Hurricanes and Residential Mortgage Loan Performance

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Abstract

We study the heterogenous impacts of Hurricanes Harvey and Maria on residential mortgage defaults and net severity. While Harvey causes the first 180-day delinquency rate to increase by about 20 basis points (bps) per quarter for a five-quarter period during and after the hurricane, Maria's impact is around 50 bps per quarter. The increases in mortgage defaults are consistent with the double-trigger perspective. In the case of Maria, damage-adjusted LTV, the annual increase in initial claims, and their interaction explain about 65% of the increase in the first 180-day delinquency rate. We also find that the cure rate for defaulted loans associated with Maria is about 12% lower than that associated with Harvey. More defaults and lower cure rates result in higher default rates for Maria. Furthermore, we find that while Harvey does not impact net severity significantly, Maria pushes net severity up by around 17%. Our paper highlights the importance of initial financial conditions and access to federal assistance.

1 Introduction

Hurricanes are the most damaging of the common meteorological events (Deryugina, 2017). A growing economics literature has emerged from Hurricane Katrina that struck New Orleans in 2005. See, for instance, McIntosh (2008), Groen and Polivka (2008), Vigdor (2008), Sacerdote (2012), Gallagher and Hartley (2017), and Deryugina et al. (2018). A consensus from this literature is that the catastrophic hurricane, Katrina, only had temporary and mild effects on hurricane victims as well as local economic conditions. This surprising finding is explained by government disaster aid and social insurance (Deryugina, 2017; Gallagher and Hartley, 2017). Recently, Billings, Gallagher, and Ricketts (2020) examine Hurricane Harvey, and document significant heterogeneity in the individual financial impacts associated with initial financial conditions and inequalities in access to federal assistance.

In this paper, we extend the economics literature on hurricanes by focusing on heterogenous impacts of hurricanes on residential mortgage performance. First, it is important to understand the impact of hurricanes on residential mortgage performance, as hurricanes damage properties and disrupt economic and social activities, and consequently could drive up residential mortgage defaults and credit losses, which can be costly for homeowners, leaders, and the economy (e.g., Campbell et al., 2011; Guren and McQuade, 2020).[1] Prior research (e.g., Overby, 2007; Gallagher and Hartley, 2017) provides evidence that mortgage foreclosures in New Orleans dropped after Hurricane Katrina. We contribute to the literature by comprehensively examining not only residential mortgage defaults but also net severity, following two recent catastrophic hurricanes in 2017, namely Hurricane Harvey that submerged the middle Texas coast and Hurricane Maria that stuck entire Puerto Rico.

Furthermore, we test if Hurricanes Harvey and Maria have heterogenous impacts on residential mortgage performance (i.e., different average treatment effects), which is motivated by the evidence that

[1] The impact of hurricanes on residential mortgages is recognized by the FDIC (2006) when Hurricane Katrina hit the US in 2005: "*Hurricane Katrina had a devastating effect on the U.S. Gulf Coast region that will continue to affect the business activities of the financial institutions serving this area for the foreseeable future. Some of these institutions may face significant loan quality issues caused by business failures, interruptions of borrowers' income streams, increases in borrowers' operating costs, the loss of jobs, and uninsured or underinsured collateral damage.*"

access to federal assistance was more limited for Maria victims in Puerto Rico. For instance, Willison et al. (2019) document that while the government aid amounted to $13 billion for Harvey victims 180 days after landfall, it was about $2.4 billion for Maria victims, despite that their overall damage estimates are close. The limited access to federal assistance is in part due to unprecedented strain on Federal Emergency Management Agency (FEMA)'s resources caused by the three concurrent category-four hurricanes in the 2017 hurricane season (FEMA, 2018), namely Hurricanes Harvey, Irma (that stuck Florida), and Maria. With an increasing frequency of the very most damaging hurricanes (Grinsted, Ditlevsen, and Christensen, 2019), resource strain and unequal access to federal assistance become more likely, making it particularly important to understand heterogenous impacts of hurricanes.

Empirically, we utilize a difference-in-differences (DID) identification strategy and focus on the comparison between Hurricanes Harvey and Maria. Since both hurricanes struck the US in 2017q3, our pretreatment period is from 2015q3 to 2017q2, and our treatment and posttreatment period is from 2017q3 to 2019q3. We use the historical loan-level data from two government-sponsored enterprises (GSEs), namely Fannie Mae and Freddie Mac. Our rich loan-level data allows us not only to identify residential mortgage loans in the affected areas (the treatment groups) but also to construct the control groups with propensity score matching. For both Harvey and Maria, the control groups are constructed from loans in Texas and Louisiana (i.e., two neighboring hurricane-prone states on the Gulf of Mexico) that are not affected by any major natural disasters during the sample period. Furthermore, we only include mortgage loans originated before 2017q3 to make our inferences less likely driven by composition changes. For instance, one possibility is that (local) banks in the affected areas may increase their lending (Gallagher and Hartley, 2017).[2] If young loans have different default rates and net severity relative to mature loans (Deng et al., 2000), more young loans (i.e., a change in the loan composition) could result in changes in these outcome variables after a hurricane.

[2] Koetter et al. (2020) find that local banks provide more lending to firms affected by the natural disaster. See also Berg and Schrader (2012)

We start our analysis with mortgage defaults. A default event is defined as 180 or more days past due. The impact of hurricanes on default rates depends on both the transition rate of mortgage loans from being current to 180 days delinquent. (i.e., the first 180-day delinquency rate) and the transition rate from being delinquent to current/prepaid (i.e., the cure rate).

We run the DID regressions on the first 180-day delinquency rate. For Hurricane Harvey, the first 180-day delinquency rate for the treatment group increases by 20 basis points (bps) per quarter (t = 15.70), relative to the control group, for a five-quarter period during and after the hurricane. For Hurricane Maria, its impact is an increase in the first 180-day delinquency rate of 50 bps per quarter (t = 52.94) over the same period. Given that the average first 180-day delinquency rates for the treatment groups in the pretreatment period are about 5 bps and 17 bps for Harvey and Maria, respectively, the impacts of the hurricanes on the first 180-day delinquency rates are not only statistically but also economically significant.

The double-trigger perspective of mortgage defaults suggests that mortgage defaults can be triggered by property damages which can reduce equity, economic disruptions which can increase illiquidity, and their interaction. We use SHELDUS™, a county-level hazard data set for the U.S, to approximate property damages associated with the hurricanes. We find that property damages have material impact on equity for mortgages in the top quartile of the borrower's combined loan-to-value ratio (LTV). We use initial claims from the Federal Reserve Economic Data (FRED) to measure economic disruptions. This variable does not capture the disruption caused by Harvey in Texas accurately, as this variable is only available at the state level and Harvey submerged part of, not entire, Texas. Nevertheless, these measures still provide evidence of economic mechanisms underlying the increases in the first 180-day delinquency rate. In the case of Maria, the damage-adjusted LTV, the increase in initial claims, and their interaction explain about 65% of the increase in the first 180-day delinquency rate.

Prior research (e.g., Gallagher and Hartley, 2017) finds that federal disaster assistance may help offset hurricanes' initial impact. In the case of residential mortgages, disaster assistance can help defaulted mortgages cure. For instance, hurricane victims may receive cash assistance from FEMA's Individual and Household Program, which can help reduce the impact of economic disruptions associated with hurricanes.

Relatively limited access to federal assistance for Maria victims, in part due to resource strain, could lead to lower cure rates for defaulted mortgages in Puerto Rico relative to defaulted loans associated with Harvey in Texas. We provide supporting evidence by comparing the cure rates in these two areas in two distinct periods. One period is from 2015q3 to 2016q2, during which both areas had no catastrophic hurricanes and therefore equal (zero) federal assistance. The second period is the five-quarter period during and after the 2017 hurricane season (i.e., from 2017q3 to 2018q3), during which both areas had catastrophic hurricanes but unequal access to federal assistance. We find that while the cure rate for defaulted loans in Puerto Rico is not statistically different from that in Taxes in the first period, it is about 12% lower in the second period ($t = -9.16$).

Higher first 180-day delinquency rate and lower cure rate suggest that Hurricane Maria could result in higher default rates in Puerto Rico. We provide evidence by running the DID regressions on the 180+ days delinquency rates. For Hurricane Harvey, the 180+ days delinquency rate for the treatment group increases by 10 bps ($t = 6.80$), relative to the control group, one year after the hurricane (i.e., from 2018q4 to 2019q3). For Hurricane Maria, the impact is an increase in the 180+ days delinquency rate of 91 bps ($t = 15.60$) over the same period. Given that the average 180+ days delinquency rates for the treatment groups in the pretreatment period are about 20 bps and 104 bps for Harvey and Maria, respectively, the impacts of the hurricanes on the 180+ day delinquency rates are not only statistically but also economically significant.

We next examine the impact of hurricanes on net severity. Economic and social disruptions following hurricanes could drive up net severity of foreclosured loans. For instance, disruptions could increase the length of resolution/workout and therefore drive up interest costs as well as maintenance costs of foreclosured properties. This impact should be particularly strong when limited access to federal assistance is not able to mitigate disruptions promptly. There is evidence that Puerto Rico experienced more disruptions after Maria, relative to Texas after Harvey. For instance, while Blake and Zelinsky (2018) document that about 336,000 victims lost power during Harvey (i.e. 2017q3), Pasch et al. (2019) report that even at the end of 2017 nearly half of 3.4 million residents of Puerto Rico still had no power and practically all cell phone service and municipal water supplies were also lost. To empirically quantify the impact of hurricanes on net severity, we run the DID regressions on net severity and its components. For Hurricane Harvey, net severity for the treatment group does not change significantly, relative to the control group, after the hurricane. However, for Hurricane Maria, net severity increases by about 17% ($t = 2.75$), which is due to a 6% increase in interest costs and a 11% increase in foreclosure expenses.

Our paper is related to Billings, Gallagher, and Ricketts (2020) in that both papers highlight the importance of initial financial conditions and access to federal assistance. Billings, Gallagher, and Ricketts (2020) study heterogeneity in the individual financial impacts associated with one hurricane, Harvey. We focus on heterogenous impacts across two recent catastrophic hurricanes, namely Harvey and Maria. Furthermore, we provide impact estimates on not only mortgage defaults but also net severity.

Our paper is also related to the literature on natural disasters and bank stability. Banks and regulators are increasingly concerned about the impact of natural disasters on bank stability. For instance, the Basel Committee recognizes natural disasters as an operational risk (BCBS, 2010). The Bank of England acknowledges that climate events (e.g., storms) can potentially cause large financial losses (Scott et al., 2017). Economic research on natural disasters and bank stability is still limited. Steindl and Weinrobe (1983) do not find bank runs after natural disasters in the US. Using country-level data, Klomp (2014) finds that natural catastrophes reduce the distance-to-default of banking sectors in developing countries, but not in developed economies. Noth and Schüwer (2017) examine the impact of natural disasters on U.S. banks with the bank-level data. Our paper adds to this literature by focusing on the impact of hurricanes on residential mortgage performance, a particularly important economic mechanism through which natural disasters can affect bank stability.

Our results have implications for the debate on mortgage foreclosure prevention policies. In response to the foreclosure crisis in 2007, federal and state governments used loan modifications to help reduce foreclosure and loan losses. There is a debate on effects of such policies (e.g., Bolton and Rosenthal, 2002; Campbell et al., 2011; Agarwal et al. (2017). Our findings that the disaster aid helps prevent increases in mortgage defaults and net severity following hurricanes provide fresh evidence for the debate.

The remainder of the paper is organized as follows: Section 2 describes the background and our data; Section 3 presents our empirical methodology; Section 4 examines mortgage defaults; Section 5 investigates net severity; Section 6 discusses our results.

2 Background and Data

2.1 Harvey and Maria

Hurricane Harvey - Billings, Gallagher, and Ricketts (2020) provide a detailed description of Hurricane Harvey. We outline its key features relevant for our empirical analysis in Table 1. Harvey intensified into a category-four hurricane before making landfall along the middle Texas coast on August 25th, 2017. It dropped historic amounts of rainfall of more than 60 inches over southeastern Texas, causing catastrophic flooding. "*Over 300,000 structures in the region were flooded … About 336,000 customers lost power during the hurricane*" (Blake and Zelinsky, 2018, p. 9). National Oceanic and Atmospheric Administration (NOAA) estimates that the damage from Harvey is about $125 billion.

Hurricane Maria – We summarize key features of Hurricane Maria in Table 1. Maria's center crossed the island of Puerto Rico roughly diagonally from southeast to northwest on September 20th, 2017, as a *high-end* category 4 hurricane. Winds and floods caused not only severe property damages but also substantial disruptions. "*Maria knocked down 80 percent of Puerto Rico's utility poles and all transmission lines, resulting in the loss of power to essentially all of the island's 3.4 million residents. Practically all cell phone service was lost and municipal water supplies were knocked out. At of the end of 2017, nearly half of Puerto Rico's residents were still without power, and by the end of January 2018, electricity had been restored to about 65% of the island*" (Pasch et al., 2019, p. 7). The NOAA estimate of damage from Maria is about $90 billion.

2.2 GSE loan-level data

Hurricanes, such as Harvey and Maria, mainly affect the areas close to the Atlantic and Gulf of Mexico coasts. In contrast, banks are generally geographically diversified particularly after the Riegle-Neal

Interstate Banking and Branching Efficiency Act of 1994. This makes it difficult to identify the effects of hurricanes on banks with bank-level data. Even if researchers focus on community banks that are not geographically diversified, it is still difficult to capture the impact of hurricanes with bank-level data, as changes in loan performance at the bank level after a hurricane could be due to changes in the composition of loan portfolios (as we have pointed out). This observation motivates us to use the loan-level data from two GSEs.

