Eviction Outcomes at the Census Tract Level

Weekly-Window	[-6 : +16]	[-6 : +16]	[-6 : +16]	[-6 : +16]
Post-period	≥ 0	≥ 2	≥ 6	≥ 10
Dependent Var.	**Filing**	**Filing**	**Filing**	**Filing**
Group	0.0493	0.0240	0.0389	0.0458*
	[0.034]	[0.031]	[0.027]	[0.024]
Post	0.0324**	0.0228*	0.0316***	0.0218**
	[0.012]	[0.011]	[0.011]	[0.011]
Group:Post	-0.0024	0.0355	0.0211	0.0059
	[0.035]	[0.033]	[0.031]	[0.034]
Census Tract Fixed Effect	Y	Y	Y	Y
Time Fixed Effect	Y	Y	Y	Y

Table 13: Weekly Difference-in-Differences Analysis of Filing Outcomes at the Census Tract Level

Monthly-Window	[-3 : +6]	[-3 : +6]	[-3 : +6]	[-3 : +6]
Post-period	≥ 0	≥ 1	≥ 2	≥ 3
Dependent Var.	**Filing**	**Filing**	**Filing**	**Filing**
Group	0.0534	0.0335	0.0323	-0.0031
	[0.056]	[0.051]	[0.048]	[0.045]
Post	0.0322	-0.0093	-0.0187	-0.0758***
	[0.022]	[0.022]	[0.021]	[0.021]
Group:Post	-0.0204	0.0135	0.0190	0.1099*
	[0.059]	[0.056]	[0.056]	[0.058]
Census Tract Fixed Effect	Y	Y	Y	Y
Time Fixed Effect	Y	Y	Y	Y

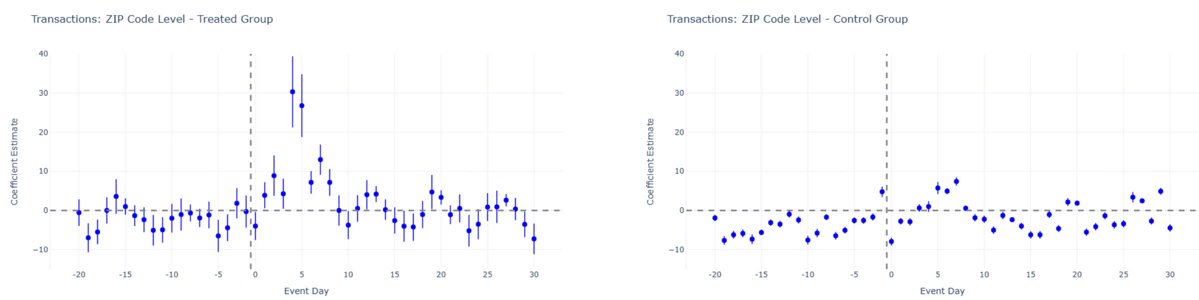
Table 14: Monthly Difference-in-Differences Analysis of Filing Outcomes at the Census Tract Level

5.2 Payday Loans

Transaction volume and default rate are two key variables that shed light on household financial liquidity and credit demand. We conducted event studies followed by a difference-in-differences analysis to illustrate the financial distress faced by households.

5.2.1 Event Study

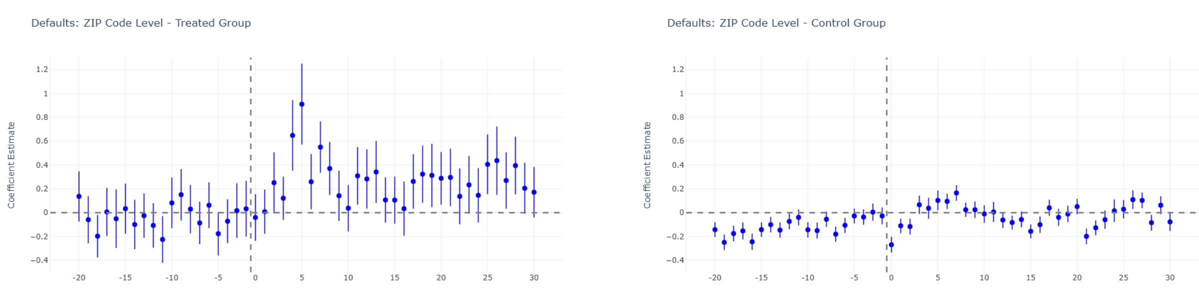
Figure 17 shows how transaction volume changes over time in the treated and control groups, proving the need for cash after the event in the treated group as transaction volume increases in the post-event period, whereas it remains stable with minor fluctuations in the control group. The same pattern is shown in default rates, as Figure 18 illustrates, where default rates rise after the event in the treated group, in contrast to the control group, which shows no significant change.



(a) Transaction Volume: Treated Group

(b) Transaction Volume: Control Group

Figure 17



(a) Defaults: Treated Group

(b) Defaults: Control Group

Figure 18

5.2.2 Difference-in-differences

Table 15 presents the difference-in-difference results for transaction volume and default rate across all tropical storms. These results confirm the event study findings, showing a positive and significant Group:Post coefficient for both transactions and defaults.