As part of a larger effort to increase transparency, Fannie Mae and Freddie Mac make available historical loan performance data on a portion of fully amortizing fixed-rate mortgages that they purchased or guaranteed from 2000 to 2019 (with some loans originated by sellers in 1999). Note that these mortgages, even the ones in Puerto Rico, must satisfy the same set of conditions (e.g., full documentation). That is, in the GSE data, residential mortgages in Puerto Rico are not systematically different from those from 50 states of the US.

The GSE data consists of the acquisition and performance data files.[3] The acquisition file includes static data at the time of a mortgage loan's origination and delivery to a GSE. We use the acquisition file to generate the following loan and borrower characteristic variables at origination: original unpaid principal balance (Initial loan amt), initial interest rate, the three-digit property zip code and property state (which we use to identify the location of a property), the minimum FICO score of the borrower and co-borrower (Initial FICO), the combined loan to value ratio (Initial LTV), the debt to income ratio (Initial DTI), the cash-out refinance indicator (Cashout refinancing) which is equal to 1 if loan purpose is "Cash-out Refinance" and 0 otherwise, the investment indicator (Investment) which is equal to 1 if occupancy status is "Investment" and 0 otherwise, the one-borrower indicator (One borrower) which is equal to 1 if the number of borrowers is 1 and 0 otherwise. These loan and borrower characteristics are used as the controls in propensity score matching to construct the control groups and in DID regressions.

[3] For more details on the GSE data, please refer to http://www.fanniemae.com/portal/funding-the-market/data/loan-performance-data.html and http://www.freddiemac.com/research/datasets/sf_loanlevel_dataset.html.

The performance file contains the monthly performance data of each mortgage loan from the time of a GSE's acquisition up until its current status. The file includes current loan delinquency status, zero balance code which indicates the reason the loan's balance was reduced to zero (e.g., prepaid, foreclosure), zero balance effective date, various expenses and proceeds variables associated with dispositions (which allow calculations of net severity and its components). Net loss for a loan in the GSE data is defined as Unpaid Principle Balance at Default + Accrued Interest + Total Expenses – Total Proceeds, where Total Expenses include foreclosure costs, property preservation and repair costs, asset recovery costs, miscellaneous holding expenses and credits, and associated taxes for holding property, and Total Proceeds account for net sales proceeds, credit enhancement proceeds, repurchase make whole proceeds, and other foreclosure proceeds. Net severity is defined as net loss divided by unpaid principle balance at default. We collapse the performance data from monthly to quarterly frequency, as defaults and foreclosures are sparse at the monthly frequency.

2.3 FEMA Disaster Declarations Summary and ZCTA Relationship File

We use FEMA Disaster Declarations Summary v2, which is a summarized dataset describing all federally declared disasters.[4] to identify the areas affected by Hurricanes Harvey and Maria. More specifically, a county in Texas or a municipio in Puerto Rico is defined as "affected" if it was eligible for individual disaster assistance. Based on this definition, all 78 municipios in Puerto Rico are affected by Maria, and 41 counties in Texas are impacted by Harvey.

To construct the control group for each hurricane, we focus on the areas (i.e., counties and parishes) in Texas and Louisiana that were not affected by major disasters in our sample period from 2015q3 to 2019q3. Note that all three states, namely Puerto Rico, Texas, and Louisiana, are hurricane prone and located nearby. In the same spirit of the classical study of Card and Krueger (1994), these nearby counties and parishes unaffected by disasters seem to form "a natural basis" for comparison. Livingston and Orleans

[4] https://www.fema.gov/openfema-dataset-disaster-declarations-summaries-v2.

in Louisiana experienced severe storms, tornadoes, and straight-line winds in February 2017, and a Major Disaster Declaration was declared (DR-4300). We therefore exclude these areas in constructing the control groups. Panel A of Fig. 1 shows the counties affected by Hurricane Harvey in Texas as well as the counties and parishes in Texas and Louisiana unaffected by major disasters, which we use to construct the control groups.

The affected and unaffected areas based on the FEMA data are identified at the county level. However, the GSE data only provides the first three-digit zip codes and state of properties. Therefore, to construct the treatment and control groups (i.e., residential mortgage loans in the affected and unaffected areas), we need a mapping between three-digit zip codes and counties. The particular mapping we use is 2010 ZIP Code Tabulation Area (ZCTA) Relationship File from US Census Bureau.[5] The ZCTA relationship file contains the number of house units as well as population and area in each zip code. Because one zip3 code may overlap multiple counties, we define a zip3 as affected when more than 80% of house units in the zip3 are affected. Panel B of Fig. 1 shows the zip3 codes affected by Hurricane Harvey in Texas as well as the zip3 codes in Texas and Louisiana unaffected by major disasters. The zip3 code 704 in Louisiana is excluded, because it contains Livingston and Orleans, which experienced a major disaster in February 2017. The Zip3 codes 778, 783 and 786 in Texas are also excluded, because less than 80% of house units in these zip3 codes were affected by Harvey. In summary, the treatment group for Harvey/Maria consists of the residential mortgage loans in the affected zip3's in Texas/Puerto Rico, and the corresponding control group is composed of loans from the unaffected zip3's in Texas and Louisiana.

2.4 HPI, SHELDUS™, and initial claims

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[5]To assign ZCTA codes, the Census Bureau first examined all of the addresses within each census block to define the list of ZIP Codes by block. Next, the most frequently occurring ZIP Code within each block was assigned to the entire census block as a preliminary ZCTA code. After all of the census blocks with addresses were assigned a preliminary ZCTA code, blocks were aggregated by code to create larger areas. ZCTAs were created using residential and nonresidential ZIP Codes that are available in the Census Bureau's MAF/TIGER database. In most instances, the ZCTA code is the same as the zip code for an area. For more information, please refer to https://www.census.gov/geographies/reference-files/time-series/geo/relationship-files.html#par_textimage_674173622.

The double-trigger perspective of mortgage defaults emphasizes the interaction between negative equity and illiquidity. To estimate home equity and LTV, we retrieve the (quarterly) zip3-level housing price indexes (HPI) for Texas and Louisiana from Federal House Finance Agency (FHFA).[6] For Puerto Rico, only the state-level HPI is available from FHFA. We compute the value of a property at origination as $v_{i,Origination} = \frac{Initial\ Loan\ Amount_i}{LTV_{i,Origination}}$, and its value in quarter t as $v_{i,t} = v_{i,Origination} \times \frac{HPI_{i,t}}{HPI_{i,Origination}}$ where $HPI_{i,t}$ is the zip3-level HPI if the loan is in Texas or Louisiana or the state-level HPI if the loan is in Puerto Rico. Then, $equity_{i,t} = v_{i,t} - Loan\ Amount_{i,t}$ and $LTV_{i,t} = \frac{Loan\ Amount_{i,t}}{v_{i,t}}$. Table 1 shows that while the average equity of the properties in the Harvey-affected zip3 codes as of 2017q2 (prior to the hurricane) is \$155,224, that in the Maria-affected zip3 codes is \$52,033. Therefore, Maria victims on average had substantially less equity or weaker initial conditions prior to the disaster, relative to Harvey victims.

Harvey and Maria result in property damages and therefore decreases in equity. We do not have property-level damage data that can be matched with the GSE loan data. Therefore, we use SHELDUS™, a county-level hazard data set,[7] to proximate property-level damages associated with hurricanes. More specifically, we use house units as weights from the ZCTA relationship file to convert county-level property damages to zip3-level damages. Then we use the population data in the ZCTA file to compute property damage per capita at the zip3 level. Table 1 shows that the average property damages per capita associated with Harvey and Maria are \$14,075 and \$5,102, respectively. To account for effects of property damages on home equity, we assume that the average household in the affected zip3 codes has three members, and compute the damage-adjusted LTV for the treatment-group loans for the period after 2017q2 as $LTV_{i,t} = \frac{Loan\ Amount_{i,t}}{v_{i,t} - 3 \times Damage\ per\ capita_i}$ where $Damage\ per\ capita_i$ is the zip3-level damage per capita. Table 1 shows that while Harvey on average causes a 27% decrease in equity, Maria's impact on home equity is 29%.

[6] https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx.
[7] The data is used in previous studies (e.g., Cortés and Strahan, 2017). For more details, please refer to https://cemhs.asu.edu/sheldus.

A common proxy for illiquidity is unemployment (e.g., Elul et al., 2010), although the official unemployment statistic is known to have measurement errors (Feng and Hu, 2013). We plot the unemployment rates from FRED in Puerto Rico, Texas, and Louisiana in Panel A of Fig. 2, with the vertical line indicating the 2017 hurricane season. Similar to the unemployment rate in Louisiana, the official unemployment series in Puerto Rico and Texas do not exhibit much variation associated with Maria and Harvey. In Panel B, we depict initial claims from FRED for the same three states over the same period. Interestingly, substantial increases in initial claims are observed in Puerto Rico and Texas, not Louisiana, in the 2017 hurricane season. Therefore, in this paper, we use the annual growth in initial claims as a crude measure of illiquidity. This measure does not capture the disruption caused by Harvey in Texas accurately, as this variable is only available at the state level and Harvey submerged part of, not entire, Texas. Nevertheless, it may still be more informative than the unemployment rate to capture the disruptions associated with the hurricanes. More specifically, the annual growth in initial claims in quarter *t* for state *s* is defined as $\Delta Claims_{s,t} = \frac{\sum_{k=0}^{3} Claims_{s,t-k} - \sum_{k=4}^{7} Claims_{s,t-k}}{\sum_{k=4}^{7} Claims_{s,t-k}}$ where $Claims_{s,t}$ is initial claims in quarter *t*.

3 Empirical methodology

Hurricanes are rare exogenous events to mortgage market participants, which helps explain why the flood insurance participation rate is low when participation is voluntary (Overby, 2007). This exogenous nature of hurricanes justifies the use of the difference-in-differences (DID) methodology to identify the impact of hurricanes on mortgage defaults and loan losses. Since both Hurricanes Harvey and Maria struck the US in 2017q3, our pretreatment period is from 2015q3 to 2017q2, and our treatment and posttreatment period is from 2017q3 to 2019q3. To allow time-varying impacts, we divide the treatment and posttreatment period into two sub-periods, namely 2017q3-2018q3 and 2018q4-2019q3. Our benchmark quarterly loan-level DID specification is:

$$y_{it} = \sum_{\tau=1}^{2} \alpha_\tau (T_i \times P_{\tau t}) + \beta T_i + \sum_{\tau=1}^{2} \gamma_\tau P_{\tau t} + X_{it}\delta + \varepsilon_{i,t} \tag{1}$$

where y_{it} is a performance measure of loan i in quarter t, T_i is equal to 1 for loans in the treatment group and 0 for loans in the control group, P_{1t} takes the value of 1 for the quarters between 2017q3 and 2018q3 and 0 otherwise, and P_{2t} takes the value of 1 for the quarters after 2018q3 and 0 otherwise. The vector X_{it} contains a set of borrower and loan controls commonly used in prior research (e.g., Agarwal, et al., 2015; Agarwal, et al., 2017), such as ln (Initial loan amt), Initial interest rate, Initial FICO[8], Initial DTI, Initial LTV, the one-borrower indicator, the cash-out refinancing indicator, and the investment indicator. The coefficients α_1 and α_2 measure the effects of a hurricane on the treatment group relative to the control group. As for the loan performance measures, we focus on loan defaults and net severity. In all the DID regressions, we cluster standard errors by zip3 to account for not only serial correlation within a loan but also correlation across loans in the same zip3. For ease of interpretation, we multiple all the coefficient estimates by 100 so that the estimates are interpretable as percentages.

The treatment groups for Hurricanes Harvey and Maria consist of the mortgage loans in the affected zip3 codes in Texas and Puerto Rico, respectively. We only include mortgage loans originated before 2017q3 to make our inferences less likely driven by composition changes. For both Harvey and Maria, the control groups are constructed with propensity score matching from loans in the zip3 codes of Texas and Louisiana that are not affected by any major natural disasters during the sample period. We compute propensity scores with ln (Initial loan amt), Initial interest rate, Initial FICO, Initial DTI, Initial LTV, the one-borrower indicator, the cash-out refinancing indicator, the investment indicator, and the vintage dummies on the common support, and use the nearest neighbor. Figure A1 in Appendix shows the geographic distribution of the loans in the control group for each hurricane. To validate our propensity score matching, we compare the treatment to the control groups for Harvey and Maria in the pretreatment period and report the results in Table 2. Imbens and Wooldridge (2009) suggest that researchers use the normalized

[8] Following Elul et al. (2010), FICO is entered quadratically to account for its nonlinear relationship with delinquency.

differences,[9] and imply that the two groups can be considered as sufficiently similar if the normalized differences are in the range of ±0.25.

In Panel A of Table 2, we focus on the treatment and control groups for Hurricane Harvey. The treatment group consists of 519,610 loans in the affected zip3 codes in Texas. We use propensity score matching to identify 519,610 loans in the unaffected zip3 codes in Texas and Louisiana as the control group. The borrower and loan characteristics at origination (e.g., Initial loan amt, Initial interest rate, Initial FICO, Initial LTV, Initial DTI, etc.) are very similar between the treatment and the control groups, with normalized differences below ±0.05. The loan performance measures are also similar. For instance, the 180+ days delinquency rates over the two years prior to Harvey are 20 bps and 24 bps for the treatment and the control groups, respectively, with the normalized difference of -0.0060.

In Panel B of Table 2, we compare the treatment and the control groups for Hurricane Maria. The treatment group consists of 87,391 loans in Puerto Rico, and the control group includes 87,391 matched loans in the unaffected zip3 codes in Texas and Louisiana. The borrower and loan characteristics at origination between the treatment and the control groups are comparable, with normalized differences below ±0.05. The loan performance measures are also alike. For instance, the 180+ days delinquency rates over the pretreatment period are 105 bps and 48 bps for the treatment and the control groups, respectively, with the normalized difference of 0.0463.