Dependent Var.	**Transaction Volume**	**Defaults**
Group	-5.1474***	-0.2251***
	[0.573]	[0.028]
Post	-4.3836***	-0.0590***
	[0.235]	[0.012]
Group:Post	3.8487***	0.2229***
	[0.693]	[0.034]
ZIP Code Fixed Effect	Y	Y
Time Fixed Effect	Y	Y

Table 15: Difference-in-Differences Analysis: Changes in Transaction and Default Outcomes Across Groups

To confirm the role of FEMA in reducing evictions post-disaster, we conduct a Difference-in-Differences analysis comparing the set of tropical storms that received FEMA to the non-FEMA group. For the tables 16 and 17, we run the difference-in-differences solely on the treated; where the treated group is divided into two subgroups: FEMA and non-FEMA. As Table 16 shows, the FEMA:Post coefficient is -0.1706 ($p < 0.05$), suggesting that ZIP codes receiving FEMA aid experienced fewer evictions. Moreover, when controlling for the MAXWIND effect as a measure of storm intensity, the coefficient becomes slightly larger (-0.1748, $p < 0.05$), further supporting the role of FEMA assistance in reducing evictions post-disaster.

Dependent Var.	**Eviction**	**Eviction**
FEMA	0.4940***	0.5312***
	[0.119]	[0.160]
Post	0.0029	0.0091
	[0.069]	[0.071]
FEMA:Post	-0.1706**	-0.1748**
	[0.083]	[0.083]
MAXWIND Fixed Effect	N	Y
ZIP Code Fixed Effect	Y	Y
Time Fixed Effect	Y	Y

Table 16: Difference-in-Differences Analysis of Eviction Outcomes at the ZIP Code Level

Expanding the analysis to add back hurricanes, we study a Triple Difference-in-Differences framework, we introduce the storm variable, which equals 1 if the event is a tropical storm and 0 if it is a hurricane. As shown in Table 17, the FEMA:Post coefficient remains negative (-0.2533, $p < 0.10$) and becomes slightly larger when controlling for storm intensity (-0.2649, $p < 0.10$), reinforcing the finding that ZIP codes receiving FEMA aid experience fewer evictions post-disaster. However, the FEMA:Post:Storm coefficient is small and not statistically significant (0.0372 and 0.0512), suggesting that the reduction in evictions associated with FEMA aid does not differ significantly between tropical storms and hurricanes.

Dependent Var.	**Eviction**	**Eviction**
FEMA	0.7076**	0.6242
	[0.353]	[0.554]
Post	0.1144	0.1155
	[0.129]	[0.130]
FEMA:Post	-0.2533*	-0.2649*
	[0.140]	[0.141]
Storm	0.4782*	0.7530**
	[0.262]	[0.381]
FEMA:Storm	-0.1134	-0.0044
	[0.398]	[0.636]
Post:Storm	-0.1273	-0.1297
	[0.130]	[0.130]
FEMA:Post:Storm	0.0372	0.0512
	[0.209]	[0.209]
MAXWIND Fixed Effect	N	Y
ZIP Code Fixed Effect	Y	Y
Time Fixed Effect	Y	Y

Table 17: Triple Difference-in-Differences Analysis of Eviction Outcomes at the ZIP Code Level

To emphasize the impact of tropical storms compared to hurricanes, and given that most tropical storms were not federally declared as disasters eligible for FEMA intervention, we extend our analysis to a Triple Difference-in-Differences framework for payday loan outcomes: transaction volume and default rates. This approach allows us to measure the financial hardship faced by households during tropical storm events.

We reintroduce the control group and incorporate the tropical storm indicator to distinguish the impact of different storm intensities. As shown in Table 18, important results emerge. The Group:Post:Storm coefficient is positive and statistically significant for both transaction volume (2.3094, $p < 0.01$) and default rates (0.6063, $p < 0.01$), suggesting that payday loan borrowing and defaults increase in affected ZIP codes following a tropical storm. This finding highlights the financial vulnerability of households exposed to tropical storms, as they appear to rely more on payday loans and face greater difficulty in repayment.

Additionally, the Post:Storm coefficient is negative and significant for both outcomes, indicating that, on average, payday loan transactions and defaults decrease in the post-storm period. However, the significant Group:Post:Storm interaction suggests that this decline does not hold for the treatment group, where both borrowing and default rates rise. These results underscore the economic strain induced by tropical storms, particularly in communities already dependent on short-term credit.

Dependent Var.	**Transactions Volume**	**Defaults**
Group	-10.0222***	0.0634**
	[0.574]	[0.029]
Post	-5.6486***	0.0054
	[0.496]	[0.025]
Group:Post	-0.6793	-0.4780***
	[0.660]	[0.034]
Storm	11.9330***	0.5115***
	[0.666]	[0.034]
Group:Storm	4.8530***	-0.2137***
	[0.805]	[0.041]
Post:Storm	-4.1390***	-0.2626***
	[0.533]	[0.027]
Group:Post:Storm	2.3094***	0.6063***
	[0.890]	[0.045]
ZIP Code Fixed Effect	Y	Y
Time Fixed Effect	Y	Y

Table 18: Triple Difference-in-Differences Analysis of Payday Loan Transactions and Defaults

6 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 substitute away from higher cost credit. Overall, this suggests that major individual level household impacts such as access to housing are sensitive to the availability of emergency liquidity, supporting the need for such programs and the need to understand the availability of other forms of disaster insurance in a world where many locations will be subject to an increasing propensity of climate shock events.

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