Note that the treatment groups for Harvey and Maria differ considerably. For instance, while the initial loan amount is on average $187,700 for the Harvey-affected loans, that amount is $117,297 for the Maria-affected loans. These differences motivate us to construct separate control groups for Harvey and Maria.

If hurricanes cause large credit losses, hurricanes may affect bank stability, as losses could spillover across institutions[10] and give rise to systemic risk. In particular, there is evidence that hurricanes are

[9] Normalized differences are calculated as “the difference in averages by treatment status, scaled by the square root of the sum of the variances" (Imbens and Wooldridge, 2009, p. 24).
[10] For instance, Goodstein et al. (2017) document contagion effects in strategic mortgage defaults.

becoming more damaging and the frequency of the very most damaging hurricanes has increased (Grinsted, Ditlevsen, and Christensen, 2019). We next examine the impacts of hurricanes on default rates and net severity, two determinants of credit losses on residential mortgages. We focus on the comparison between Hurricanes Harvey and Maria to highlight the importance of initial financial conditions and access to federal assistance.

4 Mortgage Defaults

We define a default event as 180 or more days past due. The impact of hurricanes on default rates depends on both the transition rate of mortgage loans from being current to 180 days delinquent. (i.e., the first 180-day delinquency rate) and the transition rate from being delinquent to current/prepaid (i.e., the cure rate). We examine these transition rates and resulting default rates in this section.

4.1 First 180-day delinquency rates

In Panel A of Fig. 3, we plot the first 180-day delinquency rates of the treatment and the control groups for Hurricanes Harvey (the left figure) and Maria (the right figure), with the solid line representing the treatment group and the dashed line representing the control group. First, the treatment and the control groups for Harvey (Maria) exhibit parallel trends in the pre-treatment period, suggesting that the performance of the control group is a meaningful estimate of the counterfactual performance of the treatment group in the absence of the hurricane (up to a constant difference). Second, Panel A also shows that both hurricanes have substantial impact on the first 180-day delinquency rates in the five-quarter period during and after the hurricane, particularly for Maria. Third, the first 180-day delinquency rate in neither case reverts to the pre-hurricane level one year after the hurricane, particularly for Maria, suggesting that increases in delinquency rates cannot be entirely due to the one-year forbearance policy.[11] In the case of Harvey, the first 180-day delinquency rate for the treatment group is about 5 bps in 2017q2 (prior to the

[11] See, for instance, Fannie Mae (2005). Previous research has found that delinquency rates increased dramatically in the first six months after Katrina in the affected areas (e.g., Overby, 2007), in part due to the forbearance policy.

hurricane); it peaks in 2018q1 at about 72 bps and drops to 9 bps by 2018q3 (which is still about 80% higher than the pre-hurricane level). For Maria, the pre-hurricane first 180-day delinquency rate for the treatment group is about 17 bps; the rate does not peak until 2018q2 at about 132 bps and then decreases to about 42 bps in 2018q3 (which is about 147% higher than the pre-hurricane level).

To obtain statistical inferences and to account for loan and borrower characteristics, we estimate Eq. (1).[12] The dependent variable, $y_{i,t}$, takes the value of one if loan *i* becomes 180-day delinquent for the first time in quarter *t* and zero otherwise. To ensure that we track the initial impact triggered by the hurricane rather than the cumulative effect, we drop loan observations subsequent to the first 180-day delinquency. The results for both hurricanes are reported in Table 3. We focus on the coefficient on $T \times P_1$, which captures the impact of hurricanes in the five-quarter period during and after the hurricane.

Columns (1) and (4) do not include any controls and correspond to Panel A of Fig. 3. Column (4) shows that for Hurricane Harvey, the coefficient on $T \times P_1$ is 0.196% ($t = 15.85$), suggesting that Harvey's impact on the first 180-day delinquency rate is about 20 bps on a quarterly basis in the five-quarter period during and after the hurricane. For Maria, Column (1) shows that its impact is an increase in the first 180-day delinquency rate of about 50 bps per quarter ($t = 51.95$) over the same period, which is larger (in magnitude) than that for Harvey.

In Columns (2) and (5), we include a number of loan and borrower characteristics, including log of Initial loan amount, Initial interest rate, the one-borrower indicator, the cash-out refinancing indicator, the investment indicator, Initial FICO, Initial DTI, and Initial LTV. First, the control variables generally have expected signs. For instance, higher loan amount, interest rate, DTI, and LTV and lower FICO at origination are associated with higher credit risk and therefore higher likelihood of delinquency. Second, the coefficient estimates on $T \times P_1$ for Maria and Harvey are similar as those without any controls in Columns (1) and (4).

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[12] We estimate our specifications with the OLS despite that several outcome variables (e.g., the first 180-day delinquency rate) are binary. As Agarwal et al. (2017) point out, the logit/probit estimator may result in an incidental parameters problem when there are a large number of fixed effects. We obtain qualitatively similar results when we estimate a logit specification without fixed effects (see Tables A1 and A2 in Appendix).

In Columns (3) and (6), we further account for a variety of fixed effects (FE), such as Vintage FE, Channel FE, Property-type FE, First-time buyer FE, and PMI FE. As we can see, the results do not change materially. For Hurricane Harvey, the first 180-day delinquency rate for the treatment group increases by about 20 bps per quarter (t = 15.70), relative to the control group, for the five-quarter period during and after the hurricane. For Hurricane Maria, its initial impact is an increase in the first 180-day delinquency rate of about 50 bps per quarter (t = 52.94) over the same period. Given that the average first 180-day delinquency rates for the treatment groups in the pretreatment period are about 5 bps and 17 bps for Harvey and Maria, respectively, the impacts of the hurricanes on the first 180-day delinquency rates in the five-quarter period during and after the hurricane are not only statistically but also economically significant.

4.2 Property damages and economic disruptions

In Section 4.1, we estimate the impacts of hurricanes on the first 180-day delinquency rates. In this section, we focus on economic mechanisms underlying the impacts. The double-trigger perspective of mortgage defaults suggests that mortgage defaults can be triggered by property damages which can reduce equity, economic disruptions which can increase illiquidity, and their interaction.

We first provide evidence of property damages and economic disruptions. Property damages have material impact on home equity, particularly in the case of Maria. Specifically, we divide the treatment and the control groups associated with a hurricane into quartiles by origination LTV, and report their current $LTV_{i,t}$ (derived from the HPI appreciation) in Fig. 4. For the treatment group in the period after 2017q2, we assume that an average household has three members and compute the damage-adjusted LTV. Panel A of Fig. 4 depicts the current LTV of the treatment and the control groups associated with Harvey, with the solid line representing the treatment group and the dashed line representing the control group. Property damages have little impact on the current LTV of loans in quartiles 1 to 3, but increase the average current LTV of loans in quartile 4 from 78% in 2017q2 to 92% in 2017q3. These cross-sectional differences are intuitive, as loans in quartiles 1 to 3 have more initial equity. Panel B plots the corresponding graphs for Hurricane Maria. Property damages push loans in quartile 4 in Puerto Rico closer to negative equity, as the average current LTV increases from 86% in 2017q2 to 96% in 2017q3. This is not surprising, given that mortgages in Puerto Rico have less initial equity prior to the hurricane (recall Table 1). As we have discussed, we use the annual increase in initial claims to measure economic disruptions. Figure 2 shows the substantial increases in initial claims associated with the hurricanes.

If the increases in the first 180-day delinquency rates we document in Section 4.1 are, in part, triggered by property damages, economic disruptions, and their interaction, adding these triggers to Eq. (1) should help diminish the coefficient on $T \times P_1$. We report the regression results in Table 4 for both hurricanes, with all the control variables and the fixed effects as in the specifications (3) and (6) in Table 3. Following previous studies (e.g., Elul et al., 2010), we use LTV indicator variables to allow nonlinear relationship between current LTV and defaults. In Columns (1) and (4), we only include the $LTV_{i,t}$ indicator variables. First, the marginal effect of $LTV_{i,t}$ is generally monotonic and statistically and economically significant. For instance, for the Maria sample in Column (1), going from LTV below 50 to above 110 increases default risk by 49 bps per quarter. Second, the coefficient on $T \times P_1$ decreases from about 50 bps (in Column (3) of Table 3) to about 42 bps (in Column (1) of Table 4) for Maria, and the same coefficient drops from 20 bps (in Column (6) of Table 3) to 17 bps (in Column (4) of Table 4) for Harvey. Therefore, for both hurricanes, relative changes in current LTV triggered by property damages explain about 15% of the increases in the first 180-day delinquency rates.

In Columns (2) and (5), we further account for economic disruptions with the annual increase in initial claims. We use a single indicator for a large increase in initial claims (above 5%), $\Delta Claims_{s,t}$. A large increase in initial claims is associated with higher likelihood of delinquency for the Maria sample, although only marginally significant. For Harvey, the initial claims indicator is insignificant. We emphasize that initial claims may not capture the disruption associated with Harvey in Texas accurately, as this variable is only available at the state level and Harvey submerged part of, not entire, Texas.

In Columns (3) and (6), we enhance the model by taking into account the interaction between property damages and economic disruptions. First, the interaction terms are monotonic and statistically and economically significant for Maria. Second, in the case of Maria, the annual increase in initial claims and its interaction terms with the damage-adjusted LTV help reduce the coefficient on $T \times P_1$ further from about 42 bps in Column (1) to about 18 bps in Column (3). The evidence in Tables 3 and 4 thus suggests that about 65% of the increase in the first 180-day delinquency rate in the case of Maria can be explained by the double-trigger perspective. For Harvey, the coefficient on $T \times P_1$ does not drop further after we account for the annual increase in initial claims and its interaction terms with current LTV. Again, we acknowledge that the initial claims indicator may not capture the disruption associated with Harvey in Texas accurately.

4.3 Cure rates

Hurricanes' longer-term impact in part depends on federal disaster assistance (Gallagher and Hartley, 2017). In the case of residential mortgages, disaster assistance can help defaulted mortgages cure. For instance, hurricane victims may receive cash assistance from FEMA's Individual and Household Program, which can reduce the impact of economic disruptions associated with hurricanes. We test in this section if relatively limited access to federal assistance for Maria victims (which may be in part due to resource strain) may lead to lower cure rates for delinquent mortgages in Puerto Rico relative to delinquent mortgages associated with Harvey in Texas.

One concern is that there may be systematic differences in cure rates that are unrelated with federal assistance between the two pertinent areas. To address this concern, we test if the cure rates are statistically different between the two areas in a period without major disasters. Since federal assistance in such a period is zero for both areas, insignificantly different cure rates between the two areas will weigh against the concern. We choose the period of 2015q3 to 2016q2, as we can track the performance of defaulted loans for one year from 2016q3 to 2017q2 (right before the 2017 hurricane season). In the period of 2015q3 to 2016q2, 1,259 loans became 180-day delinquent for the first time in the zip3 codes that were later struck by Harvey and Maria in 2017q3. We track the performance of these 1,259 loans in the following one year, and estimate a simple cross-sectional regression model to test if cure rates differ between the two pertinent areas:

$$c_i = \alpha Maria_i + X_i\delta + \varepsilon_i \quad (2)$$

where c_i takes the value of one if the defaulted loan i becomes current (less than 180-day delinquent) or prepaid in the following one-year period and zero otherwise, $Maria_i$ is equal to 1 for loans in the zip3 codes that were later struck by Maria and zero otherwise, and the vector X_i contains a set of borrower and loan controls. We cluster standard errors by zip3 to account for correlation across loans in the same zip3, and multiple all the coefficient estimates by 100 so that the estimates are interpretable as percentages. The results are reported in Table 5 under "2015q3-2016q2". In Column (1), we do not include any controls. As we can see, the coefficient estimate on the dummy variable, $Maria_i$, is -4.12% with a t-statistic of -1.13, suggesting that the average cure rates are not statistically different between the two pertinent areas. In Column (2), we account for a set of loan and borrower characteristics at origination. The coefficient estimate on $Maria_i$ is materially unchanged. In Column (3), we further include the current LTV indicator variables, and find that the results are qualitatively similar. The evidence thus is inconsistent with the notion that there are systematic differences in cure rates between the two pertinent areas.

We next test if the cure rates differ between the two pertinent areas for loans that defaulted in the five-quarter period during and after the 2017 hurricane season (i.e., from 2017q3 to 2018q3). Since 2017q3-2018q3 is only one year apart from 2015q3-2016q2, structural changes in cure rates are unlikely. That is, if cure rates differ between the two pertinent areas for loans that defaulted in this period, it is likely due to unequal access to federal assistance, a major variation between the two periods. We re-estimate Eq. (2) on 7,289 loans that became 180-day delinquent for the first time in 2017q3-2018q3, and report the results in Table 5 under "2017q3-2018q3". In Column (1), we do not include any controls. The coefficient estimate on the dummy variable, $Maria_i$, is -12.16% with a t-statistic of -12.88, suggesting that the average cure rate of defaulted loans associated with Maria is 12.16% lower than that associated with Harvey, both statistically and economically significant. In Column (2), we account for a set of loan and borrower characteristics at origination to address the concern that the difference in the cure rates may be due to differences in loan and borrower characteristics. As we can see, the coefficient estimate on $Maria_i$ does not change materially. In Column (3), we further include the current LTV indicator variables. As can be seen, the results are qualitatively similar. The evidence in Table 5 thus supports the notion that unequal access to federal assistance may result in different cure rates between the two pertinent areas after Harvey and Maria.

4.4 Default rates

We have shown that Hurricane Maria results in a higher first 180-day delinquency rate in Puerto Rico, and that delinquent loans in Puerto Rico have a lower cure rate. These findings imply that Hurricane Maria could cause larger increases in the default rate (i.e., the 180+ days delinquency rate) in Puerto Rico. We provide evidence in this section.

In Panel B of Fig. 3, we plot the 180+ days delinquency rates of the treatment and the control groups for Hurricanes Harvey (the left figure) and Maria (the right figure), with the solid line representing the treatment group and the dashed line representing the control group. First, the treatment and the control groups for Harvey (Maria) exhibit parallel trends in the pre-treatment period. Second, the 180+ days delinquency rate of the treatment group does not revert to the pre-hurricane level two years after the hurricane, particularly for Maria. In the case of Harvey, the 180+ days delinquency rates for the treatment group are about 20 bps in 2017q2 (prior to the hurricane) and 28 bps in 2019q3 (two years after the hurricane), respectively. For Maria, the corresponding rates for the treatment group are 100 bps and 165 bps, respectively.

To provide formal evidence, we estimate the DID model, Eq. (1). The dependent variable, $y_{i,t}$, takes the value of one if loan *i* is 180+ days delinquent in quarter *t* and zero otherwise. The results for both hurricanes are reported in Table 6. We focus on the coefficient on $T \times P_2$, which captures the longer-term impact of hurricanes on default rates. Columns (1) and (4) do not include any controls and correspond to Panel B of Fig. 3. Column (4) shows that for Hurricane Harvey, the coefficient on $T \times P_2$ is 0.098% (t = 6.85), suggesting that even with federal assistance Harvey causes the default rate to increase on average by about 10 bps one year after the hurricane. For Maria, Column (1) shows that its average impact is larger, an increase in the default rate of about 86 bps (t = 14.60). In Columns (2) and (5), we include the same set of loan and borrower characteristics. First, the control variables generally have expected signs. Second, the coefficient estimates on $T \times P_2$ for Maria and Harvey do not change materially. In Columns (3) and (6), we further account for a number of fixed effects. Again, the results are qualitatively similar. For Hurricane Harvey, the 180+ days delinquency rate for the treatment group increases on average by about 10 bps (t = 6.80), relative to the control group, two years after the hurricane (i.e., from 2018q4 to 2019q3). For Hurricane Maria, its average impact is an increase in the 180+ days delinquency rate of 91 bps (t = 15.60) over the same period. Given that the average 180+ days delinquency rates for the treatment groups in the pretreatment period are about 20 bps and 104 bps for Harvey and Maria, respectively, the impacts of the hurricanes on the 180+ day delinquency rates are not only statistically but also economically significant.

5 Net Severity and Its Components

Credit losses on residential mortgages depend on not only default rates but also net severity. To the best of our knowledge, prior research has not empirically examined the impact of hurricanes on net severity. We fill this research gap.

5.1 Net severity

Intuitively, net severity could increase or stay unchanged after a disaster. For instance, if government aid promptly mitigates economic and social disruptions after a hurricane, net severity may not change. However, if government disaster assistance is limited, disruptions after a hurricane could increase net severity. For instance, disruptions could increase the length of resolution/workout and therefore drive up interest costs as well as maintenance costs of defaulted properties.

In Panel A of Fig. 5, we plot net severity of the treatment and the control groups for Hurricanes Harvey (the left figure) and Maria (the right figure), with the solid line representing the treatment group and the dashed line representing the control group. First, the treatment and the control groups for Harvey (Maria) exhibit parallel trends in the pre-treatment period. Second, it is interesting to note that all groups, except the treatment group associated with Maria, experience a decrease in net severity after 2017q2, suggesting that economy-wide shocks drive down net severity across the US in this period. Net severity in Puerto Rico would also decrease in the absence of the disruptions caused by Maria. That is, Maria causes an increase in net severity in Puerto Rico to offset the economy-wide trend. This interpretation is plausible. Pasch et al. (2019) report that even at the end of 2017 nearly half of 3.4 million residents of Puerto Rico still had no power, and that practically all cell phone service and municipal water supplies were also lost.

To provide more formal evidence, we estimate a variant of the DID model for loans that have completed the resolution process (completed loans):

$$y_i = \alpha(T_i \times P_t) + \beta T_i + \gamma P_t + X_i \delta + \varepsilon_i \tag{3}$$

where y_i is net severity (or one of its components) of loan i. The GSE data's coverage on completed loans is limited after 2018q4. For instance, the numbers of completed loans in the data are 479, 78, 64, and 0 for 2018q4, 2019q1, 2019q2, and 2019q3, respectively. Therefore, we drop the observations after 2018q4, and P takes the value of one for the quarters between 2017q3 and 2018q4 and zero otherwise.

The results for both hurricanes are reported in Table 7. We focus on the coefficient on T × P, which captures the impact of hurricanes on the treatment group. Columns (1) and (4) do not include any controls and correspond to Panel A of Fig. 5. Column (4) shows that for Hurricane Harvey, the coefficient on T × P is -0.007% (t = -0.00), suggesting that Harvey has insignificant impact on net severity. For Maria, Column (1) shows that its average impact is 20.94% (t = 3.06), both statistically and economically significant. In Columns (2) and (5), we include a set of loan and borrower characteristics. First, the control variables generally have expected signs. For instance, high LTV loans have high net severity, consistent with prior research (Qi and Yang, 2009). Second, the coefficient estimates on T × P for Maria and Harvey do not change materially. In Columns (3) and (6), we further account for a number of fixed effects. Again, the results are qualitatively similar. For Hurricane Harvey, net severity for the treatment group does not change significantly, relative to the control group, after the hurricane. However, for Hurricane Maria, net severity increases by 17.61% (t = 2.75). Given that net severity in Puerto Rico is about 55% in the pretreatment period, the impact of Maria on net severity is not only statistically but also economically significant.

5.2 Components of net severity

To shed further light, we examine the components of net severity, namely Interest Cost, Expenses, and Proceeds.

$$Net\ Severity = \frac{Net\ Loss}{Default\ unpaid\ balance}$$

$$= \frac{Default\ unpaid\ balance + Accrued\ Interest + Total\ Expenses - Total\ Proceeds}{Default\ unpaid\ balance}$$

$$= 1 + \left(\frac{Accrued\ Interest}{Default\ unpaid\ balance} + \frac{+\,Total\ Expenses}{Default\ unpaid\ balance}\right) - \frac{Total\ Proceeds}{Default\ unpaid\ balance}$$

$$= 1 + (Interest\ Cost + Expenses) - Proceeds$$

$$= 1 + Costs - Proceeds$$

In Panel B of Fig. 5, we plot the proceeds component of net severity for the treatment and the control groups associated with Hurricanes Harvey (the left figure) and Maria (the right figure), with the solid line representing the treatment group and the dashed line representing the control group. The key take-away is that the proceeds component of the treatment groups of both hurricanes do not experience noticeable changes relative to the control groups. In Panel C, we plot the costs component of net severity (accounting for both Interest Cost and Expenses) in the same fashion. Interestingly, all groups, except the treatment group associated with Maria, experience a decrease in the costs in the post-2017q2 period, suggesting that the change in net severity of completed loans in Puerto Rico is driven by the change in its costs component. In Fig. 6, we further examine the Interest Cost in Panel A and Expenses in Panel B associated with the two hurricanes in the same fashion. First, the treatment and control groups for Harvey (Maria) exhibit parallel trends in the pre-treatment period. Second, all groups, except the treatment group associated with Maria, experience decreases in Interest Cost and Expenses after 2017q2, suggesting that both components contribute to the change in the foreclosure costs associated with Maria.

In Table 8, we report the regression results based on the components of net severity, with all the control variables and the fixed effects as in the specifications (3) and (6) in Table 7. In Columns (1) and (4), the dependent variable is the proceeds component of net severity. The coefficient estimates on T × P are -4.06% (t = -1.86) and -0.57% (t = -0.13) for Harvey and Maria, respectively, Given that the average values of this component for the treatment groups of Harvey and Maria in the pretreatment period are 111% and 76% respective, the impacts are not statistically and economically significant in both cases. In Columns (2) and (5), we focus on the interest-cost component of net severity. Column (5) shows that for Hurricane Harvey, the coefficient on T × P is -0.091% (t = -0.14), suggesting that Harvey has insignificant impact on the interest-cost component of net severity. For Maria, Column (2) shows that its average impact is an increase in the interest cost of about 6.20% (t = 5.96). Since the average value of this component in the pretreatment period for the Maria treatment group is about 14%, the impact of Maria on Interest Cost is not only statistically but also economically significant. In Columns (3) and (6), we investigate the expense component of net severity. The coefficient estimates on T × P for Harvey and Maria are -2.59% (t = -1.08) and 10.85% (t = 1.92), respectively. Given the average value of this component in the pretreatment period for the Maria treatment group is about 17%, the impact of Maria on Expenses is both statistically and economically significant.

6 Discussion

Logit regressions – Although several outcome variables (e.g., the first 180-day delinquency rate) are binary, to avoid the incidental parameters problem, we follow previous research (e.g., Agarwal et al., 2017) and estimate our specifications with the OLS estimator. In Tables A1 and A2 in Appendix, we estimate a logit specification without fixed effects and report the predictive margins (i.e., the expected probabilities). For instance, the outcome variable in Table A1 takes the value of one if a loan becomes 180-day delinquent for the first time in quarter *t* and zero otherwise. In Columns (1) and (3), we do not include any loan and borrower controls. For Hurricane Harvey, the expected probability of being first 180-day delinquent for the treatment group increases by (0.0025 – 0.0005) – (0.0006 – 0.0006) = 0.0020 = 20 bps, relative to the control group, for a five-quarter period during and after the hurricane. For Hurricane Maria, its impact is an increase in the expected probability of (0.0068 – 0.0017) – (0.0009 – 0.0009) = 0.0051 = 51 bps over the same period. Both estimates are very close to those in Table 3 based on the OLS estimator.

In Columns (2) and (4), we include a number of loan and borrower controls and obtain qualitatively similar results. In Table A2, the outcome variable takes the value of one if a loan is 180+ days delinquent and zero otherwise. The inferred DID estimates are materially similar to those in Table 6 based on the OLS estimator.

Prepayment rate – Previous research (e.g., Gallagher and Hartley, 2017) finds evidence that the prepayment rate increases after Hurricane Katrina, in part due to that reconstruction costs are more than home values. In Table A3 in Appendix, we estimate a variant of our benchmark specification of Eq. (1) with the prepayment rate as the dependent variable. Interestingly, for both Harvey and Maria, we do not find any evidence that the prepayment rate of the treatment group increases relative to the control group. This result may be plausible, as Table 1 shows that property damages on average are about 27%-29% of home equity.

Implications – Our results show that hurricanes could cause significant increases in not only probability of default (i.e., PD) but also net severity (i.e., LGD), two determinants of credit losses, particularly when access to government disaster aid is limited. Given that hurricanes are becoming more damaging and the frequency of the very most damaging hurricanes has increased (Grinsted, Ditlevsen, and Christensen, 2019), hurricanes could potentially affect bank stability through the residential-mortgage channel we examine in this paper, as losses could spillover across institutions and give rise to systemic risk.

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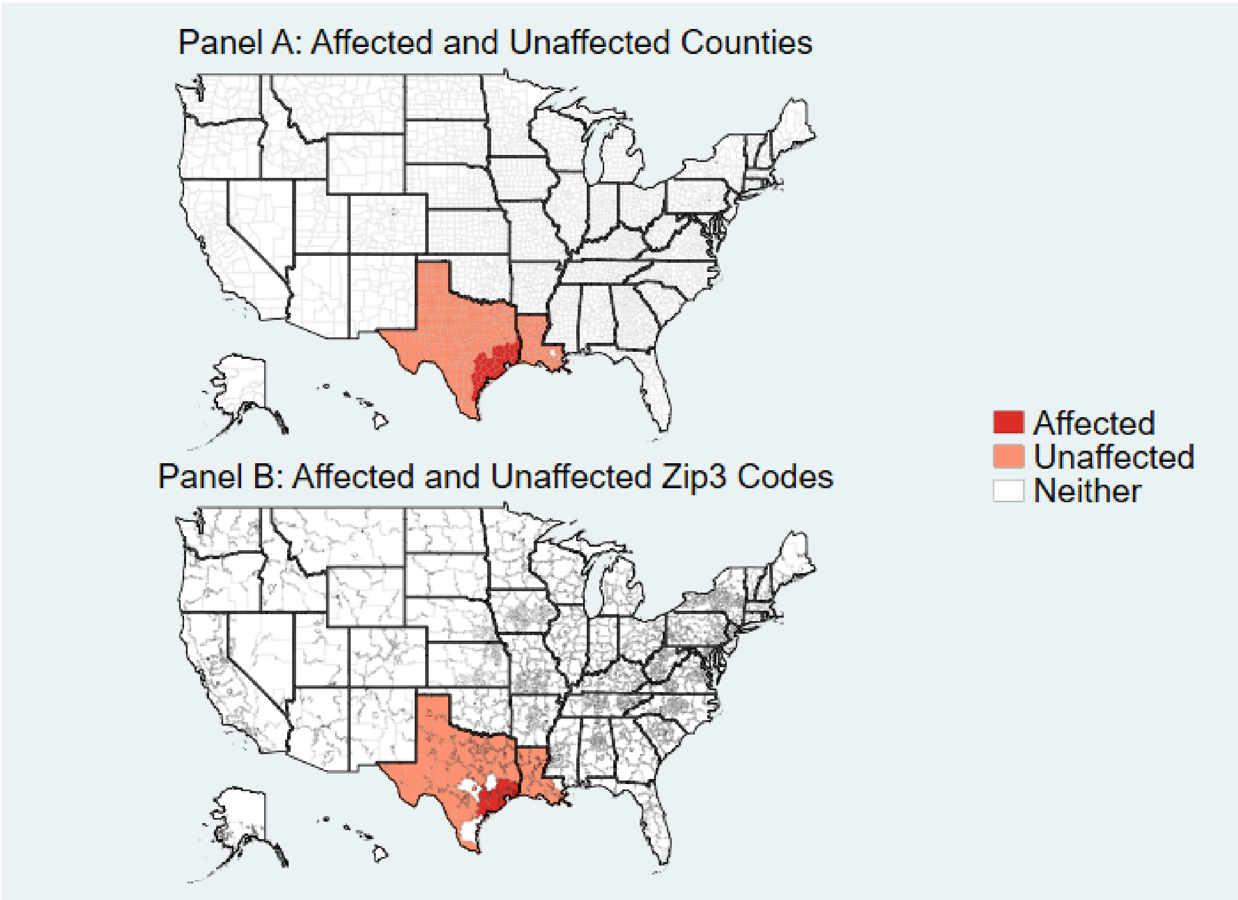
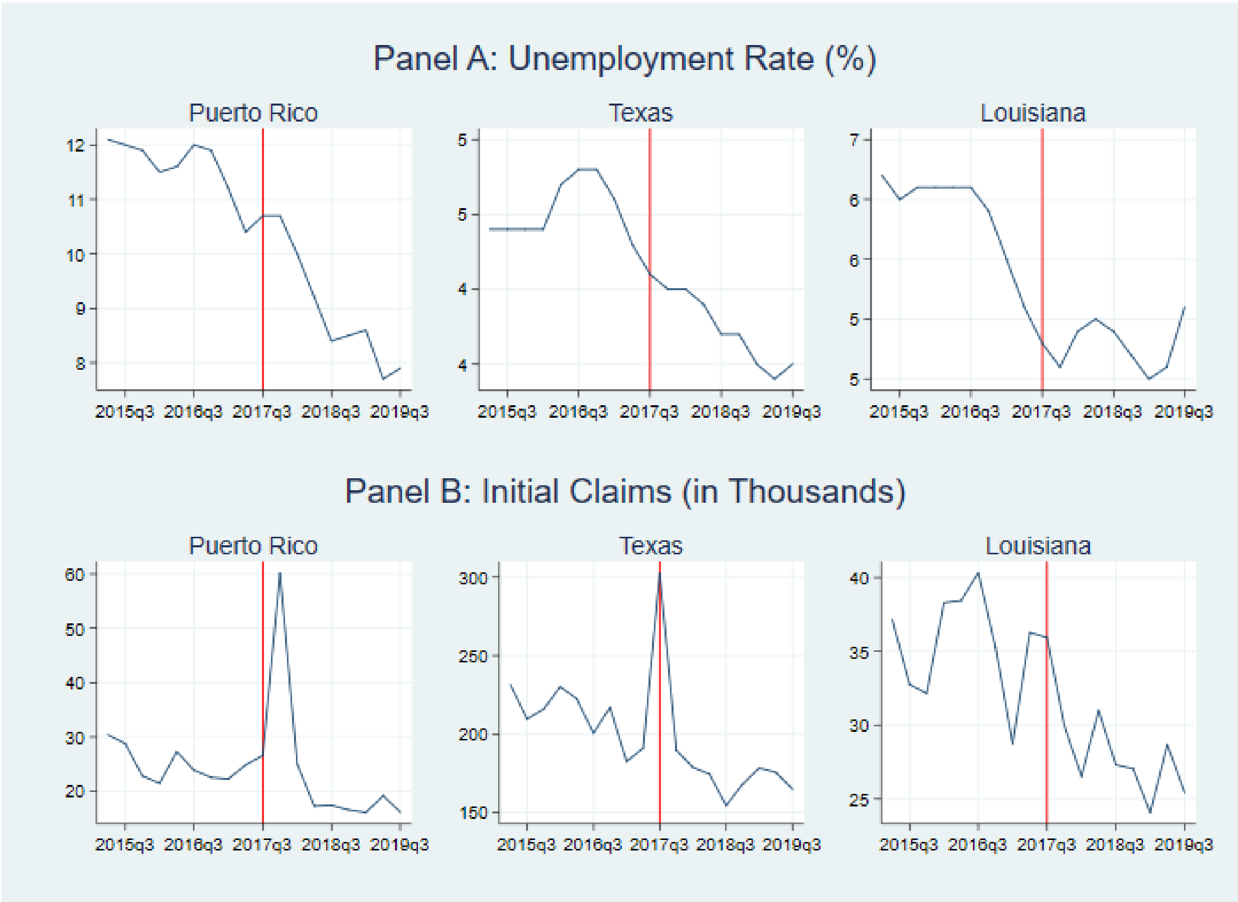
Figure 1 Affected and Unaffected Areas



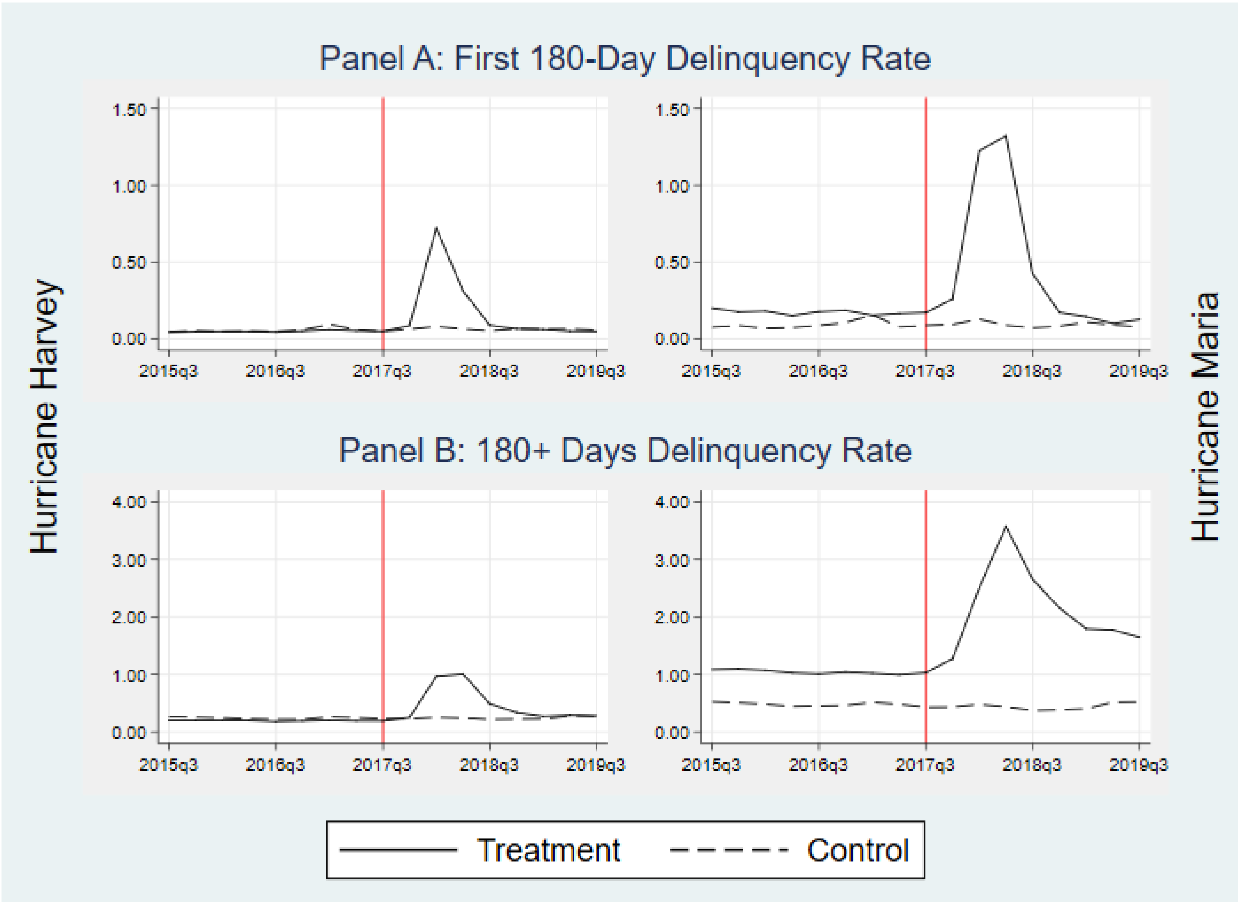
Panel A shows the counties affected by Hurricane Harvey in Texas as well as the counties and parishes in Texas and Louisiana unaffected by major disasters, which we use to construct the control groups. Panel B shows the zip3 codes affected by Hurricane Harvey in Texas as well as the zip3 codes in Texas and Louisiana unaffected by major disasters. The zip3 code 704 in Louisiana is excluded, because it contains Livingston and Orleans, which experienced a major disaster in February 2017. The Zip3 codes 778, 783 and 786 in Texas are also excluded, because less than 80% of house units in these zip3 codes were affected by Harvey.

Figure 2 Unemployment and initial claims



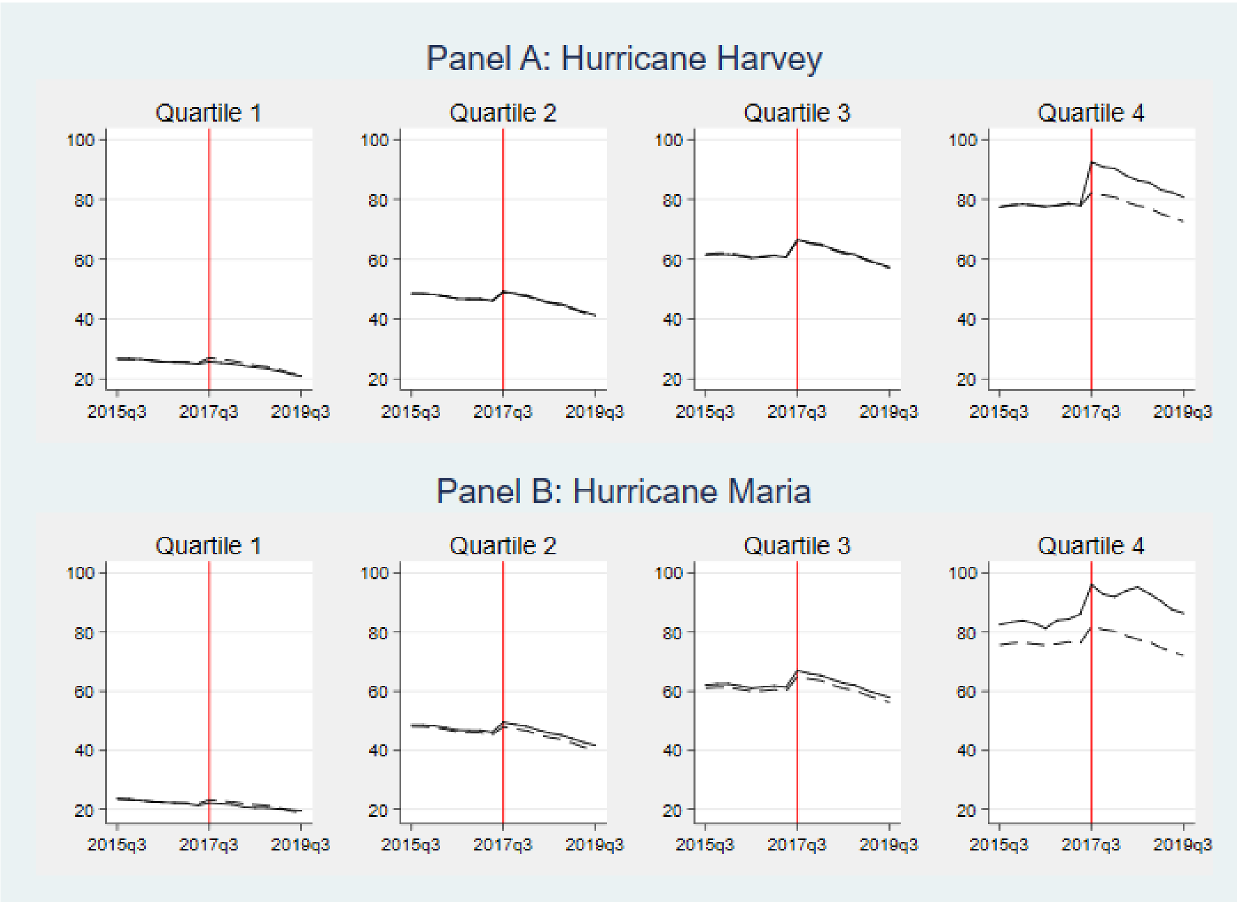
We plot the unemployment rates from FRED in Puerto Rico, Texas, and Louisiana in Panel A, with the vertical line indicating the 2017 hurricane season. In Panel B, we depict initial claims from FRED for the same three states over the same period.

Figure 3 Delinquency rates



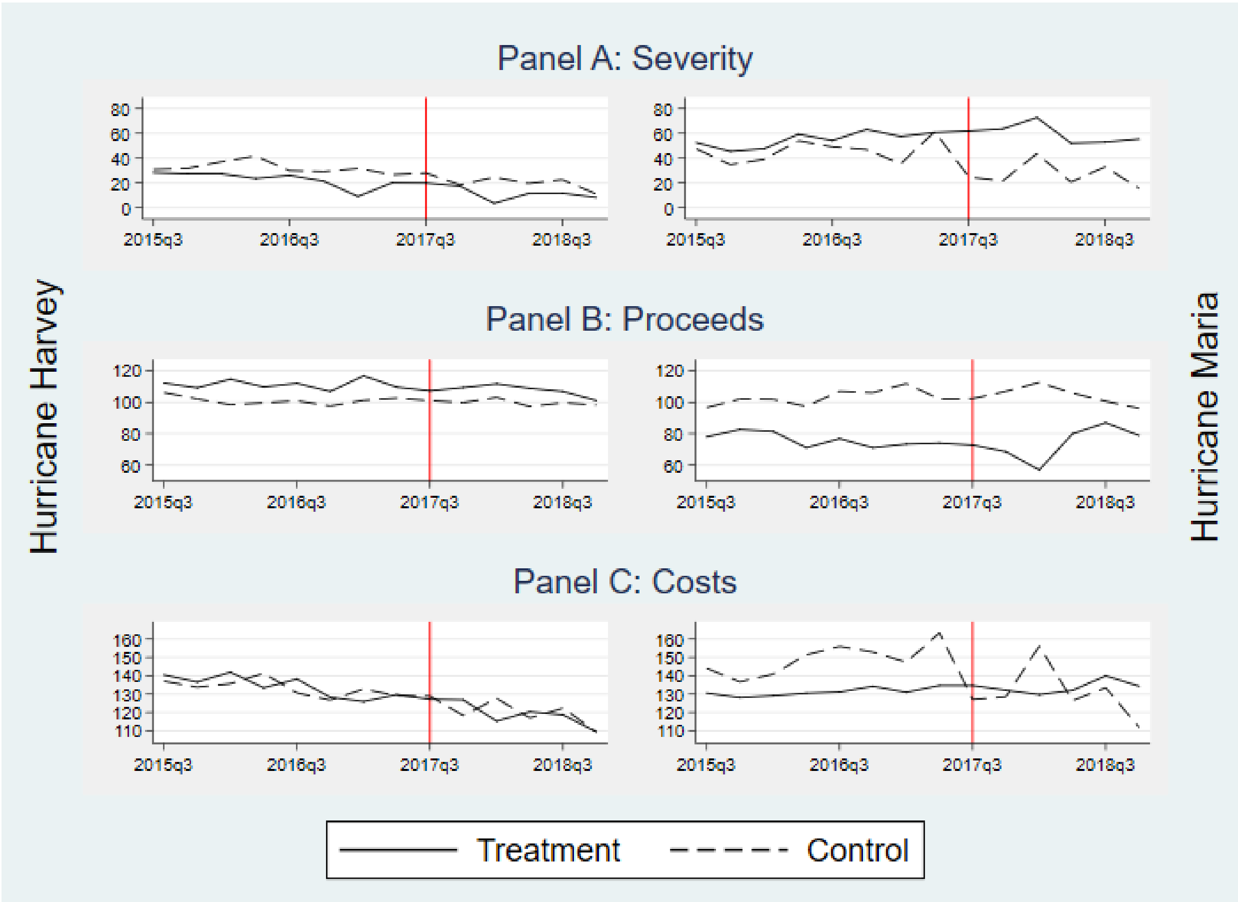
In Panel A, we plot the first 180-day delinquency rates of the treatment and control groups for Hurricanes Harvey (the left figure) and Maria (the right figure), with the solid line representing the treatment group and the dashed line representing the control group. In Panel B, we plot the 180+ days delinquency rates in the same fashion.

Figure 4 LTV and property damages



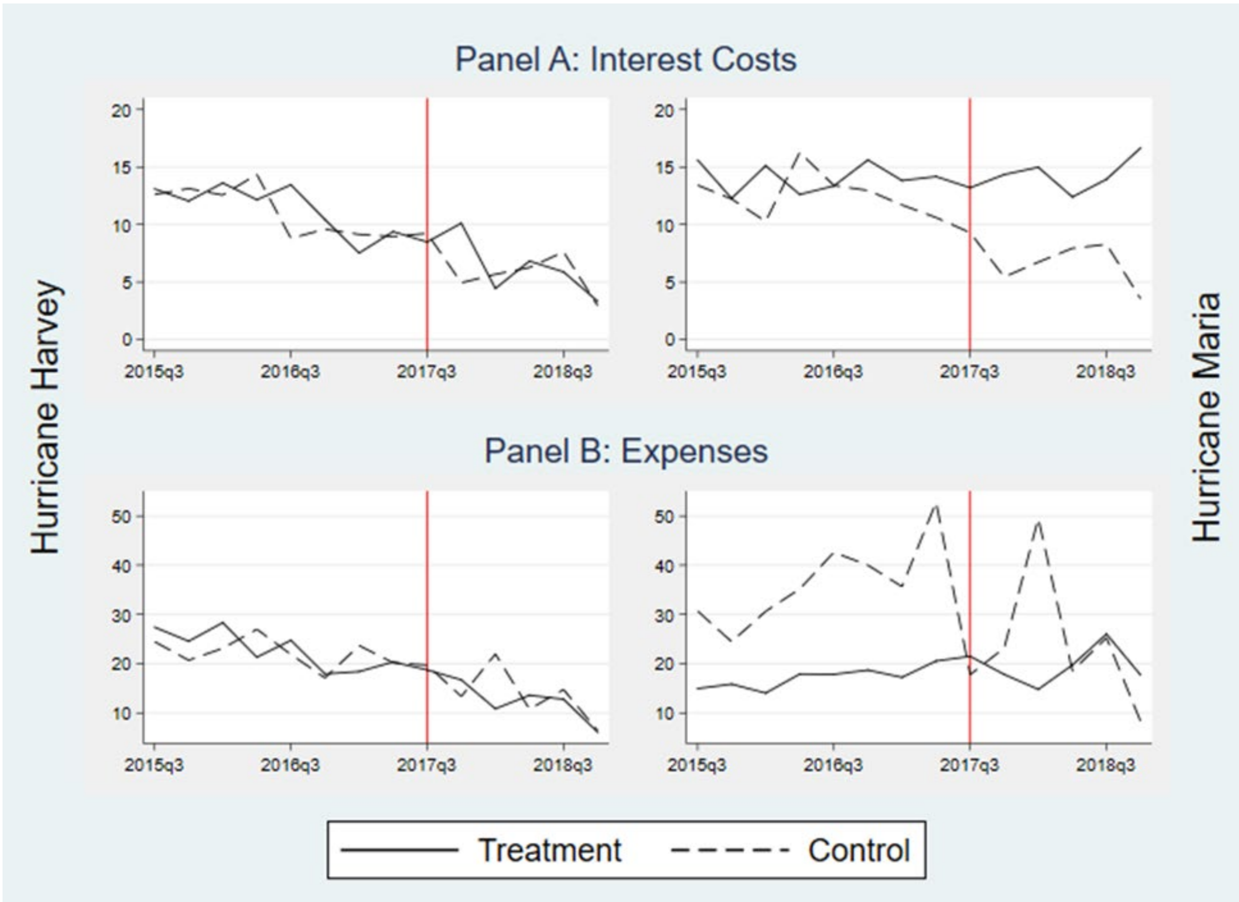
We divide the treatment and control groups associated with a hurricane into quartiles by origination LTV, and report their current LTV (derived from the HPI appreciation). For the treatment group in the period after 2017q2, we assume that an average household has three members and compute the damage-adjusted LTV. Panel A depicts the current LTV of the treatment and control groups associated with Harvey, with the solid line representing the treatment group and the dashed line representing the control group. Panel B shows the current LTV for the Maria treatment and control groups in the same fashion.

Figure 5 LGD and its components



In Panel A, we plot net severity of the treatment and control groups for Hurricanes Harvey (the left figure) and Maria (the right figure), with the solid line representing the treatment group and the dashed line representing the control group. Panels B and C depict the corresponding graphs for the proceeds and costs components in the same fashion.

Figure 6 Interest costs and expenses



We plot the interest-cost component and the expenses component of net severity in Panels A and Panel B, respectively. The solid line represents the treatment group, and the dashed line represents the control group.

Table 1 Hurricanes Harvey and Maria

	Hurricane Harvey 17 August – 1 September 2017 Texas	Hurricane Maria 16–30 September 2017 Porte Rico
Category	Category 4	High-end Category 4
Property damage	\$90 billion	\$20 billion
Property damage per capita	\$14,075	\$5,102
Average home value as of 2017Q2	\$315,803	\$141,655
Average loan amount as of 2017Q2	\$160,579	\$89,622
Average equity as of 2017Q2	\$155,224	\$52,033
3 × Damage per capita/Average Equity	27%	29%
Other damages	About 336,000 customers lost power during the hurricane.	All of 3.4 million residents lost power. At the end of 2017, nearly half were still without power. Practically all cell phone service and municipal water supplies were lost.
NOAA damage estimate	\$125 billion	\$90 billion
Government aid 180 days after landfall	\$13 billion	\$2.4 billion
Government aid/Total damages	10.4%	2.7%

We summarize the key features of Hurricanes Harvey and Maria relevant for our empirical analysis in this table.

Table 2: Comparison of the treated and control groups: 2015q3-2017q3

	Treatment		Control		Normalized Diff
	Mean	SD	Mean	SD	.
	(1)	(2)	(3)	(4)	(1) – (3)
Panel A: Hurricane Harvey					
Initial loan amt ($)	187,700	95,964	189,222	98,304	-0.0111
Initial interest rate (%)	4.32	0.97	4.32	0.96	0.0000
One borrower (%)	52.38	49.94	52.39	49.94	-0.0001
Cash-out refinance (%)	17.78	38.24	17.87	38.31	-0.0017
Investment (%)	7.47	26.30	7.51	26.36	-0.0011
Initial FICO	738.76	51.42	738.73	51.95	0.0004
Initial DTI (%)	33.31	9.95	33.33	9.98	-0.0014
Initial LTV (%)	75.91	15.02	75.92	15.18	-0.0005
180+ delinquent (%)	0.20	4.47	0.24	4.94	-0.0060
Prepaid (%)	3.08	17.28	3.24	17.70	-0.0065
Repurchase (%)	0.00	0.67	0.00	0.62	0.0000
Foreclosure (%)	0.02	1.49	0.04	1.88	-0.0083
Net severity (%)	23.31	31.78	32.73	36.10	-0.1959
Resolution (Months)	24.40	19.87	25.03	18.15	-0.0234
Loan count	519,610		519,610		
Panel B: Hurricane Maria					
Initial loan amt ($)	117,297	70,096	115,844	70,485	0.0146
Initial interest rate (%)	4.67	1.22	4.75	1.23	-0.0462
One borrower (%)	42.23	49.39	40.73	49.13	0.0215
Cash-out refinance (%)	54.27	49.82	55.81	49.66	-0.0219
Investment (%)	5.51	22.83	6.26	24.23	-0.0225
Initial FICO	724.42	55.07	723.78	58.02	0.0080
Initial DTI (%)	35.50	10.69	35.66	11.52	-0.0102
Initial LTV (%)	68.24	16.72	68.73	17.05	-0.0205
180+ delinquent (%)	1.05	10.17	0.48	6.95	0.0463
Prepaid (%)	1.34	11.48	3.74	18.96	-0.1083
Repurchase (%)	0.01	0.85	0.00	0.52	0.0100
Foreclosure (%)	0.10	3.16	0.06	2.54	0.0099
Net severity (%)	55.95	35.20	44.82	48.69	0.1852
Resolution (Months)	32.10	15.90	26.99	17.94	0.2132
Loan count	87,391		87,391		

We compare the treatment to the control groups for Harvey and Maria in the pretreatment period and report the results in this table. Normalized differences are calculated as "the difference in averages by treatment status, scaled by the square root of the sum of the variances" (Imbens and Wooldridge, 2009, p. 24).

Table 3 First 180-day delinquency rates

	Maria			Harvey		
	(1)	(2)	(3)	(4)	(5)	(6)
$T \times P_1$	0.499***	0.499***	0.498***	0.196***	0.196***	0.196***
	(51.95)	(52.81)	(52.94)	(15.85)	(15.71)	(15.70)
$T \times P_2$	-0.036***	-0.029**	-0.030**	0.004	0.004	0.004
	(-2.74)	(-2.15)	(-2.26)	(0.66)	(0.65)	(0.63)
T	0.083***	0.093***	0.093***	-0.009	-0.009	-0.006
	(5.00)	(7.46)	(7.67)	(-0.91)	(-1.14)	(-0.79)
P_1	0.003	0.012*	0.016**	0.004	0.009**	0.012***
	(0.49)	(1.96)	(2.42)	(1.09)	(2.30)	(2.78)
P_2	0.001	0.016*	0.018**	0.005	0.013**	0.015***
	(0.06)	(1.78)	(2.03)	(1.05)	(2.49)	(2.91)
Ln (initial loan amt)		0.103***	0.098***		0.031***	0.032***
		(3.34)	(3.72)		(4.12)	(5.24)
Initial interest rate		0.077***	0.111***		0.043***	0.049***
		(5.70)	(5.20)		(23.25)	(10.16)
One borrower		0.060***	0.058***		0.054***	0.054***
		(10.79)	(11.78)		(9.63)	(10.41)
Cashout refinancing		0.063***	0.060***		0.032***	0.033***
		(4.86)	(4.77)		(4.53)	(5.43)
Investment		0.012	-0.003		-0.021***	-0.021***
		(0.88)	(-0.34)		(-5.45)	(-6.05)
Initial FICO		-0.004**	-0.004**		-0.013***	-0.013***
		(-2.30)	(-2.41)		(-12.18)	(-12.13)
Initial DTI		0.001**	0.001***		0.001***	0.001***
		(2.64)	(2.74)		(6.66)	(6.70)
Initial LTV		0.002***	0.001**		0.001***	0.000***
		(3.02)	(2.02)		(8.01)	(2.92)
Vintage FE	No	No	Yes	No	No	Yes
Channel FE	No	No	Yes	No	No	Yes
Property-type FE	No	No	Yes	No	No	Yes
First-time buyer FE	No	No	Yes	No	No	Yes
PMI FE	No	No	Yes	No	No	Yes
Observations	2,226,542	2,226,542	2,226,542	12,453,090	12,453,090	12,453,090
Adj-R^2	0.002	0.003	0.003	0.001	0.002	0.002

Our DID specification is:

$$y_{it} = \sum_{\tau=1}^{2} \alpha_\tau (T_i \times P_{\tau t}) + \beta T_i + \sum_{\tau=1}^{2} \gamma_\tau P_{\tau t} + X_{it}\delta + \varepsilon_{i,t}$$

where y_{it} takes the value of one if loan *i* becomes 180-day delinquent for the first time in quarter *t* and zero otherwise, T_i is equal to 1 for loans in the treatment group and 0 for loans in the control group, P_{1t} takes the value of 1 for the quarters between 2017q3 and 2018q3 and 0 otherwise, and P_{2t} takes the value of 1 for the quarters after 2018q3 and 0 otherwise. The vector X_{it} contains a set of borrower and loan controls, such as ln (Initial loan amt), Initial interest rate, Initial FICO, Initial DTI, Initial LTV, the one-borrower indicator, the cash-out refinancing indicator, and the investment indicator. Following Elul et al. (2010), FICO is entered quadratically to account for its nonlinear relationship with delinquency. We cluster standard errors by zip3. For ease of interpretation, we multiple all the coefficient estimates by 100 so that the estimates are interpretable as percentages.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 Property damages, illiquid, and mortgage defaults

	Maria			Harvey		
	(1)	(2)	(3)	(4)	(5)	(6)
$T \times P_1$	0.419***	0.253**	0.175**	0.169***	0.169***	0.169***
	(30.57)	(2.64)	(2.52)	(11.11)	(11.18)	(11.06)
$T \times P_2$	-0.097***	-0.168***	-0.107***	-0.019***	-0.019***	-0.019***
	(-8.26)	(-3.69)	(-3.13)	(-3.23)	(-3.22)	(-3.15)
T	-0.007	0.068**	0.076***	-0.005	-0.005	-0.006
	(-0.47)	(2.06)	(3.42)	(-0.87)	(-0.88)	(-0.92)
P_1	0.038***	0.088**	0.068***	0.024***	0.024***	0.023***
	(4.84)	(2.66)	(2.95)	(5.65)	(5.23)	(5.04)
P_2	0.052***	0.122**	0.090***	0.035***	0.035***	0.034***
	(4.64)	(2.64)	(2.87)	(6.92)	(6.08)	(6.05)
LTV∈(50,70]	0.121***	0.114***	0.099***	0.047***	0.047***	0.048***
	(7.72)	(7.46)	(8.10)	(9.33)	(9.24)	(9.97)
LTV∈(70,80]	0.202***	0.195***	0.130***	0.071***	0.071***	0.074***
	(6.28)	(6.11)	(5.22)	(10.32)	(9.78)	(9.36)
LTV∈(80,90]	0.276***	0.268***	0.171***	0.103***	0.104***	0.111***
	(7.46)	(7.34)	(7.67)	(10.54)	(10.25)	(9.79)
LTV∈(90,100]	0.370***	0.363***	0.209***	0.147***	0.147***	0.143***
	(7.95)	(7.77)	(4.13)	(10.10)	(9.89)	(9.66)
LTV∈(100,110]	0.434***	0.428***	0.216***	0.180***	0.181***	0.171***
	(7.91)	(7.69)	(4.74)	(9.80)	(9.74)	(12.09)
LTV>110	0.487***	0.482***	0.201***	0.175***	0.175***	0.139***
	(7.08)	(6.90)	(3.32)	(12.35)	(11.91)	(9.35)
ΔClaims		0.146*	0.053		-0.001	-0.001
		(1.79)	(1.38)		(-0.26)	(-0.14)
LTV∈(50,70] × ΔClaims			0.053			-0.002
			(1.25)			(-0.39)
LTV∈(70,80] × ΔClaims			0.254***			-0.008
			(3.79)			(-1.04)
LTV∈(80,90] × ΔClaims			0.403***			-0.028**
			(6.03)			(-2.43)
LTV∈(90,100] × ΔClaims			0.504***			0.024
			(7.41)			(0.96)
LTV∈(100,110] × ΔClaims			0.654***			0.094**
			(12.98)			(2.19)
LTV>110 × ΔClaims			0.659***			0.318***
			(23.35)			(4.50)
Controls and FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,197,532	2,197,532	2,197,532	12,044,037	12,044,037	12,044,037
Adj-R^2	0.004	0.004	0.004	0.002	0.002	0.002

We use LTV indicator variables to allow nonlinear relationship between current LTV and defaults and a single indicator for a large increase in initial claims (above 5%), $\Delta Claims_{s,t}$. We cluster standard errors by zip3. For ease of interpretation, we multiple all the coefficient estimates by 100 so that the estimates are interpretable as percentages.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5 Cure rates of defaulted loans

	2015q3-2016q2			2017q3-2018q3		
	(1)	(2)	(3)	(4)	(5)	(6)
Maria	-4.116	-3.636	4.804	-12.159***	-13.082***	-12.451***
	(-1.13)	(-0.70)	(0.67)	(-12.88)	(-11.50)	(-9.16)
Ln (initial loan amt)		4.382	6.753**		0.660	0.354
		(1.50)	(2.30)		(0.53)	(0.26)
Initial interest rate		0.536	-0.867		-1.954***	-2.110***
		(0.38)	(-0.64)		(-3.22)	(-3.48)
One borrower		2.871	3.825		-2.833***	-2.698***
		(0.89)	(1.19)		(-5.28)	(-5.34)
Cashout refinancing		1.826	1.462		0.957	0.977
		(0.42)	(0.33)		(1.12)	(1.09)
Investment		-13.990*	-11.456		0.326	0.453
		(-1.86)	(-1.51)		(0.15)	(0.21)
Initial FICO		0.043	0.024		0.152	0.159
		(0.27)	(0.16)		(1.08)	(1.15)
Initial DTI		0.011	0.027		0.019	0.020
		(0.08)	(0.18)		(0.45)	(0.48)
Initial LTV		-0.128	0.118		-0.119***	-0.082*
		(-1.00)	(0.74)		(-3.51)	(-2.12)
LTV∈(50,70]			-5.179			-1.212
			(-1.45)			(-0.65)
LTV∈(70,80]			-11.892**			-1.238
			(-2.59)			(-0.68)
LTV∈(80,90]			-22.049***			1.046
			(-4.09)			(0.59)
LTV∈(90,100]			-5.882			-3.197
			(-1.02)			(-1.10)
LTV∈(100,110]			-33.729***			-2.990
			(-4.80)			(-1.02)
LTV>110			24.339**			-2.987
			(2.64)			(-1.74)
ΔUN			-7.647			-14.024***
			(-1.31)			(-11.17)
Observations	1,259	1,259	1,259	7,289	7,289	7,289
Adj-R^2	0.001	0.007	0.022	0.024	0.031	0.031

We estimate the following cross-sectional regression for two distinct periods.

$$c_i = \alpha Maria_i + X_i\delta + \varepsilon_i$$

where c_i takes the value of one if the defaulted loan i becomes current (less than 180-day delinquent) or prepaid in the following one-year period and zero otherwise, $Maria_i$ is equal to 1 for loans in the zip3 codes that were later struck by Maria and zero otherwise, and the vector X_i contains a set of borrower and loan controls. We cluster standard errors by zip3. For ease of interpretation, we multiple all the coefficient estimates by 100 so that the estimates are interpretable as percentages.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 180+ Days delinquency rates

	Maria			Harvey		
	(1)	(2)	(3)	(4)	(5)	(6)
T × P_1	1.200***	1.196***	1.187***	0.383***	0.380***	0.380***
	(37.86)	(38.02)	(37.82)	(15.65)	(15.29)	(15.15)
T × P_2	0.858***	0.895***	0.908***	0.098***	0.095***	0.095***
	(14.60)	(14.97)	(15.60)	(6.85)	(6.78)	(6.80)
T	0.561***	0.607***	0.616***	-0.044	-0.041*	-0.028
	(5.95)	(10.61)	(9.20)	(-1.19)	(-1.83)	(-1.38)
P_1	-0.053*	0.001	0.035	-0.008	0.021**	0.043***
	(-1.73)	(0.04)	(1.05)	(-0.90)	(2.48)	(5.04)
P_2	-0.042	0.046	0.056	-0.000	0.041***	0.060***
	(-1.09)	(1.16)	(1.40)	(-0.02)	(3.56)	(5.12)
Ln (initial loan amt)		0.631***	0.599***		0.144***	0.168***
		(4.08)	(4.55)		(6.80)	(8.91)
Initial interest rate		0.493***	0.587***		0.263***	0.173***
		(6.05)	(5.87)		(23.78)	(12.03)
One borrower		0.276***	0.282***		0.172***	0.182***
		(8.21)	(7.48)		(11.84)	(13.08)
Cashout refinancing		0.306***	0.284***		0.150***	0.166***
		(6.85)	(7.29)		(6.46)	(7.79)
Investment		-0.043	-0.069**		-0.110***	-0.050***
		(-0.93)	(-2.02)		(-8.39)	(-3.28)
Initial FICO		-0.065***	-0.064***		-0.067***	-0.063***
		(-6.43)	(-6.28)		(-15.01)	(-14.28)
Initial DTI		0.010***	0.011***		0.003***	0.003***
		(3.17)	(3.31)		(6.21)	(6.38)
Initial LTV		0.003	0.001		0.001***	-0.000
		(1.44)	(0.32)		(4.43)	(-0.02)
Vintage FE	No	No	Yes	No	No	Yes
Channel FE	No	No	Yes	No	No	Yes
Property-type FE	No	No	Yes	No	No	Yes
First-time buyer FE	No	No	Yes	No	No	Yes
PMI FE	No	No	Yes	No	No	Yes
Observations	2,330,786	2,330,786	2,330,786	12,631,231	12,631,231	12,631,231
Adj-R^2	0.004	0.013	0.014	0.001	0.008	0.008

Our DID specification is:

$$y_{it} = \sum_{\tau=1}^{2} \alpha_\tau (T_i \times P_{\tau t}) + \beta T_i + \sum_{\tau=1}^{2} \gamma_\tau P_{\tau t} + X_{it}\delta + \varepsilon_{i,t}$$

where y_{it} takes the value of one if loan i is 180+ days delinquent in quarter t and zero otherwise, T_i is equal to 1 for loans in the treatment group and 0 for loans in the control group, P_{1t} takes the value of 1 for the quarters between 2017q3 and 2018q3 and 0 otherwise, and P_{2t} takes the value of 1 for the quarters after 2018q3 and 0 otherwise. The vector X_{it} contains a set of borrower and loan controls, such as ln (Initial loan amt), Initial interest rate, Initial FICO, Initial DTI, Initial LTV, the one-borrower indicator, the cash-out refinancing indicator, and the investment indicator. Following Elul et al. (2010), FICO is entered quadratically to account for its nonlinear relationship with delinquency. We cluster standard errors by zip3. For ease of interpretation, we multiple all the coefficient estimates by 100 so that the estimates are interpretable as percentages.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 Net severity

	Maria			Harvey		
	(1)	(2)	(3)	(4)	(5)	(6)
T × P	20.941***	19.399***	17.606***	-0.007	0.907	1.380
	(3.06)	(2.97)	(2.75)	(-0.00)	(0.29)	(0.45)
T	11.125**	19.004***	19.765***	-9.425***	-8.614***	-7.599***
	(2.66)	(4.89)	(5.00)	(-2.96)	(-3.09)	(-2.79)
P	-18.281***	-15.489***	-13.826**	-12.830***	-10.464***	-10.790***
	(-3.25)	(-2.89)	(-2.58)	(-3.99)	(-3.42)	(-3.70)
Ln (initial loan amt)		-14.260***	-17.084***		-6.629***	-6.112***
		(-3.56)	(-3.87)		(-3.73)	(-3.32)
Initial interest rate		5.952***	8.779***		4.323***	6.266**
		(6.53)	(4.98)		(4.16)	(2.36)
One borrower		-5.433	-6.230		1.794	2.137
		(-1.47)	(-1.66)		(1.25)	(1.41)
Cashout refinancing		14.664***	11.196***		16.207***	13.955***
		(5.67)	(4.82)		(12.72)	(9.91)
Investment		8.422	4.920		7.784*	5.977
		(1.43)	(0.78)		(1.77)	(1.35)
Initial FICO		-0.040	-0.072		-0.005	0.013
		(-0.24)	(-0.44)		(-0.05)	(0.15)
Initial DTI		-0.144	-0.212		-0.037	-0.034
		(-1.24)	(-1.64)		(-0.63)	(-0.57)
Initial LTV		0.259***	0.480***		0.058	0.197**
		(2.97)	(3.41)		(0.77)	(2.59)
Vintage FE	No	No	Yes	No	No	Yes
Channel FE	No	No	Yes	No	No	Yes
Property-type FE	No	No	Yes	No	No	Yes
First-time buyer FE	No	No	Yes	No	No	Yes
PMI FE	No	No	Yes	No	No	Yes
Observations	1,606	1,606	1,606	3,574	3,574	3,574
Adj-R^2	0.048	0.110	0.123	0.027	0.074	0.080

We estimate a variant of the DID model for loans that have completed the resolution process (completed loans):

$$y_i = \alpha(T_i \times P_t) + \beta T_i + \gamma P_t + X_i\delta + \varepsilon_i$$

where y_i is net severity of loan *i*. The GSE data's coverage on completed loans is limited after 2018q4. For instance, the numbers of completed loans in the data are 479, 78, 64, and 0 for 2018q4, 2019q1, 2019q2, and 2019q3, respectively. Therefore, we drop the observations after 2018q4, and *P* takes the value of one for the quarters between 2017q3 and 2018q4 and zero otherwise. We cluster standard errors by zip3.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8 Components of net severity

	Maria			Harvey		
	(1)	(2)	(3)	(4)	(5)	(6)
	Proceeds	Interest	Expense	Proceeds	Interest	Expense
T × P	-0.565	6.196***	10.846*	-4.058*	-0.091	-2.586
	(-0.13)	(5.96)	(1.92)	(-1.86)	(-0.14)	(-1.08)
T	-27.518***	2.577***	-10.330***	8.524***	0.204	0.721
	(-9.56)	(4.01)	(-2.99)	(3.60)	(0.44)	(0.57)
P	1.888	-5.279***	-6.659	-0.707	-4.785***	-6.712***
	(0.76)	(-7.44)	(-1.19)	(-0.53)	(-8.03)	(-3.00)
Ln (initial loan amt)	1.070	0.349	-16.363***	-0.068	1.074***	-7.253***
	(0.47)	(0.97)	(-5.31)	(-0.05)	(4.14)	(-9.28)
Initial interest rate	-7.366***	2.428***	-1.015	-1.276	2.432***	2.558
	(-4.93)	(7.46)	(-0.50)	(-1.19)	(9.02)	(1.09)
One borrower	2.428	0.504	-4.307	1.374	1.290***	2.220
	(1.46)	(0.73)	(-1.24)	(1.14)	(4.08)	(1.48)
Cashout refinancing	-7.906***	2.193***	1.097	-4.196**	4.860***	4.899***
	(-4.04)	(3.39)	(0.54)	(-2.53)	(7.21)	(4.09)
Investment	-8.020*	0.598	-3.698	-7.143*	0.771	-1.937
	(-1.91)	(0.68)	(-0.96)	(-1.85)	(0.69)	(-0.86)
Initial FICO	-0.091	0.047	-0.211	-0.042	-0.009	-0.019
	(-0.68)	(1.01)	(-1.36)	(-0.51)	(-0.39)	(-0.37)
Initial DTI	0.104	-0.023*	-0.085	0.026	0.003	-0.011
	(1.04)	(-1.92)	(-0.58)	(0.57)	(0.13)	(-0.31)
Initial LTV	-0.649***	-0.004	-0.165	-0.339***	-0.027	-0.114
	(-6.91)	(-0.21)	(-1.45)	(-3.58)	(-1.48)	(-1.46)
Vintage FE	Yes	Yes	Yes	Yes	Yes	Yes
Channel FE	Yes	Yes	Yes	Yes	Yes	Yes
Property-type FE	Yes	Yes	Yes	Yes	Yes	Yes
First-time buyer FE	Yes	Yes	Yes	Yes	Yes	Yes
PMI FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,606	1,606	1,606	3,574	3,574	3,574
Adj-R^2	0.206	0.205	0.078	0.081	0.209	0.044

We estimate a variant of the DID model for loans that have completed the resolution process (completed loans):

$$y_i = \alpha(T_i \times P_t) + \beta T_i + \gamma P_t + X_i\delta + \varepsilon_i$$

where y_i is a component of net severity of loan *i*. The GSE data's coverage on completed loans is limited after 2018q4. For instance, the numbers of completed loans in the data are 479, 78, 64, and 0 for 2018q4, 2019q1, 2019q2, and 2019q3, respectively. Therefore, we drop the observations after 2018q4, and *P* takes the value of one for the quarters between 2017q3 and 2018q4 and zero otherwise. We cluster standard errors by zip3.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure A1 The Control Groups

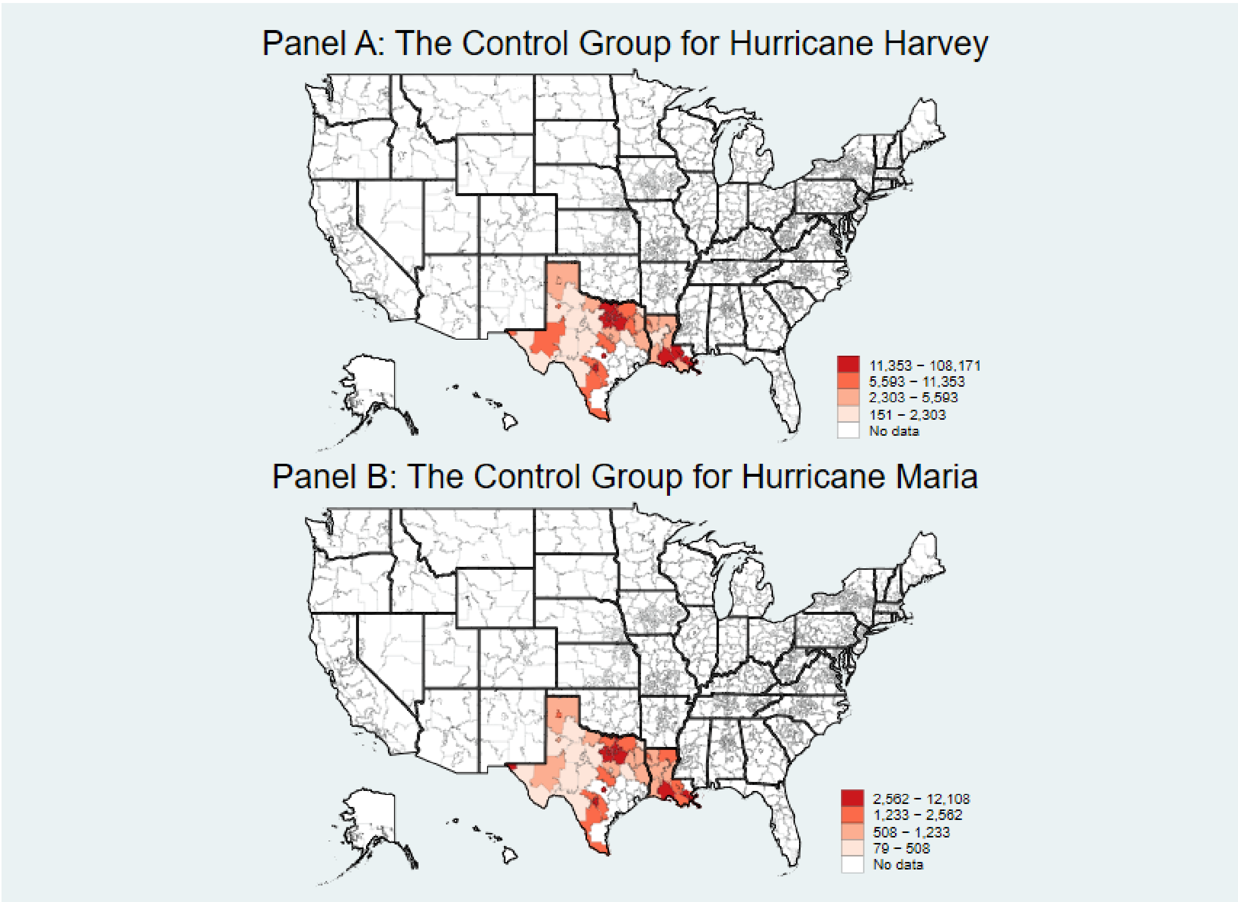


Table A1 First 180-day delinquency: logit regressions

	Maria		Harvey	
	(1)	(2)	(3)	(4)
	Margin	Margin	Margin	Margin
Control $_{\text{Pretreatment}}$	0.0009***	0.0009***	0.0006***	0.0006***
	(22.86)	(22.97)	(42.97)	(43.09)
Control $_{\text{Posttreatment1}}$	0.0009***	0.0009***	0.0006***	0.0006***
	(16.56)	(16.60)	(34.62)	(34.59)
Control $_{\text{Posttreatment2}}$	0.0009***	0.0009***	0.0006***	0.0007***
	(12.21)	(12.23)	(26.58)	(26.56)
Treatment $_{\text{Pretreatment}}$	0.0017***	0.0018***	0.0005***	0.0005***
	(32.56)	(32.54)	(39.78)	(39.92)
Treatment $_{\text{Posttreatment1}}$	0.0068***	0.0071***	0.0025***	0.0026***
	(49.41)	(49.77)	(69.84)	(70.24)
Treatment $_{\text{Posttreatment2}}$	0.0014***	0.0015***	0.0006***	0.0006***
	(18.12)	(18.11)	(25.58)	(25.59)
Controls	No	Yes	No	Yes
Observations	2,226,542	2,226,542	12,453,090	12,453,090

Our DID specification is:

$$y_{it} = \sum_{\tau=1}^{2} \alpha_\tau (T_i \times P_{\tau t}) + \beta T_i + \sum_{\tau=1}^{2} \gamma_\tau P_{\tau t} + X_{it}\delta + \varepsilon_{i,t}$$

where y_{it} takes the value of one if loan *i* becomes 180-day delinquent for the first time in quarter *t* and zero otherwise, T_i is equal to 1 for loans in the treatment group and 0 for loans in the control group, P_{1t} takes the value of 1 for the quarters between 2017q3 and 2018q3 and 0 otherwise, and P_{2t} takes the value of 1 for the quarters after 2018q3 and 0 otherwise. The vector X_{it} contains a set of borrower and loan controls, such as ln (Initial loan amt), Initial interest rate, Initial FICO, Initial DTI, and Initial LTV. FICO is entered quadratically to account for its nonlinear relationship with delinquency. The table reports predictive margins.

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2 180+ days delinquency: logit regressions

	Maria		Harvey	
	(1)	(2)	(3)	(4)
	Margin	Margin	Margin	Margin
Control $_{Pretreatment}$	0.0048***	0.0046***	0.0024***	0.0023***
	(53.52)	(53.91)	(88.75)	(89.49)
Control $_{Posttreatment1}$	0.0043***	0.0043***	0.0024***	0.0025***
	(36.06)	(36.19)	(67.85)	(68.07)
Control $_{Posttreatment2}$	0.0044***	0.0045***	0.0024***	0.0027***
	(27.30)	(27.38)	(52.49)	(52.70)
Treatment $_{Pretreatment}$	0.0105***	0.0104***	0.0020***	0.0019***
	(82.12)	(82.47)	(80.55)	(81.06)
Treatment $_{Posttreatment1}$	0.0219***	0.0227***	0.0058***	0.0060***
	(92.46)	(93.14)	(106.83)	(107.67)
Treatment $_{Posttreatment2}$	0.0186***	0.0206***	0.0030***	0.0032***
	(69.72)	(70.25)	(58.43)	(58.69)
Controls	No	Yes	No	Yes
Observations	2,330,786	2,330,786	12,631,231	12,631,231

Our DID specification is:

$$y_{it} = \sum_{\tau=1}^{2} \alpha_\tau (T_i \times P_{\tau t}) + \beta T_i + \sum_{\tau=1}^{2} \gamma_\tau P_{\tau t} + X_{it}\delta + \varepsilon_{i,t}$$

where y_{it} takes the value of one if loan *i* is 180+ days delinquent in quarter *t* and zero otherwise, T_i is equal to 1 for loans in the treatment group and 0 for loans in the control group, P_{1t} takes the value of 1 for the quarters between 2017q3 and 2018q3 and 0 otherwise, and P_{2t} takes the value of 1 for the quarters after 2018q3 and 0 otherwise. The vector X_{it} contains a set of borrower and loan controls, such as ln (Initial loan amt), Initial interest rate, Initial FICO, Initial DTI, and Initial LTV. FICO is entered quadratically to account for its nonlinear relationship with delinquency. The table reports predictive margins.

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3 Mortgage prepayment rate

	Maria			Harvey		
	(1)	(2)	(3)	(4)	(5)	(6)
T × P	-0.078	-0.075	-0.091	0.023	0.023	0.023
	(-1.25)	(-1.21)	(-1.44)	(0.24)	(0.22)	(0.23)
T	-2.399***	-2.391***	-2.429***	-0.156	-0.157	-0.244**
	(-36.69)	(-28.41)	(-24.30)	(-1.52)	(-1.26)	(-2.01)
P	0.103	0.185***	0.365***	-0.255***	-0.157*	0.109
	(1.67)	(3.00)	(5.46)	(-3.33)	(-2.00)	(1.49)
Ln (initial loan amt)		0.012	0.142***		0.207***	0.372***
		(0.25)	(2.91)		(3.54)	(5.39)
Initial interest rate		0.548***	-0.492***		0.848***	0.332***
		(10.09)	(-15.12)		(34.09)	(4.87)
One borrower		-0.418***	-0.240***		-0.172***	-0.038**
		(-10.48)	(-9.69)		(-9.18)	(-2.35)
Cashout refinancing		0.032	0.041		0.157***	0.275***
		(0.84)	(0.74)		(6.02)	(8.21)
Investment		-0.258***	0.291***		-0.364***	-0.013
		(-5.30)	(5.21)		(-6.22)	(-0.15)
Initial FICO		0.031***	0.031***		0.051***	0.057***
		(3.95)	(3.74)		(11.24)	(14.74)
Initial DTI		-0.006***	-0.005***		-0.012***	-0.008***
		(-3.24)	(-4.37)		(-6.62)	(-5.28)
Initial LTV		-0.020***	-0.015***		-0.012***	-0.006***
		(-8.34)	(-5.17)		(-6.80)	(-4.55)
Vintage FE	No	No	Yes	No	No	Yes
Channel FE	No	No	Yes	No	No	Yes
Property-type FE	No	No	Yes	No	No	Yes
First-time buyer FE	No	No	Yes	No	No	Yes
PMI FE	No	No	Yes	No	No	Yes
Observations	2,330,789	2,330,789	2,330,789	12,631,244	12,631,244	12,631,244
Adj-R^2	0.006	0.008	0.014	0.000	0.002	0.004

Our DID specification is:

$$y_{it} = \sum_{\tau=1}^{2} \alpha_\tau (T_i \times P_{\tau t}) + \beta T_i + \sum_{\tau=1}^{2} \gamma_\tau P_{\tau t} + X_{it}\delta + \varepsilon_{i,t}$$

where y_{it} takes the value of one if loan i is prepaid in quarter t and zero otherwise, T_i is equal to 1 for loans in the treatment group and 0 for loans in the control group, P_{1t} takes the value of 1 for the quarters between 2017q3 and 2018q3 and 0 otherwise, and P_{2t} takes the value of 1 for the quarters after 2018q3 and 0 otherwise. The vector X_{it} contains a set of borrower and loan controls, such as ln (Initial loan amt), Initial interest rate, Initial FICO, Initial DTI, Initial LTV, the one-borrower indicator, the cash-out refinancing indicator, and the investment indicator. FICO is entered quadratically to account for its nonlinear relationship with delinquency. We cluster standard errors by zip3. For ease of interpretation, we multiple all the coefficient estimates by 100 so that the estimates are interpretable as percentages.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1